Large Scale Character Classification

Thesis submitted in partial fulfillment
of the requirements for the degree of

Master of Science (by Research)
in
Computer Science

by

Neeba N.V
200650016
neeba@research.iiit.ac.in
http://research.iiit.ac.in/~neeba

International Institute of Information Technology
Hyderabad, India
August 2010

INTERNATIONAL INSTITUTE OF INFORMATION TECHNOLOGY
Hyderabad, India

CERTIFICATE

It is certified that the work contained in this thesis, titled *Large Scale Character Classification* by Neeba N.V, has been carried out under my supervision and is not submitted elsewhere for a degree.

Date

Advisor: Dr. C. V. Jawahar

To my Loving parents.

O Lord, May I accept gracefully, what I can not change.
O Lord, May I have the will and effort to change what I can change.
O Lord, May I have the wisdom to understand, what I can change, and What I can not Change.

Acknowledgements

I am deeply indebted to my advisor Dr. C. V. Jawahar for his kindness, dedication, encouragement, motivation and also for his inspiring guidance and supervision throughout my thesis work. I am also greatly indebted to Dr. P. J. Narayanan (PJN) for his concern, encouragement and advise. My sincere thanks also forwarded to Dr. Anoop M. Namboodiri for his critical comments on my conference papers.

I would also like to thank document understanding research groups at Centre for Visual Information Technology (CVIT), who had made great contribution by sharing ideas, comments and materials. My dearest thanks goes to Anand Kumar, Million Meshesha, Jyotirmoy, Rasagna, and Jinesh for their valuable suggestions and kindness to help me in any way possible. A special thanks goes to my friend Ilayraja, who was my project partner for the work "Efficient Implementation of SVM for Large Class Problems". I extend my thanks to my friends Lini, Satya, Pooja and Uma for their support during my MS.

Last, but not the least, the almighty, my parents, my relatives and all those from CVIT who had at some or the other point in time helped me with their invaluable suggestions and feedback, and my research center, Center for Visual Information Technology (CVIT), for funding my MS by research in IIIT Hyderabad.

Abstract

Large scale pattern classification systems are necessary in many real life problems like object recognition, bio-informatics, character recognition, biometrics and data-mining. This thesis focuses on pattern classification issues associated with character recognition, with special emphasis on Malayalam. We propose an architecture for the character classification, and proves the utility of the the proposed method by validating on a large dataset. The challenges we address in this work includes: (i) Classification in presence of large number of classes (ii) Efficient implementation of effective large scale classification (iii) Simultaneous performance analysis and learning in large data sets (of Millions of examples).

Throughout this work, we use examples of characters (or symbols) extracted from real-life Malayalam document images. Developing annotated data set at the symbol level from a coarse (say word-level) annotated data is addressed first with the help of a dynamic programming based algorithm. Algorithm is then generalized to handle the popular degradations in the form of cuts, merges and other artifacts. As a byproduct, this algorithms allows to quantitatively estimate the quality of the books, documents and words. The dynamic programming based algorithm aligns the text (in UNICODE) with images (in Pixels). This helps in developing a large data set which could help in conducting large scale character classification experiments.

We then conduct an empirical study of classifiers and feature combination to explore their suitability to the problem of character classification. The scope of this study include (a) applicability of a spectrum of popular classifiers and features (b)scalability of classifiers with the increase in number of classes (c) sensitivity of features to degradation (d) generalization across fonts and (e) applicability across scripts. It may be noted that all these aspects are important to solve practical character classification problems. Our empirical studies provide convincing evidences to support the utility of SVM (multiple pair-wise) classifiers for solving the problem.

However, a direct use of multiple SVM classifiers has certain disadvantages: (i) since there are nC_2 pairwise classifiers, storage and computational complexity of the final classifier becomes high for many practical applications. (ii) they directly provide a class label and fail to provide an estimate of the posterior probability. We address these issues by efficiently designing a Decision Directed Acyclic Graph (DDAG) classifier and using the appropriate feature space. We also propose efficient methods to minimize the storage complexity of support vectors for the classification purpose. We also extend our algebraic simplification

method for simplifying hierarchical classifier solutions.We use SVM pair-wise classifiers with DDAG architecture for classification. We use linear kernel for SVM, considering the fact that most of the classes in a large class problem are linearly separable.

We carried out our classification experiments on a huge data set, with more than 200 classes and 50 million examples, collected from 12 scanned Malayalam books. Based on the number of cuts, merges detected, the quality definitions are imposed on the document image pages. The experiments are conducted on pages with varying quality. We could achieve a reasonably high accuracy on all the data considered. We do an extensive evaluation of the performance on this data set which is more than 2000 pages.

In presence of large and diverse collection of examples, it becomes important to continuously learn and adapt. Such an approach could be more significant while recognizing books. We extend our classifier system to continuously improve the performance by providing feedback and retraining the classifier. We also discuss the limitations of the current work and scope for future work.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Pattern Classifiers

"Pattern recognition is the study of how machines can observe the environment, learn to distinguish patterns of interest from their background, and make sound and reasonable decisions about the categories of the patterns" [1]. A complete pattern recognition system consists of a sensor that gathers the observations to be classified or described, a feature extraction mechanism that computes numeric or symbolic information from the observations, and a classification scheme or classifier that does the actual job of classifying or describing observations, relying on the extracted features [1, 2].

The classification scheme is usually based on the availability of a set of patterns that have already been classified or described. This set of patterns is termed the training set, and the resulting learning strategy is characterized as supervised learning. Learning can also be unsupervised, in the sense that the system is not given any *apriori* labeling of patterns, instead it itself establishes the classes based on the statistical regularities of the patterns. A wide range of algorithms exist for pattern recognition, from naive Bayes classifiers and neural networks to the powerful SVM decision rules.

Traditional pattern recognition literature aims at designing optimal classifiers for two class classification problems. However, most of the practical problems are multi-class in nature. When the number of classes increases, the problem becomes challenging, both conceptually as well as computationally. Large scale pattern recognition systems are necessary in many real life problems like object recognition, bio-informatics, character recognition, biometrics and data-mining. This thesis proposes a classifier system for effectively and efficiently solving the large class character classification problem. The experiments are con-

ducted on large Indian language character recognition datasets. We demonstrate our results in the context of a Malayalam optical character recognition (OCR) system.

1.2 Overview of an OCR System

A generic OCR process starts with the pre-processing of the document. Preprocessing includes, noise removal, thresholding of a gray-scale or colour image to obtain a binary image, skew-correction of the image, etc. After pre-processing, the layout analysis of the document is done. It includes, various levels of segmentation, like block/paragraph level segmentation, line level segmentation, word level segmentation and finally component/character level segmentation. Once the segmentation is achieved, the features of the symbols are extracted. The classification stage recognizes each input character image by computing the detected features. The script-dependent module of the system will primarily focus on robust and accurate symbol and word recognition.

The symbol recognition algorithm employs a base classifier(BC) with very high performance to recognize isolated symbols. Any error at this stage can get propagated, if not avalanched into the next phase. We approach this critical requirement of high performance by a systematic analysis of the confusion and providing additional intelligence into the system. However, such a symbol classifier can not directly work in presence of splits, merges and excessive noise. They are addressed at the word recognizer level, which internally uses the symbol recognizer.

Figure 1.1 gives the overall design of the OCR system. We will take a quick look at the pre-processing and post-processing modules and then explore the core recognition engine in further detail.

- *Binarization:* The first step in recognition is the conversion of the input image into a binary one and removal of noise. Popular approaches such as adaptive thresholding and median filtering work well with most documents.

- *Skew Correction:* Popular techniques for skew detection in English documents such as component distribution based estimates do not work in the case of Malayalam due to the complexity of its glyph distribution. Instead, horizontal projection profile based approaches yield better results, although they require multiple lines of text to function well.

- *Page Segmentation:* The segmentation module divides the text regions into blocks, lines, words and connected components. The recognition module assumes that the

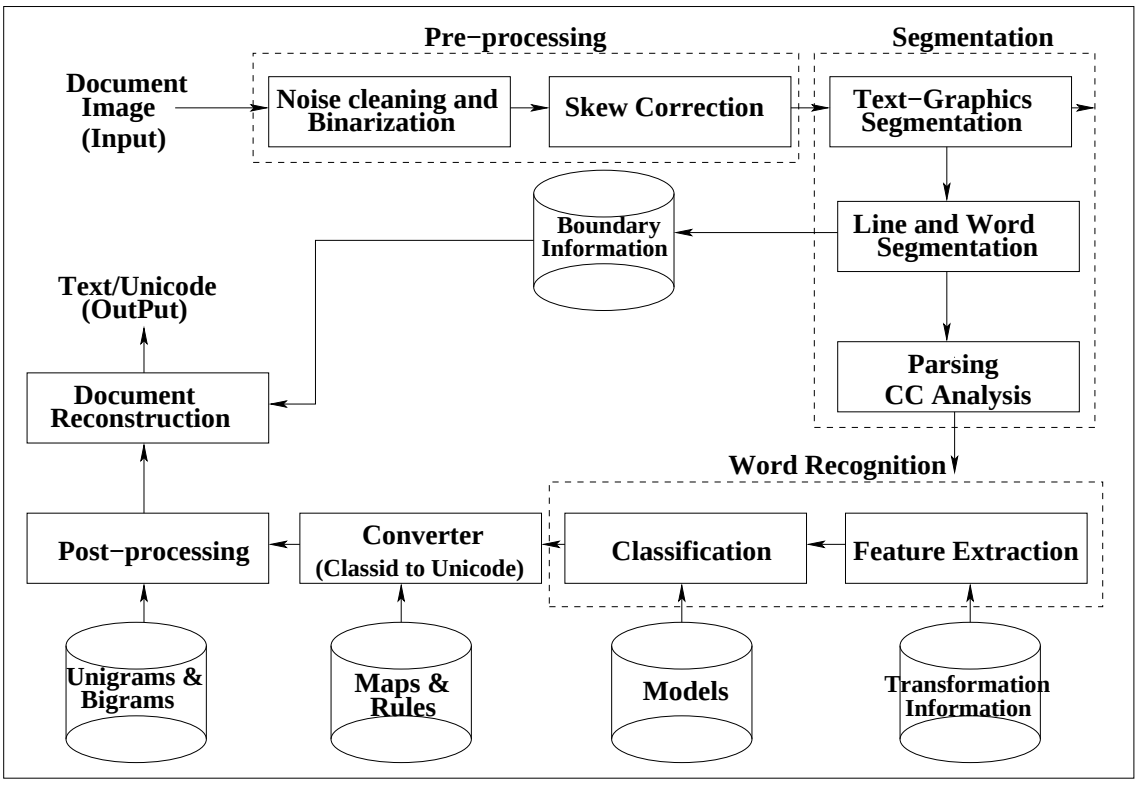


Figure 1.1: Overall architecture of an OCR system.

input is a set of components corresponding to a single word. Many efficient algorithms are known for identification of connected components in binary images.

- *Feature extraction for components:* Feature extraction is an important step of the pattern classification problem. With high dimensionality of the features, the process of pattern classification becomes very cumbersome. Hence there is a need to reduce the dimensions of the features without loss of useful information. Dimensionality reduction techniques such as, principal component analysis(PCA) and linear discriminant analysis(LDA) transform the features into a lower dimensional space without much loss in information. However, there are methods for the subset selection such as forward search, backward search and Tabu search which can be used to select only a few features that can be helpful in classification. We explore appropriate feature selection methods for (i)performance improvement and (ii)enhancing computational efficiency.

- *Component Recognizer:* The component classifier is designed to develop a hypothesis for the label of each connected component in a given word. The goal is to make

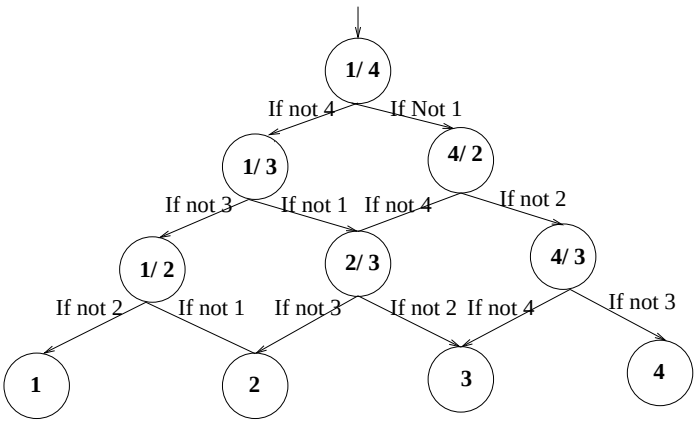


Figure 1.2: A four class DAG arrangement of pairwise classifiers.

it efficient and accurate in presence of noise. Instead of using a direct multi-class classifier, use of multiple small classifiers can provide accurate and efficient pattern classification. These modular classifiers can be organized in a hierarchical manner, using the popular divide and conquer strategy, which breaks down the huge and complex task into small manageable sub-tasks. A multi-class classifier can be built using DDAG (Decision Directed Acyclic Graph). A DDAG is a generalization of a decision tree. It is used to combine pair-wise classifiers. An example of a DAG for a 4-class classification problem is given in the Figure 1.2.

- *Word Recognizer:* The task of the word recognizer is to combine the recognition results of the individual components and generate the most likely hypotheses regarding the underlying word. Language models of various complexities are often employed at this step.

- *Component to Unicode generation:* This process depends on a map-file, which contains all the mappings from components to Unicode. In the case of Malayalam, some of the matras and aksharas are missing in the Unicode list. So, we need some rules, which maps to a set of characters which is producing an alternative representation of the same akshara/ matra. A rules file contain the required rules for this purpose.

1.3 Indian Language OCR : Literature Survey

Research for character recognition started with the optical character system (OCR) developed in the 1960's, which can recognize certain characters mainly, numbers and the English

alphabet. The use and applications of OCRs are well developed for most languages in the world that use both Roman and non-Roman scripts [3, 4]. An overview on the last forty years of technical advances in the field of character and document recognition is presented by Fujisawa [5].

However, the optical character recognition for Indian languages is still an active research area [6]. There are a large number of studies conducted on the recognition of Indian languages [7][8]. Summary of the works done are presented in Table 1.1. A comprehensive review of Indian scripts recognition is reported by Pal and Chaudhuri [8]. A brief discussion of some of the works on Indian scripts is reported in [9]. Structural and topological features with tree-based and Neural Network classifiers are mainly used for the recognition of Indian scripts.

Printed *Devanagari* character recognition has been attempted based on K-nearest neighbor (KNN) and Neural Networks classifiers [10][11]. For classification purpose, the basic, modified and compound characters are separated. Modified and basic characters are recognized by a structural features (such as concavities and intersections) based binary tree classifier [10]. A hybrid of structural and run-based template features were used for the recognition of compound characters. They reported an accuracy of 93%. Another study with using Tree classifier and structural and template features reported an accuracy of 96.5% [11]. Both the cases did not mention the size of the test dataset.

These results were also extended to Bangla script [12][11]. A complete OCR system for printed Bangla script is presented by Chaudhuri and Pal [12], where the compound characters are recognized using a tree classifier followed by template-matching approach. Stroke features are used to design the tree classifiers. The character unigram statistics is used to make the the tree classifier efficient. Several heuristics are also used to speed up the template matching approach. A dictionary-based error-correction scheme has been integrated where separate dictionaries are compiled for root word and suffixes that contain Morphy's-syntactic information as well. The test dataset is not mentioned in this case.

A similar approach was tried for Urdu [13] in which a tree-classifier is employed for the recognition of Urdu script after extracting a combination of topological, contour and water reservoir features. It reports an accuracy of 97.8% on 3050 characters tested.

Script	Ref.	Classifiers	Features	Accuracy Claimed	Data Tested
Hindi/ Devanagari	[10]	Distance based	Structural , Moments	93	NM*
	[14]	multiple connectionist	Structural, density Features	93	NM*
	[15]	Tree Classifier	Structural and template features	96.5	NM*
Bangla	[12]	Tree Classifier	Stroke based features	94-97	NM*
Gurmukhi	[16]	Binary decision tree and KNN	Structural Features	97.34	25 pages
	[17]	Binary tree classifier	Structural Features	96.6	100 pages
Gujarati	[18]	Hamming distance; K-NN	Moments	67	NM*
Oriya	[19]	Matching	Structural Features	74-86	NM*
	[20]	Hybrid Tree Classifier	Stroke based, water overflow from reservoir	96.3	NM*
Tamil	[21]	Time Delay Neural Networks	Gabor Filters	90-97	2700 chars
Telugu	[22]	KNN	Directional Features	92	30 pages
	[23]	Fringe Distance	Fringe Map	92	2524 chars.
	[24]	Matching	Quantized relative directional features	78-95	507 chars.
Kannada	[25]	Support Vector Machines	Fisher Discriminant analysis	93	NM*
	[26]	Support Vector Machines	Structural Features	86	NM*
Malayalam	[27]	Binary decision tree	Pixels	94-97	500 pages
Urdu	[13]	Tree classifier	Structural features; run-based template	97.8	3050 chars

Table 1.1: Major works for the recognition of document images in Indian languages. * - Not mentioned

Antanani and Agnihotri [18] reported character recognizer for Gujarathi script that uses minimum Euclidean distance, hamming distance and KNN classifier with regular and Hu invariant moments. The test dataset is not mentioned in this case.

Lehal and Singh reported a complete OCR system for Gurmukhi Script [16]. They use two feature sets: primary features like number of junctions, number of loops, and their positions and secondary features like number of endpoints and their locations, nature of profiles of different directions. A multistage classifications scheme is used by combining binary tree and nearest neighbor classifier. They supplement the recognizer with post-processor for Gurmukhi Script where statistical information of Panjabi language syllable combinations, corpora look-up and certain heuristics have been considered. They reports an accuracy of 96.6% on a test dataset of 100 pages.

An OCR system was also reported on the recognition of *Tamil and Kannada* script [28]. Recognition of Kannada script using Support Vector machine (SVM) has been proposed [29]. To capture the shapes of the Kannada characters, they extract structural features that characterizes the distribution of foreground pixels in the radial and angular directions. The size of test dataset is not mentioned in this case. A Tamil [21] OCR using *Time Delay neural Networks* and Gabor Filters as feature, reports an accuracy of $90-97\%$ on their test dataset of 2700 characters in 2003.

For the recognition of *Telugu* script, Negi *et al.* [23] proposed a compositional approach using connected components and fringe distance template matching. The system is tested on 2524 characters and reported an accuracy of 92%. Another system is developed with directional features and KNN as classifier reported an accuracy of 92%. Yet another Telugu OCR using quantized relative directional features and template matching reported an accuracy of $78-95\%$ accuracy on 507 characters tested.

An OCR system for *Oriya* script was reported recently [19]. Structural features (such as vertical line, number and position of holes, horizontal and vertical run code) are extracted for modifiers (matra) and run length code, loop and position of hole for composite characters, and a tree-based classification is developed for recognition. The system has been integrated with spell checker with the help of dictionary and a huge corpus to post-process and improve the accuracy of the OCR. Another OCR system for Oriya is reported with stroke based features and template matching. Even though they report an accuracy of 96.3% and $74-86\%$ respectively, these studies have not mentioned about the test dataset used.

An OCR system for *Malayalam* language is also available [27] in the year of 2003. A two level segmentation scheme, feature extraction method and classification scheme, using binary decision tree, is implemented. This system is tested on around 500 printed and

real pages, and report an accuracy of $94 - 97\%$. Not enough technical details and analysis available for this system.

Though there are various pieces of works reported by many research institutions, the document analysis technology on Indian scripts is not so mature. This is attributed to the existence of large number of characters in the scripts and their complexity in shape [7]. As a result of which a bilingual recognition systems has been reported in recent past [11][30]. An OCR system that can read two Indian language scripts: Bangla and Devanagari (Hindi) is proposed in [11]. In the proposed model, document digitization, skew detection, text line segmentation and zone separation, word and character segmentation, character grouping into basic, modifier and compound character category are done for both scripts by the same set of algorithms. The feature sets and classification tree as well as the lexicon used for error correction differ for Bangla and Devanagari. Jawahar *et al.* [30] presents character recognition experiments on printed Hindi and Telugu text. The bilingual recognizer is based on principal component analysis followed by support vector classification. Attempts that focused on designing a hierarchical classifier with hybrid architecture [31], as well as a hierarchical classifiers for large class problems [32] are also reported in the recent past.

1.4 Challenges

Compared to European languages, recognition of printed documents in Indian languages is a more challenging task even at this stage. It becomes challenging because of the complexity of the script, lack of resources, non-standard representations, and the magnitude of the pattern recognition task. Sample paragraphs from various Indian languages are given in the Figure 1.3. Some of the specific challenges are listed below.

- Large number of characters are present in Indian scripts compared to that of European languages. This makes the recognition difficult for conventional pattern classifiers. In addition, applications related to character recognition demand extremely high accuracy at symbol level. Something closer to perfect classification is often demanded.
- Complex character graphemes with curved shaped images and the added inflation make the recognition difficult.
- Unicode/display/font related issues in building, testing and deploying working systems, slowed down the research in the development of character recognition system.
- Large number of similar/confusing characters: There are a set of characters which

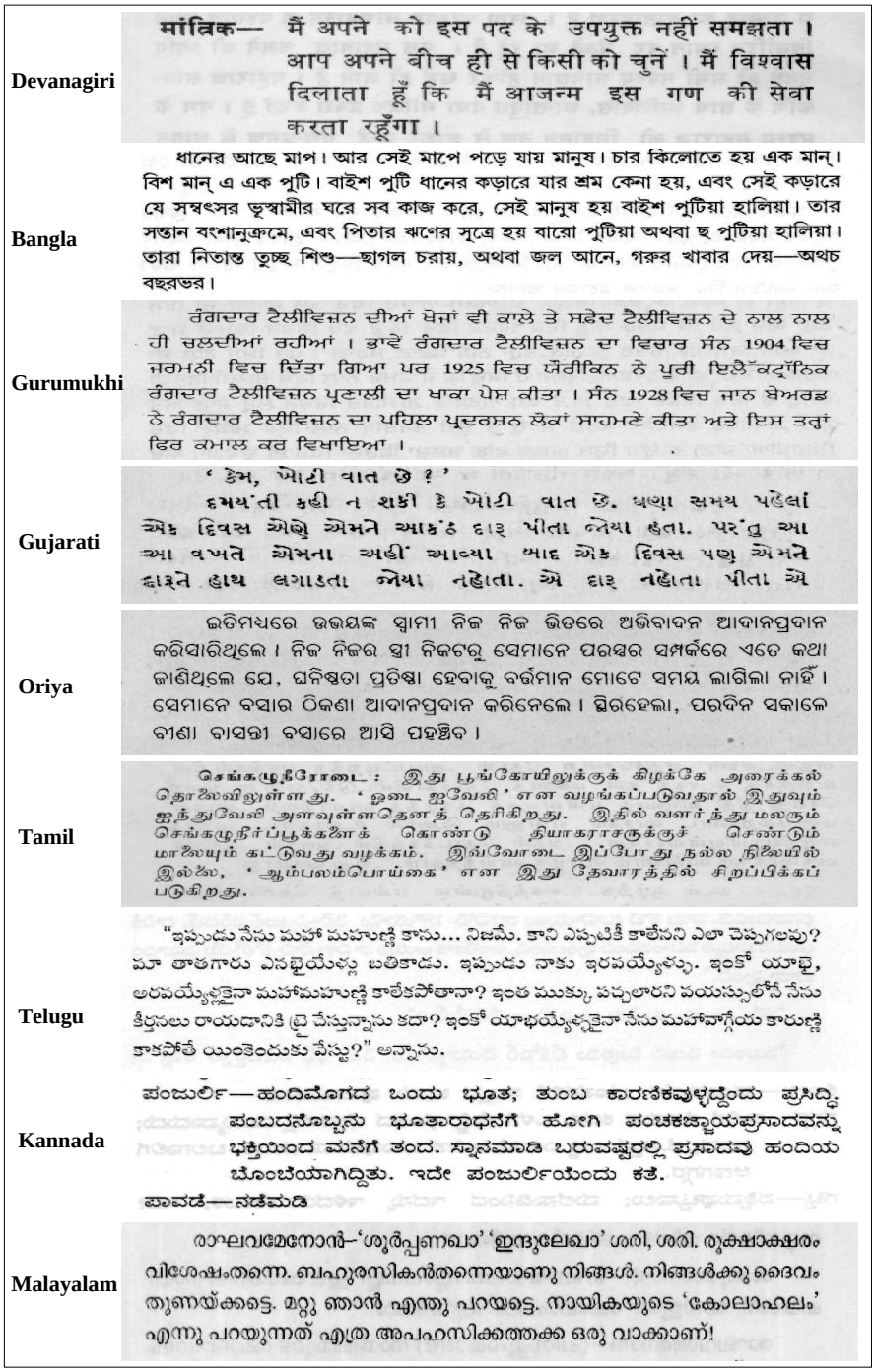


Figure 1.3: Sample paragraphs from various Indian language books.

look similar to each other. The variation between these characters is extremely small. Even humans find it difficult to recognize them in isolation. However, we usually read them correctly from the context.

- Variation in glyph of a character with change in font/style: As the font or style changes the glyph of a character also changes considerably, which makes the recognition difficult.

- Lack of standard databases, statistical information and benchmarks for testing, are another set of challenges in developing robust OCRs.

- Lack of well developed language models, makes the conventional post-processor practically impossible.

- Quality of documents in terms of paper quality, print quality, age of document, the resolution at which the paper is scanned etc. affects the pattern recognition considerably. The document image may have undergone various kinds of degradations like cuts, merges or distortion of the symbols, which reduces the performance of the recognizers.

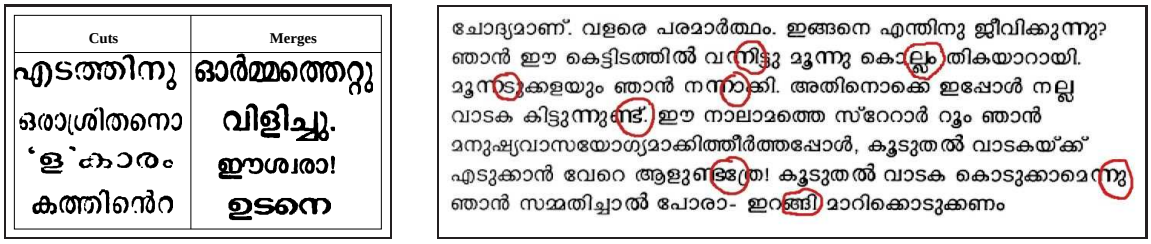
- Increased computational complexity and memory requirements due to large number of classes, become a bottleneck in developing systems.

- Appearance of foreign or unknown symbols in the document makes the recognition difficult, and sometimes unpredictable. Many of the Indian language documents have foreign symbols present.

1.4.1 Challenges Specific to Malayalam Script

The recognition of printed or handwritten Malayalam has to deal with a large number of complex glyphs, some of which are highly similar to each other. However, recent advances in classifier design, combined with the increase in processing power of computers have all but solved the primary recognition problem. The challenges in recognition comes from a variety of associated sources:

- *Non-Standard Font Design:* The fonts used in Malayalam printing were mostly developed by artists in the individual publishing houses. The primary goal was to map the ASCII codes to glyphs useful to typesetting the language and no standards were adopted in both the character mapping as well as glyph sizes or aspect ratios. This



(a) Words with cuts and merges.

(b) Merges in electronic typesetting.

Figure 1.4: Examples of cuts and merges in Malayalam printing.

introduced the problem of *touching glyphs non-uniform gaps* (see Figure 1.4) for many character pairs in the electronic document itself, which gets transferred to the printed versions. This makes the problem of word and character segmentation extremely difficult and error prone, and the errors are passed on to the recognition module. The introduction of Unicode has standardized the font mappings for newly developed fonts. However, the problem of standardizing glyph sizes still remains.

- *Quality of Paper:* To make the publications affordable to large portions of the society, publications often use low quality paper in the printing process, even with offset printing. The presence of fibrous substances in the paper used changes its ability to absorb ink, resulting in large number of broken characters in print. The issues of touching and broken characters are very difficult to handle for the recognition module.

- *Script Variations:* As mentioned in the previous section, the script in Malayalam underwent a revision or simplification, which was partly reversed with the introduction of electronic typesetting. This results in a set of documents that could contain either the old lipi, the new lipi, or a mixture of the two. Any recognition system has to deal with the resulting variety intelligently, to achieve good performance.

- *Representation Issues:* Another related problem is that of limitations in the initial versions of Unicode, that prevented textual representations of certain glyphs. Unicode did not have separate codes for *chillus* and they were created from non-vowel versions of the consonants using 'ZWNJ' (Zero-Width Non-Joiner) symbols. This causes substitution of one with the other in certain fonts, and can create significant differences in meaning of certain words. However these issues have been resolved in Unicode 5.0 onwards.

- *Compound Words and Dictionaries:* A characteristic of the Malayalam language as mentioned before is the common usage of compound words created from multiple root words, using the *sandhi* rules. This creates a combinatorial explosion in the number of distinct words in the language.

1.5 Overview of this work

The thesis mainly aims at addressing the problems character classification in Indian languages, giving a special emphasis to a south Indian language Malayalam. To ensure the scalability and usability of the system, it is extremely important to test on a large dataset. This work designs and implements methods for creating large dataset for testing and training of the recognition system. In the following sections we discuss the problem, contributions of this work and organization of the thesis.

1.5.1 Contribution of the work

This thesis focuses on pattern classification issues associated with character recognition, with special emphasis on Malayalam. We propose an architecture for the character classification, and proves the utility of the the proposed method by validating on a large dataset. The challenges in this work includes, (i) Classification in presence of large number of classes (ii) Efficient implementation of effective large scale classification (iii) Performance analysis and learning in large data sets (of Millions of examples).

The major contributions of this work are listed below.

1. A highly script independent dynamic programming (DP) based method to build large dataset for testing and training character recognition systems.

2. Empirical studies on large dataset of various Indian languages to evaluate the performance of state of the art classifiers and features on large datasets.

3. A hierarchical method to improve the computational complexity of SVM classifier for large class problems.

4. An efficient design and implementation of SVM classifier to effectively handle large class problems. The classifier module has employed for a OCR system for Malayalam.

5. The performance evaluations of the above mentioned methods on a large dataset. We tested on a large dataset of twelve Malayalam books, which is more than 2000 document pages.

6. A novel system for adapting a classifier for recognizing symbols in a book.

1.5.2 Organization of the thesis

We start with building large datasets from real life documents for the efficient training and testing of the system. In chapter 2, we propose script independent automatic methods for creating such large datasets. The problem is to align a word image and its corresponding text and label each components in the word image. We use a dynamic programing(DP) based method to solve this problem.

Large number of pattern classifiers exist in the literature. It is important to study the effectiveness of various state of the art classifiers on the character classification problem. We empirically study the strengths of various classifier feature combinations on large datasets. We present the results of our empirical study on character classification problem focusing on Indian scripts, in Chapter 3. The dimensions of the study included performance of classifiers using different features, scalability of classifiers, sensitivity of features on degradation, generalization across fonts and applicability across five scripts etc.

Traditional pattern recognition literature aims at designing optimal classifiers for two class classification problems. When the number of classes increases, problem becomes more and more challenging, both conceptually as well as computationally. In Chapter 4, we discuss the design and efficient implementation issues of the classifiers to handle large class problems. We give focus on Support Vector Machines (SVM), which is proved to perform the best in our empirical studies presented in chapter 3. In Chapter 5, we give various performance achieved using the methods mentioned in the previous chapters.

In Chapter 6, we demonstrate a novel system for adapting a classifier for recognizing symbols in a book. We employed a verification module as a post-processor for the classifier, and make use of an automatic learning framework for the continuous improvement of classification accuracy. Finally, Chapter 7 presents the summary of contributions of this work, possible directions of the work in future and the final conclusions.

Chapter 2

Building Datasets from Real Life Documents

2.1 Introduction

The character recognition problem in Indian languages is still an active research area. One of the major challenge in the development of such a system for Indian languages is the lack of bench mark datasets for training and testing the classifier system. Because of challenges involved in developing and handling a huge real life dataset, most of the research are restricted with a small set of in-house dataset. Most of them employ synthetically generated data for the experiments. But the experiments conducted on such a small or syntactic data will not be statistically valid when the OCR is put upon a real testing session with real life images. These OCRs fail drastically when they put for a practical use. To trigger the research and development of highly accurate OCR, a large amount of annotated data is necessary. The data with its corresponding labeling is called annotated data. The annotated data is also called ground truth.

The ground truth can be generated in many ways providing annotation data with details of different level granularity. During the annotation phase, different level of hierarchies can be generated in the data set. That is, we can have corresponding text associated at the page level, the paragraph level, the sentence level, the word level, and the character or stroke level. Typically this annotation information is also very useful for segmentation based routines that can also build up on their segmentation results so that they can further improve. Refer [33] for further details on annotation which describes large scale annotation of document images.

For the development of a classifier we need annotation at symbol level. Similar type symbols will belong to a single class in the recognition. Availability of large collections of labeled symbols plays a vital role in developing recognition techniques. In this chapter we discuss a method to generate large dataset of labeled symbols, given a coarse (the word level) annotated data. The problem is to align the word image and its corresponding text and label each components in the word image. We use a dynamic programing(DP) based method to solve this problem.

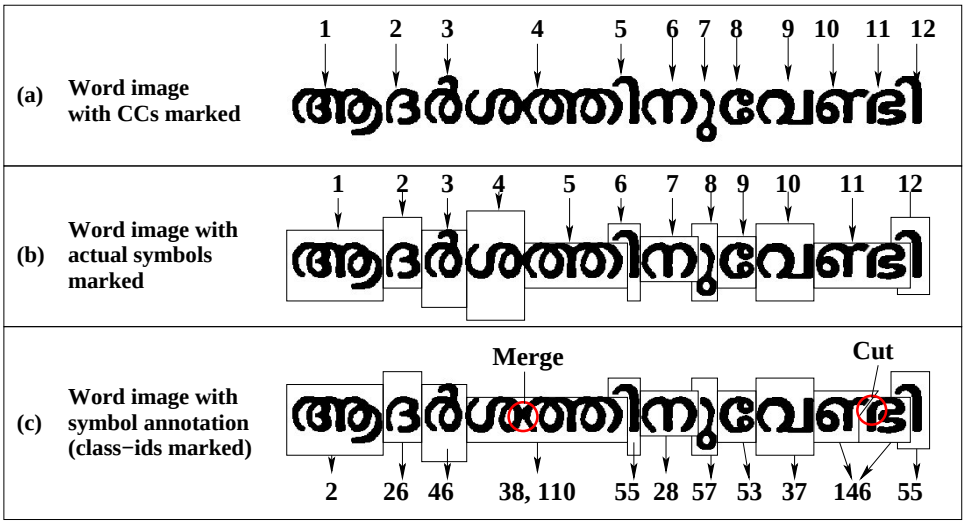


Figure 2.1: (a) A word in Malayalam script, each symbol (connected component) is numbered. (b) The actual boundaries of the symbols. (c) The output of symbol annotation algorithm based on DP method.

Figure 2.1 shows an example of symbol level annotation. In the Figure 2.1(a) we show a word image with a cut and a merge. It has 12 connected components. Figure 2.1(b) shows the actual symbol level annotation of the word, if the annotation is done manually. It considers the two components of the cut character together and split the merged characters at the appropriate position. Figure 2.1(c) shows the output of the DP based symbol annotation algorithm. For the merge, since we do not know the exact position where the merge has happened, we annotate the constituent symbols together and label the merged symbols with the class-ids corresponding to the constituent symbols. On the other hand, a cut symbol produces two or more connected components. These symbols together produce the actual character. Therefore, we need to annotate these symbols or connected components together and label them with a single class-id. In the next section we discuss the challenges involved in solving the symbol annotation problem.

2.2 Challenges in Real-life Documents

A wide variety of degradations can exist in a real-life document image. Documents in digital libraries are extremely poor in quality. The major challenges in alignment of word image with its corresponding text in real-life document images can be broadly classified into three levels, namely document level, content level and representational level.

2.2.1 Document level Issues

Document level challenges in generating such a huge dataset arise from the degradations in the document image. An important aspect which directly affect the document quality is the scanning resolution. Popular artifacts in printed document images include (a) Excessive dusty noise, (b) Large ink- blobs joining disjoint characters or components, (c) Vertical cuts due to folding of the paper, (d) Degradation of printed text due to the poor quality of paper and ink or low scanning resolution, (f) Floating ink from facing pages, (e) back page reflection etc [34]. Figure 2.2 shows examples of various degradations. Salt and pepper noise is flipping the white pixels to black and the black pixels to white. The degradation cut occurs when a group of black pixels from a component flipped to white pixel, so that the component become two or more pieces. Similarly merge is a degradation that a group of white pixels at a region flipped to black, so that two or more components get connected.

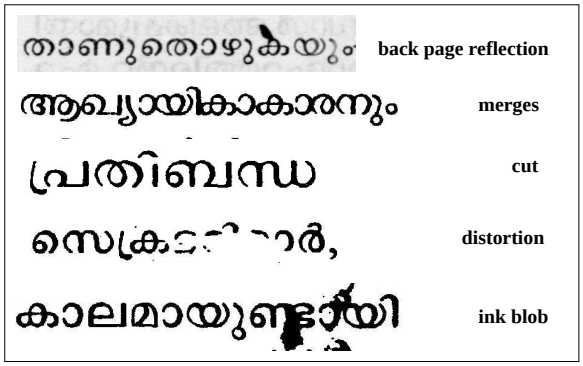


Figure 2.2: Example word images of various degradations from the book "Marthandavarma" (Malayalam script).

Some of the degradations can occur during preprocessing. During thresholding the image, if the threshold is low, it might increase the number of cuts and if the threshold is high, the number of merges in the components might increase. The thickness of the character image might be different in different portions of the image. This can happen either during scanning

or some portions of the pages might be dull even in the original document itself. Using a global threshold might increase the degradation of such pages. Some of the punctuations, if it is very small in size, might be taken away from the image during noise cleaning.

The density of the page is another aspect which decides the document quality. If the character spacing in the words is too low the chances of merges in the components are high. In the new digitalized type settings the character spacing of the documents can be varied from font to font and word-processor to word-processor.

2.2.2 Content level Issues

There are various content level issues comes into picture when we deal with real life documents.

- Presence of foreign language content: It is very common to see English words in between an Indian language script content. It is common to see the English word written in the Indian script also. The mathematical symbols or rare punctuations are also considered as foreign symbols.
- Violation of language rules: We could find the examples of character combinations, which is not possible by the language rules in the text. These types of combinations occur when the content is specific to any regional slang of the language or when some vocal expressions has to be expressed (e.g. exclamation sounds) in a different way. This can be considered as a language and author or book type specific problem.
- Invalid typesetting: The problem with invalid typesetting occurs when the word processor uses some ASCII font for the typesetting. These may cut a word where by language rules the word should not be cut. An example is, consider the situation of a character where the modifier attached to that character appears in the left most portion of a line. The modifier does not have an independent existence by language rules. But, using invalid typesetting it is possible to put a *newline* in between the modifier and the character to which the modifier attached to.

2.2.3 Representational level Issues

Images of the same words that occur at different places of the same book or a different book differ in a number of ways due to pixel variations, noise, changes in font face, font type and font size etc. Even in the same page the same characters might be written differently. Most popular example is the presence of a header in a different font, style or/and size, or

a presence of a drop cap which is much bigger in size etc. A description or representation is required for the words of the documents which will allow matching in spite of these differences.

Building an appropriate description is critical to the robustness of the system against signal noise. In general, color, shape or/and texture features are used for characterizing the content. More specific features are required for word representation in document images. These features can be more specific to the domain as they contain an image-description of the textual content in it. It is observed that many of the popular structural features work well for good quality documents. Word images, particularly from newspapers and old books, are of extremely poor quality. Common problems in such document databases will have to be analyzed before identifying the relevant features. We use structural, profile and scalar features for effectively representing and matching the word images. More explanation on these features are given in the Subsection 2.7.1.

In the following Section 2.3 we give a brief explanation about standard dynamic programming(DP) algorithm. This is followed by the explanation (in Sections 2.4, 2.5 and 2.6) of how a modified version of DP based algorithm is used for the alignment of word with its corresponding text.

2.3 Background on Dynamic Programming

Dynamic programming is a method of solving problems that exhibit the properties of overlapping sub problems and optimal substructure. A problem is said to have *overlapping sub problems* if it can be broken down into sub problems which are reused multiple times. For example, the problem of calculating the nth Fibonacci number does, however, exhibit overlapping sub problems. The problem of calculating $fib(n)$ thus depends on both $fib(n-1)$ and $fib(n-2)$, where $fib(x)$ is the function to calculate x^{th} Fibonacci number.

A problem is said to have *optimal substructure* if the globally optimal solution can be constructed from locally optimal solutions to sub-problems. The general form of problems in which optimal substructure plays a roll goes something like this. Let's say we have a collection of objects called A. For each object O in A we have a "cost" $C(O)$. Now find the subset of A with the maximum (or minimum) cost, perhaps subject to certain constraints. The brute-force method would be to generate every subset of A, calculate the cost, and then find the maximum (or minimum) among those values. But if A has n elements in it we are looking at a search space of size 2^n if there are no constraints on A. Often n is huge making a brute-force method computationally infeasible.

There are several algorithms which use dynamic programming. String matching, Viterbi Algorithm used for hidden Markov models, Floyd's All-Pairs shortest path algorithm, Travel ling salesman problem are a few examples. Lets look at a worked out example to get a feel of Dynamic Programming.

2.3.1 A worked out Example - String Matching

There are three steps involved in dynamic programming. (a) Initialization, (b) Filling the matrix (c) Back-tracking. An algorithm to find the edit distance by matching two strings are given in Algorithm 1. Edit distance is the cost of matching two strings. In the Algorithm 1 the steps 1 to 7 describes the ways to initialize the cost matrix, which is generally called DP table. Each cell in the DP table is filled using the formula given in step 20 in Algorithm 1. The first term in this equation corresponding to the cost of insertion. Second term corresponds to the cost of deletion and third term corresponds to the cost of match or mismatch. In the diagonal path an increase of cost in the DP table represents a mismatch and if the values remains same. A parent table also can be filled along with the DP table for the ease of doing the step (c) in the dynamic programming, which is back tracking. This is relevant from the point of implementation. Corresponding to each cell in the DP table, the parent table also will have an entry, which represents which one of the 3 terms mentioned above is used to calculate the cost of that cell. In backtracking, we are finding the minimum cast path in the DP table with the help of parent table. A 0 in the parent table represents a diagonal path, 1 represents a vertical path and 2 represents a horizontal path. The value corresponding to the the last cell $D[m, n]$ is the cost of the path, which is called *edit distance* or *levenshtein distance*.

Consider the two strings *fast* and *caps*. The initialization of the DP table and the parent table are shown in the Table 2.1 and the Table 2.2. The filled DP table and the corresponding Parent table shown in Table 2.3 and Table 2.4.

		c	a	p	s
	0	1	2	3	4
f	1				
a	2				
s	3				
t	4				

Table 2.1: Initialize dp-table.

		c	a	p	s
	-1	-1	-1	-1	-1
f	-1				
a	-1				
s	-1				
t	-1				

Table 2.2: Initialize parent table.

Algorithm 1 int EditDistance(char ($s[1..m]$, char $t[1..n]$)

```
1: #define MATCH 0
2: #define INSERT 0
3: #define DELETE 0
4: declare struct D[0..m, 0..n]
5: for i = 1 to m do
6:    D[i, 0].cost := i
7:    D[i, 0].parent := −1
8: end for
9: for j = 1 to n do
10:   D[j, 0].cost := j
11:   D[i, 0].parent := −1
12: end for
13: for i = 1 to m do
14:   for j = 1 to n do
15:      if s[i] = t[j] then
16:         cost = 0
17:      else
18:         cost = 1
19:      end if
                                  D[i − 1, j] + 1, //insertion
20:      D[i, j].cost = min{      D[i, j − 1] + 1, //deletion
                                  D[i − 1, j − 1] + cost//substitution
                                      D[i − 1, j] + 1(INSERT), //insertion
21:      D[i, j].parent = argmin{ D[i, j − 1] + 1(DELETE), //deletion          .
                                  D[i − 1, j − 1] + cost(MATCH)//substitution
22:   end for
23: end for
24: return D[m, n]
```

		c	a	p	s
	0	1	2	3	4
f	1	1	2	3	4
a	2	2	1	2	3
s	3	3	2	2	2
t	4	4	3	2	3

Table 2.3: Fill dp-table.

		c	a	p	s
	0	-1	-1	-1	-1
f	-1	0	1	1	1
a	-1	2	0	1	1
s	-1	2	2	0	0
t	-1	2	2	0	1

Table 2.4: Fill parent table.

The value 0 in the parent table indicates that the parent of that cell is diagonally connected to the particular cell. This corresponds to a *match* or a *mismatch*. The value 1 in the parent table indicate that the parent is vertically connected to the cell, which means that an *insert* has occurred. Similarly, the value 2 in the parent cell indicates the a horizontal connection and represents a *delete*. The lowest cost path is shown in color in the Table 2.5 and the Table 2.6.

		c	a	p	s
	0	-1	-1	-1	-1
f	-1	0	1	1	1
a	-1	2	0	1	1
s	-1	2	2	0	0
t	-1	2	2	0	1

Table 2.5: Backtracking using parent table.

		c	a	p	s
	0	1	2	3	4
f	1	1	2	3	4
a	2	2	1	2	3
s	3	3	2	2	2
t	4	4	3	2	3

Table 2.6: Alignment path in the DP-table.

The match string and the alignment of the two words are shown in the Figure 2.3.

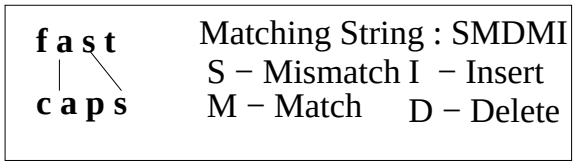


Figure 2.3: Example-1 of string alignment.

2.4 A Naive Algorithm to Align Text and Image for English

The word(text) and word image alignment attempts to search the best match between each character in the text with the corresponding component in the image. We use dynamic programming based approach to solve this problem. The problem is to find a global alignment between the text and word image, and label each component in the word image with the corresponding text. The problem is tough in the presence of noise, degradations, cuts and merges in the components etc.

We solve the problem in the image domain. For this the text has to be rendered (using a rendering engine) to get the corresponding image. This image is called *rendered word image*, say R. We have to label each component in R with the corresponding text. This can be done easily for English by finding the connected components in the word image. The connected components has to be sorted with respect to its left coordinate to get the components in order. Once this is done, the labeling will be sequential, since most of the characters in English are composed of only one component. We need to take care of characters like *i and j* and punctuations like *colon(:), semicolon (;), question mark (?), exclamation mark(!), double quote("), percentile symbol (%), and equal to (=).* Now we have two word images, R and the original word image, say W. Our problem is now to align R and W and propagate the labeling of components in R to the corresponding components in W.

The algorithm for the word alignment in English is given in Algorithm 2. Each cell in the DP table will have the best possible score for aligning the two word images to that point. Each cell in the DP table(D) is filled using the equation given in step 5 of the algorithm. The function $MC(R_i, W_j)$ returns the matching cost of i^{th} component of R and j^{th} component of W. In our implementation the matching cost will be minimum if the component matches. In this the first term corresponds to match or mis-match, which represents a diagonal path. The second term finds a merge or a delete, which represents a vertical path. The third term finds a cut or an insert, which represents a horizontal path to reach the particular cell. The function $MC((R_{i-1}, R_i), W_j)$ returns the matching cost of the combined components $(i-1)^{th}$ and i^{th} components of R with the j^{th} component of W. This check is to find the merge. Similarly, the function $MC(R_i, (W_{j-1}, W_j))$ returns the matching cost between the i^{th} component of R and the combined components $(j-1)^{th}$ and j^{th} component of W. This check is performed to find the cuts in W. Figure 2.4 shows an example of word alignment for the English word *glamour*.

After creating the DP table the process called *backtracking* is done to find the path corresponding to minimum cost. From an implementation point of view, we can use a

Algorithm 2 DP based algorithm to align text and image for English

1: Input: Word image W and the corresponding text from annotation.
2: **Render the text to get a word image R, and label each component, with the corresponding character in the text.**
3: **Find the connected components in the original word image.**
4: Initialize the dynamic programming table D of size $m \times n$, where $(m-1)$ and $(n-1)$ are the no. of connected components in R and W respectively.
5: Fill each cell, $D(i,j)$ in the table using the following equation.

$$D(i,j) = \min \begin{cases} D(i-1,j-1) + MC(R_i, W_j) \\ D(i-1,j) + MC((R_{i-1}, R_i), W_j) \\ D(i,j-1) + MC(R_i, (W_{j-1}, W_j)) \end{cases}$$

where, $MC(R_i, W_j)$ is the matching Cost of symbol R_i in the text(rendered as image) with symbol W_j in the original image.
6: Get the matching String by reconstructing the path, by following the minimum cost path.
7: Propagate the labels of symbols in R to W.

Parent table to make this process faster. The purpose of the parent table is described in the previous section. At each point, we need to identify possibilities for match, mis-match, insert, delete, cut and merge. In the matching string, if at a point the path taken to get the minimum cost is diagonal, there are two interpretations for it. Either it will be a match or a mis-match. We use a threshold to distinguish between match and mis-match. A mis-match can be either a typing mistake in the annotated text or the appearance of a character which is having high featural match with the character in the word image. We selected 0.4 as the threshold, if the matching cost is less than the threshold we consider it as a match, otherwise a mismatch. The threshold is chosen by statistical analysis of the data.

At any point, if the path taken to get the minimum cost is horizontal it represents either a cut in the components or an insert. The presence of spurious noise is considered as a noise the word image. Another chance of insert is an additional character in the typed text. At this stage we are taking care of only the cases of a single cut, which makes the component into two pieces. These two scenarios, a cut or an insert, can be distinguished by the following way. The cut will be associated with two cells in the DP table, which will contribute two entries to the matching string. Most of the time, a sequence like, a mis-match followed by an insert or an insert followed by a mismatch would have been resulted

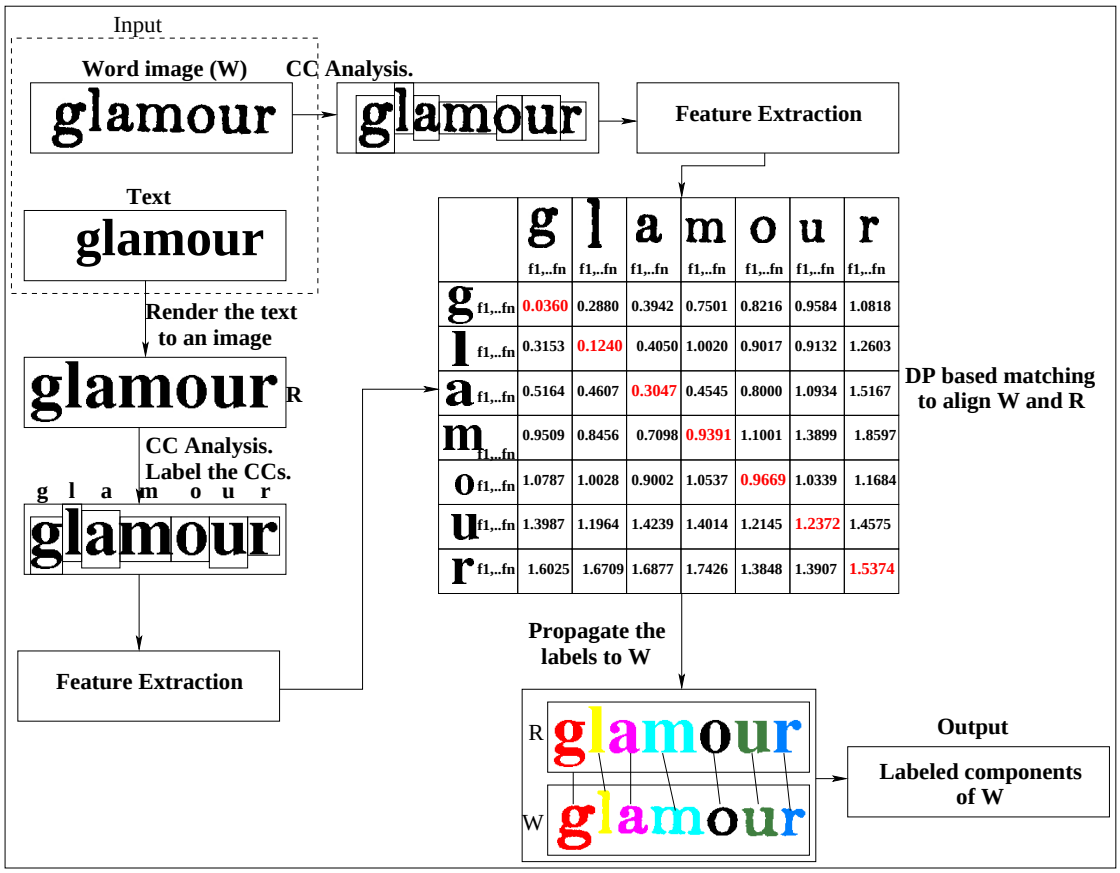


Figure 2.4: Example of aligning English words.

by a cut. To confirm this, we are doing a double check at the time of backtracking. Most of the spurious noise are represented by an isolated insert. In some cases the cut of a symbol will be in such a way that a small portion of the symbol is separated out and most of the portion of the symbol will be the other part. In this condition the R_i will match with W_i (say) and W_{i+1} or W_{i-1} will remain as an insert. In other words, in this condition, a cut will be represented by a match followed by an insert or and insert followed by a match. So, the same set of checking as explained above needs to be done here also.

In the similar way, at any point the path taken to get the minimum cost is vertical it is representing either a merge in the components or a delete. A delete usually is a missing character in the typed text. The rendered image, R will not have any noise in it. As in the cut case, we are taking care of the merge cases caused by joining two components. These two scenarios, a merge or a delete, can be distinguished in the same way as we did in the cut case. A merge will be associated with 2 cells in the DP table. Most of the time it appear as

a mismatch followed by a delete or a delete followed by a mismatch. We are double checking to verify whether it is a merge during backtracking. If it is, the components will be marked as merged components other wise it will be considered as a delete. Also an isolated delete will be considered as a delete. As explained in the case of cuts, sometimes a match followed by delete or a delete followed by a match can also be a merge. This also needs to be taken care while backtracking.

2.5 Algorithm to Align Text and Image for Indian Scripts

In this section we discuss about how the Algorithm 2 can be extended to fit Indian language scripts. Aligning Indian language scripts is a much more difficult problem compared to English. One reason is the size of the problem. The total number of characters present in English are around 70. In the case of any Indian languages it comes out to be in the order of hundreds. There are also many similar characters present in this set. We need to use more features to get proper match between the components.

Languages like English have characters as their building blocks. The smallest entity that can be easily extracted from a document in such language is the character. Indian scripts have oriented from the ancient Brahmi script which is phonetic in nature. Thus in Indian languages, syllables form the basic building blocks. If all the syllables are considered as independent classes and recognized, a very large amount of information has to be stored. This creates the need for splitting syllables into their constituent components, which is not a trivial task.

In other words, the challenge comes from the definition of text(Unicode) used to annotate the word image. Before going to the details we will define the basic terminologies that is used to describe the problems.

- *Character:* is an entity used in a data exchange.
- *Glyph:* is a particular shape of a character and part of a character. Glyphs can have variations with font to font.
- *Unicode:* provides a unique number for every character, no matter what the platform, no matter what the program, no matter what the language.
- *Component/Symbol:* connected component(CC) present in the glyph of a character.

These terminologies have a broader meaning in the context of Indian languages compared to English language. In English a character represents a single alphabet. A character,

Algorithm 3 DP based algorithm to align text and image for Indian Languages

1: Input: Word image W and the corresponding Unicode/text from annotation.
2: **convert the Unicode to the class labels using a map file MAP.**
3: **Reorder the symbols, using the language rules in the $RULES$ file.**
4: Render the symbols to get a word R, and label each symbol with the corresponding class label.
5: Find the connected components in the original word image.
6: Initialize the dynamic programming table D of size $m \times n$, where $(m-1)$ and $(n-1)$ are the no. of connected components in R and W respectively.
7: Fill each cell, $D(i,j)$ in the table using the following equation.

$$D(i,j) = \min \begin{cases} D(i-1,j-1) + MC(R_i, W_j) \\ D(i-1,j) + MC((R_{i-1}, R_i), W_j) \\ D(i,j-1) + MC(R_i, (W_{j-1}, W_j)) \end{cases}$$

where, $MC(R_i, W_j)$ is the matching Cost of symbol R_i in the text(rendered as image) with symbol W_j in the original image.
8: Get the matching String by reconstructing the path, by following the minimum cost path.
9: Propagate the labels of symbols in R to W.

Unicode, glyph or a component/symbol is representing a single entity in English. Each character in English has its corresponding Unicode. Most of the characters in English can be represented using a *single* glyph. Most of the glyphs in English are single component. However, there are a few exceptions like the character 'i' and 'j', which composed of 2 components. There are one to one mappings between Unicode, characters, glyphs and components.

But in the case of Indian languages, all these four terminologies mentioned above has different meaning. A character is called *akshara* in Indian context. It can be any combination of *cv, ccv or cccv* sequences where c stands for consonant and v stands for vowel. An *akshara* can be represented using a single or multiple Unicode. Similarly to represent an *akshara* we might use single glyph or multiple glyphs. An *akshara* might consists of single or multiple components. Also, a single component can represent multiple Unicode and a single Unicode can represent multiple components.

Considering all these facts, given a word image and its corresponding text in Unicode, the labeling of the connected components with the text is not trivial as we did in English. We are tackling this problem by converting the Unicode text to symbol level, which is a proprietary numbering which has a unique representation for all the existing symbols in that particular language. Each symbol will be composed of either a single Unicode or multiple Unicode. The conversion from symbol to Unicode is trivial when it comes in a single unit. So, if we get a labeling at symbol level, that is good enough.

The conversion from Unicode to symbols uses a *MAP FILE*, which maps each Unicode to

its corresponding symbol representations, which is called *class labels*. We need to represent the symbols in the order in which it appears in the word image. A trivial mapping of a Unicode word will not give us this order. This is again because of the specialties in which Indian scripts are represented using Unicode. Suppose we have a modifier, (called *Matra* in Indian context) symbol. The modifier can appear on the right, left, top or bottom of a character. Sometimes it come as a modification to the base character. Which ever way it actually appears in the script, the Unicode follows a common rule to represent a matra, that is, the Unicode that represents a *Matra* appears after the Unicode of the character to which the *Matra* is associated. It is the responsibility of the *font* to put the symbols in the right place it should appear. Unfortunately most of the popular Unicode fonts are not doing this job correctly at present. There are errors in the order in which these fonts displays the characters. As a result most of the rendering engines (QT or ImageMagick) are not able to render the words correctly. We use language rules for the reordering of the symbols to get it in the correct order as it appears in the image, with the help of a *RULES FILE*. Also, Unicode represents the *conjunct symbols* using more than one Unicode. A group of Unicode (usually a group of 3), might be representing another symbol representation in the language. For the conversion of this case also the *RULES FILE* is used.

We use our own implementation for rendering the Unicode to get the corresponding rendered word image. The labeling of each component is done in the class label level. Once we get the the labeled rendered word image(R), the rest of the algorithm proceeds as discussed in the previous section. Algorithm 3 explains the modified dynamic programming based algorithm to align word and Unicode in Indian scripts.

The method that we employ is a generic one that can be used for any Indian language. The language specific files, *MAP FILE and RULES FILE* have to be changed when we change the language. Also, since the rendering is proprietary, the rules, which specifies the positioning of the matras, used for rendering also need to changed from script to script. We use language independent structural features for matching the components. So, the same set of features will be sufficient for any Indian language. The method is generic in such a way that, we can add another feature to improve the performance of matching module. Figure 2.5 shows an example of word alignment in the Malayalam script.

2.6 Challenges for Degraded Documents

In this section we will discuss how the degradation in the document images are handled in the Algorithm 3. The major degradations include cuts in the components, merges in the

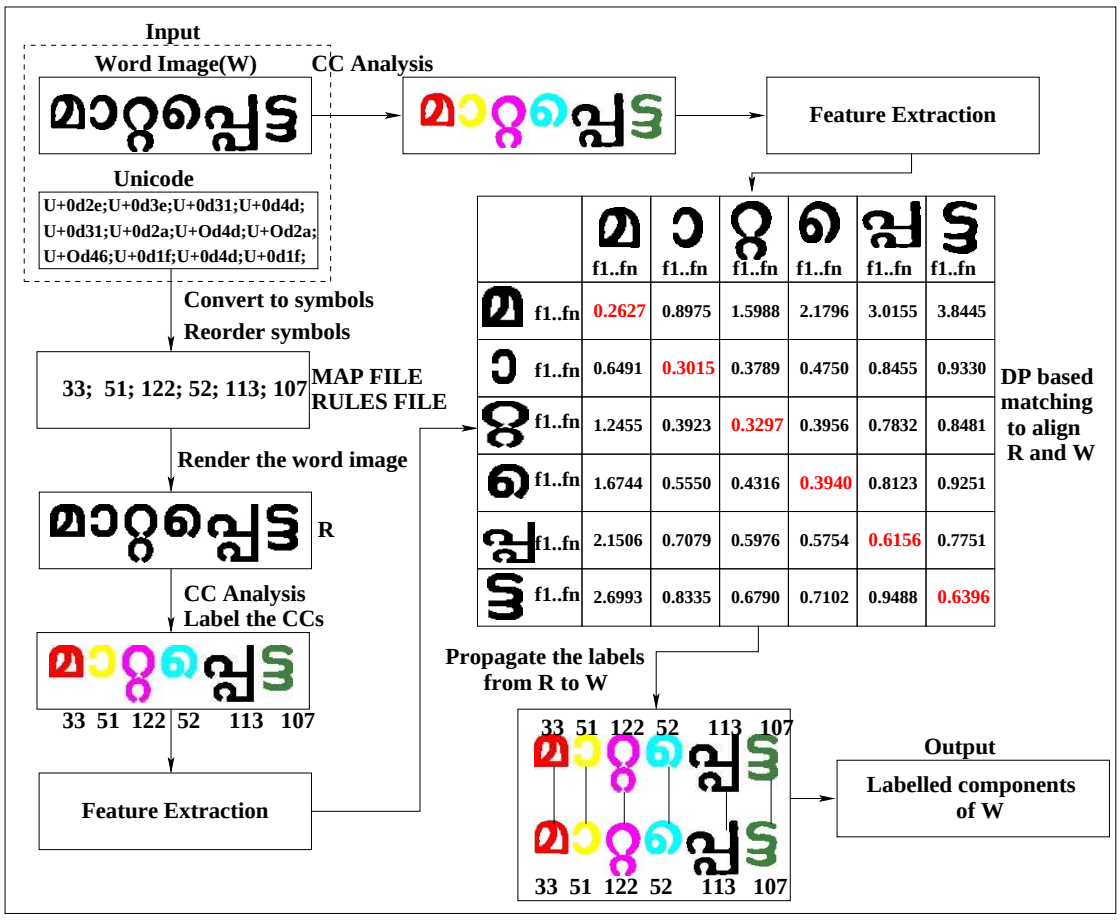


Figure 2.5: Example of aligning word with the corresponding text in Malayalam script.

components, presence of spurious noise etc. While filling the DP table, we are taking care of these scenarios as well. The step 5 in the Algorithm 3 shows how the DP table is filled.

An example for how the path is taken when a cut is occurred is shown in the Figure 2.6. It is more tricky when a component cut into more then two pieces. Similarly, a straight forward backtracking algorithm cannot find multiple merges, i.e., more than two components got merged to result in a single connected component. Figure 2.6 shows an example for alignment of a word with more than one merge. Without making the forward pass(Algorithm 3) more complex, we handle these issues in the backtracking, by a double checking scheme.

After a normal backtracking, we get a match string, which has values corresponding to MATCH, MIS-MATCH, INSERT, and DELETE. Other than these values we also introduce *DEL-MISMATCH* and *INS-MISMATCH*. *DEL-MISMATCH* comes when the component

matching gives a *DELETE* and the match score is greater than the selected threshold. Similarly, *INS-MISMATCH* appears when the component matching returns an *INSERT* and the match score is greater than a selected threshold. Once we get the first set of decision string, we make the decisions based on the double check shown in the Table 2.7. We check the match string in pair. *First* and *Second* in Table shows a pair of result from the match string.

	First	Second	R - 1	R - 2	Condition	Decision1	Decision2
1.	M	I	M1	M2	$M1 < M2$	M, N	CUT
2.	MM	I	M1	M2	$M1 < M2$	MM/DS, N	CUT
3.	M	D	M1	M3	$M1 < M3$	M, MS	MERGE
4.	MM	D	M1	M3	$M1 < M3$	MM/DS, MS	MERGE
5.	M	IM	M1	M2	$M1 < M2$	M, N	CUT
6.	MM	DM	M1	M3	$M1 < M3$	MM/DS, MS	MERGE
7.	I	M	M1	M2	$M1 < M2$	M, N	CUT
8.	I	MM	M1	M2	$M1 < M2$	MM/DS, N	CUT
9.	D	M	M1	M3	$M1 < M3$	M, MS	MERGE
10.	D	MM	M1	M3	$M1 < M3$	MM/DS, MS	MERGE
11.	IM	M	M1	M2	$M1 < M2$	M, N	CUT
12.	DM	MM	M1	M3	$M1 < M3$	MM/DS, MS	MERGE

Table 2.7: Decision making rules in the backtracking.R-1 = Routine 1, R-2 = Routine 2, M= MATCH, MM= MIS-MATCH, I= INSERT, D= DELETE, IM= INS-MISMATCH, DM=DEL-MISMATCH, N=NOISE, MS=(Typing) Mistake, DS=Distortion, if condition is true, we chose Decision1 , otherwise Decision2.

The routines for double checking are M1, M2 and M3. M1 is a one to one matching between the rendered component and the original component. Routine M2 is a matching between a component in the rendered word image and a compound symbol obtained by putting two symbols from the original word image. Routine M3 is a matching between a compound symbol obtained by taking two symbols from the rendered word image and one symbol from the original word image. We use more features at this stage for the final decision.

Other than these conditions, there are some cases where multiple INSERTs and DELETEs comes together. This happens when, a single symbol cut into more than two components and when more than two symbols get merged into a single component. At this stage we have not explored the method to detect the above mentioned cases. In the case of multiple

cut of a component, now we find only two pieces as a part of that component and the rest of the pieces are considered as spurious noise. And similarly, we consider only two merge at a place, and the rest of the components will be counted to deletes. Still we can extend the backtracking method to find multiple cuts and merges on a component.

Another important challenge in the alignment of word image with the rendered word is the change in the font used to render the word. If the font in the original word image is very different from the font used to render the word, especially in the case of fancy fonts (headers of the book), the matching may go wrong. To solve these problem we may need to work at the feature level.

2.7 Implementation and Discussions

2.7.1 Features for matching

Effective features for word matching should take care the popular artifacts discussed in the Subsection 2.2.1 that can occur in the word images. We found that three categories of features are effective for addressing these artifacts. The features could be a sequential representation of the word shape, content or a structural representation of the word image. We employ a combination of scalar, profile, structural features used in [35, 36, 37]. The images we operate on are all binary with two intensity levels $[0, 255]$. We refer to an image of height h as $I(r, c)$, where r and c indicate the row and column, respectively, index of the pixel.

Scalar Features:

Scalar features include an estimate of the number of ascenders and descenders in the image, the aspect ratio of the image, and number of loops in the image.

Profile Features:

The profile features include projection profiles, background to ink transitions, upper and lower word profiles.

Projection profile: It is a measure of ink distribution of the word image. Each value in the profile is calculated by summing over the pixel values in the corresponding image column is given by

$$pp(I, c) = \sum_{k=1}^{h} (255 - I(r, c)) \tag{2.1}$$

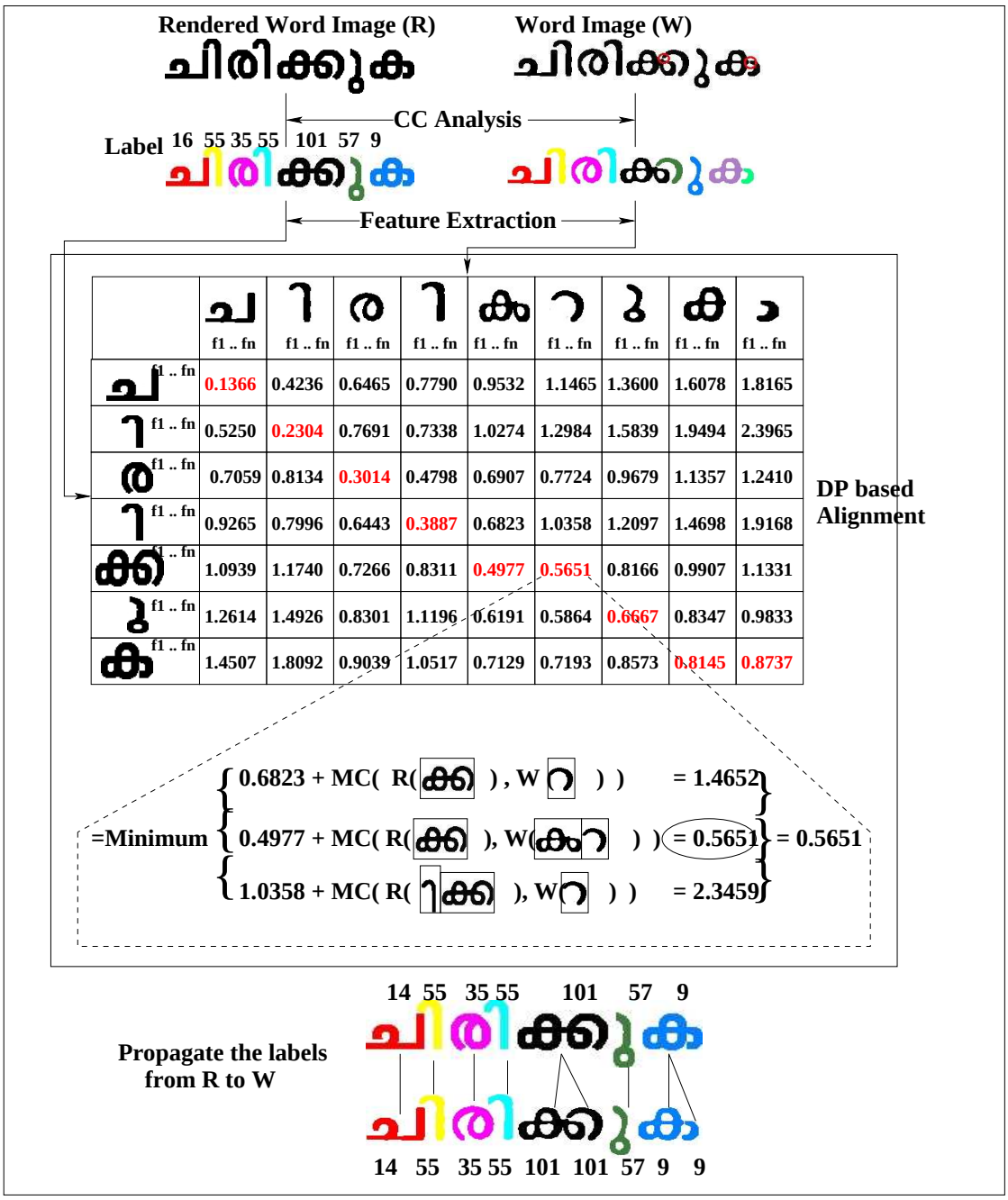
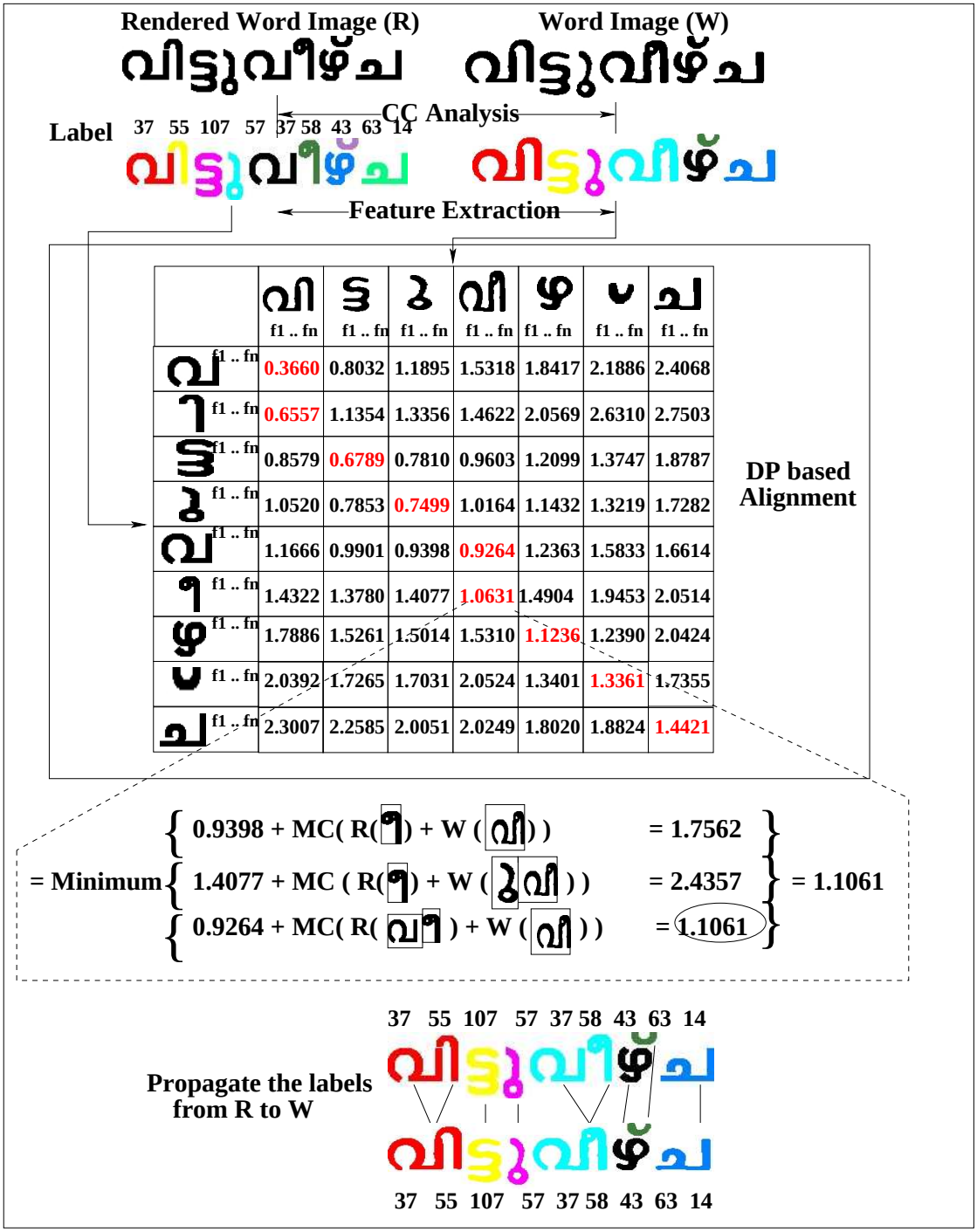


Figure 2.6: Example of aligning word with two cuts.

Figure 2.8 shows the plot of a typical projection profile. We invert the image before the calculation, causing concentrations of ink to create peaks, because we would like to measure the ink contained in each column. The descriptive power of the modied profile



	f1 .. fn	f1 .. fn	f1 .. fn	f1 .. fn	f1 .. fn	f1 .. fn	f1 .. fn
f1 .. fn	0.3660	0.8032	1.1895	1.5318	1.8417	2.1886	2.4068
f1 .. fn	0.6557	1.1354	1.3356	1.4622	2.0569	2.6310	2.7503
f1 .. fn	0.8579	0.6789	0.7810	0.9603	1.2099	1.3747	1.8787
f1 .. fn	1.0520	0.7853	0.7499	1.0164	1.1432	1.3219	1.7282
f1 .. fn	1.1666	0.9901	0.9398	0.9264	1.2363	1.5833	1.6614
f1 .. fn	1.4322	1.3780	1.4077	1.0631	1.4904	1.9453	2.0514
f1 .. fn	1.7886	1.5261	1.5014	1.5310	1.1236	1.2390	2.0424
f1 .. fn	2.0392	1.7265	1.7031	2.0524	1.3401	1.3361	1.7355
f1 .. fn	2.3007	2.2585	2.0051	2.0249	1.8020	1.8824	1.4421

Figure 2.7: Example of aligning word with two merges.

remains unchanged.

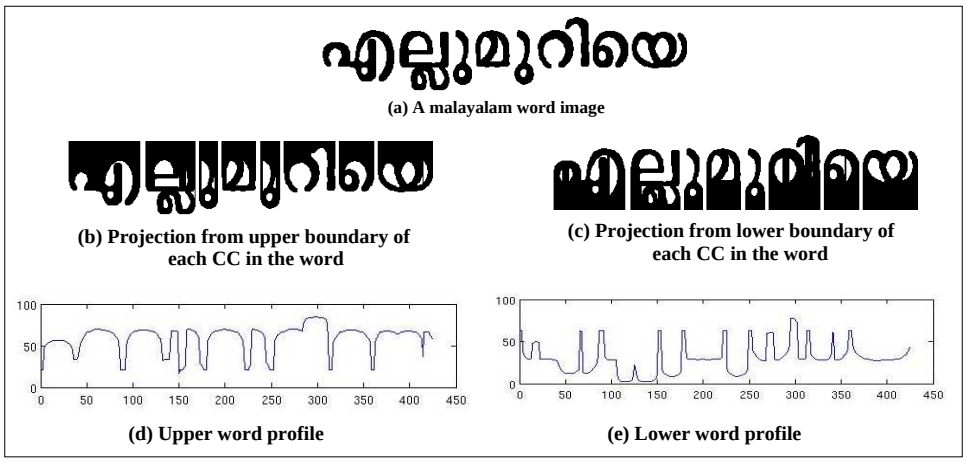


Figure 2.8: Projection Profiles.

Ink transition: Ink transition represent the internal shape of the image, computed by counting the number of transitions from background (paper) to *ink* for every column of the image (see Figure 2.8).

Structural Features:

The structure of the word image is described by statistical moments and region-based moments. Each moment order carries different structural information about the same image. Many of the pattern recognition problems are addressed used different moment orders. Normalized moments, such as first-order moments (M_{00} , M_{01}), central moments (CM_{pq}), and statistical moments (mean, standard deviation) are employed in this work for describing the structure of the word. Structural features are also robust for representing images containing various artifacts and noise like, salt and pepper noise. Moments of order (p + q) for image I are given by the following equations.

$$M_{p,q} = \sum_{r} \sum_{c} r^p c^q I(r, c) \tag{2.2}$$

$$CM_{pq} = \sum_{r} \sum_{c} (r - \bar{r})(c - \bar{c}) I(r, c) \tag{2.3}$$

where, the region-based moments along the row and column of the image are given by:

$$\bar{r} = \frac{M_{10}}{M_{00}}, \bar{c} = \frac{M_{01}}{M_{00}} \tag{2.4}$$

2.7.2 Malayalam script related issues

The major Malayalam related issue that came in the implementation of alignment of a word image and its corresponding Unicode comes from the script revision. During the 1970s and 1980s, simplifications of the Malayalam script were introduced. The reform aimed to reduce the complexity of two particular aspects of Malayalam. First, it recommended the replacement of irregular ligatures by a predictable sequence of in-varying components. Second, it recommended the formation of consonant clusters out of in-varying 'letter fragments' or by using the vowel suppressor on all but the final part of a concatenated sequence. Some of the examples of script revision is given in the Figure 2.9. While it has had some effect on daily practice, this reform has only partially changed the well-established traditional approach. By the arrival of modern word-processors, which can generate any complex shape, most of the old lipi characters again came into picture. Also, among the word processors and fonts, there is no standardization followed. Nowadays, a mixture of old and new lipi characters are used by different word-processors. Thus the choice of the between different forms of the same character is done by font used by the publisher. We solve this problem with the help of separate rules files for different books under consideration.

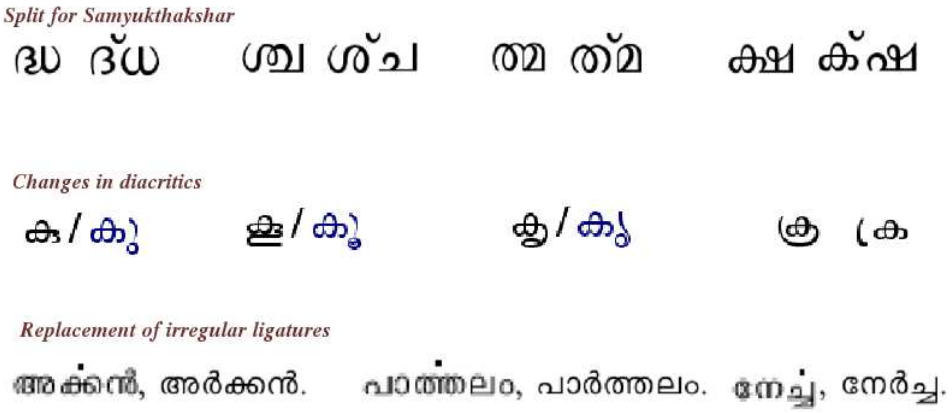


Figure 2.9: Script Revision: Major Changes Occurred.

2.8 Results

The various experiments and results shown in this thesis are conducted on 12 selected books in Malayalam. These books are selected carefully based on various factors such as font and printing quality, the publishing period and publisher, quality of documents, the historical

importance of the books etc. The summary of statistics of the books used is given in Table 2.8.

S.No	Book Name	# Pages	# Words	# Unicode	# Symbols
1	Indulekha	235	46281	423850	321470
2	ValmikiRamayanam	170	31360	293602	228188
3	Sarada	156	32897	300353	235791
4	Sanjayan	36	4079	35914	28661
5	Hitlerude Athmakadha	87	16403	166307	125658
6	BhagatSingh	284	57252	489534	458016
7	Ramarajabahadoor	440	81021	283497	664836
8	Thiruttu	86	15654	143654	117403
9	Dharmaraja	421	95931	947419	897449
10	IniNjanUrangatte	168	39785	375877	277257
11	ViddhikaluteSwargam	69	8793	77826	62396
12	Janmadinam	93	12112	110763	86269
	Total	**2245**	**441568**	**3648596**	**3503394**

Table 2.8: Statistics of Malayalam books used in the experiments.

In this section we describe the various estimates and results obtained by symbol annotation process. The major output of this process is an estimate of the cuts, merges and spurious noise present in the document. This gives a quantitative measure of the quality of a document, for recognition. Also with the help of the large corpus, we calculated the symbol level Unigram and Bigram.

2.8.1 Symbol level Unigram and Bigram

Symbol level unigram and bigram are some products of symbol annotation. Symbol level unigrams and bigrams are not equal to the language Unigram and Bigram used by the linguists. The normal Unigram and Bigram are based up on the combination of *sounds* which makes an *Akshara* or combination of *Aksharas*. This is more or less similar to the Unigram and Bigram represented in Unicode. This kind of normal grams may not be useful for an OCR to aid classification accuracy, since the representation of a character is not a single unit. A single component may represent two or more characters. Here we are calculating symbol level unigram and bigram. This type of statistics are not available in

the literature.

Unigram can be defined as the frequency of occurrence of a symbol in the language. From an OCR point of view, this measure helps in post-processing. In other words if two classes are very similar and the classifier quite often mis-recognized them, in this case, we can make a decision based upon the unigram probability of the characters. The best method is to combine the confidence of the classifier and the unigram probability as a weighted average.

S.No	Char	Unigram	S.No	Char	Unigram
1.		0.0812	11.		0.0271
2.		0.0777	12.		0.0262
3.		0.0746	13.		0.0242
4.		0.0399	14.		0.0233
5.		0.0339	15.		0.0211
6.		0.0323	16.		0.0193
7.		0.0305	17.		0.0177
8.		0.0297	18.		0.0172
9.		0.0295	19.		0.0164
10.		0.0292	20.		0.0151

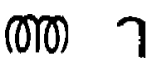
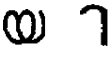
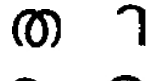
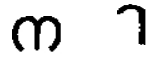
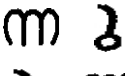
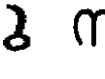
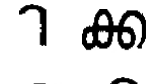
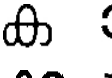
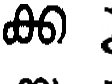
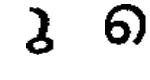
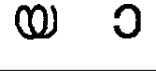
S.No	Char Pair	S.No	Char Pair
1.		11.	
2.		12.	
3.		13.	
4.		14.	
5.		15.	
6.		16.	
7.		17.	
8.		18.	
9.		19.	
10.		20.	

Figure 2.10: Top 20 (a) Unigrams and (b) Most popular pairs for Malayalam, calculated at symbol level.

The higher N-grams can also be referred as joint probability. Symbol level *Bi-gram* give the probability of two symbols occurring together. For example, the probability of symbols w_1 and w_2 occur together is given by:

$$P(w_1, w_2) = P(w_1)P(w_2|w_1) \tag{2.5}$$

Figure 2.10 shows the Unigram and the most popular pairs in Malayalam, calculated from the corpus.

2.8.2 Estimate of Degradations

Here we present the quantitative measure of cuts, merges and spurious noise in the document images from various books. These degradations effects the quality of the document images significantly and degrades the recognition rate.

S.No	Book Name	# Symbols	% Cuts	% Merges	%Noise
1	Indulekha	321470	1.5709	0.4585	0.4420
2	ValmikiRamayanam	228188	0.8361	0.1831	0.3834
3	Sarada	235791	3.4377	0.5174	0.7006
4	Sanjayan	28661	4.1799	0.2233	0.8513
5	Hitlerude Athmakadha	125658	1.6775	0.8435	0.1575
6	BhagatSingh	458016	5.3412	0.8931	0.1261
7	Ramarajabahadoor	664836	7.3801	0.3931	1.0291
8	Thiruttu	117403	7.1395	0.2333	0.5587
9	Dharmaraja	897449	4.6714	0.7349	0.8793
10	IniNjanUrangatte	277257	1.8185	0.7532	0.1558
11	ViddhikaluteSwargam	62396	3.5066	0.5446	1.6475
12	Janmadinam	86269	1.9242	0.4798	0.2619

Table 2.9: Quality analysis of Malayalam books based on degradations.

2.8.3 Estimate of various Quality Measures

To define the quality of a document, we also consider the factors like, density of the document, character spacing, word spacing and line spacing and the thickness of the character.

Density of the document is defined as:

$$Density\ of\ the\ Document = O\ (\ \frac{No.\ of\ Symbols\ in\ the\ Document}{Area\ of\ the\ Document}\ ) \qquad (2.6)$$

While calculating the area of the document page, we eliminate the blank area in the border and the blank area between paragraphs, the area where graphics is present. In other words, we consider only the area where content is present.

Character spacing is the average pixel distance between symbols. Similarly word and line spacing are the average pixel distance between words and lines respectively. Thickness of the character is calculated by applying erosion in the character image until we get a blank/ white image. The average values of these quality measures are given in Table 2.10.

S.No	Book Name	Average				
		Page Density	Char Thickness	Line Spacing	Word Spacing	Char Spacing
1	Indulekha	1.93	7.64	36.45	50.52	7.06
2	ValmikiRamayanam	1.97	9.34	24.71	58.95	7.77
3	Sarada	1.91	7.17	29.15	36.94	9.1
4	Sanjayan	1.69	7.34	34.22	42.27	7.69
5	Hitlerude Athmakadha	2.00	8.87	31.71	43.37	9.46
6	BhagatSingh	2.04	6.34	27.12	50.56	9.17
7	Ramarajabahadoor	1.94	5.53	26.10	42.10	9.32
8	Thiruttu	1.86	4.22	31.48	46.52	8.66
9	Dharmaraja	2.03	5.37	31.37	42.24	11.55
10	IniNjanUrangatte	2.04	7.66	23.37	46.09	7.52
11	ViddhikaluteSwargam	1.74	6.01	29.41	45.60	8.92
12	Janmadinam	1.73	6.23	28.79	45.76	8.92

Table 2.10: Statistics of character density, thickness of the character, character spacing, word spacing, line spacing on Malayalam books.

A high value of page density means that, large number of symbols present in a small area. This happens when the font size is small or the scanning resolution is small. Note that these experiments are conducted on documents scanned with 600dpi resolution, which is considered as a good choice of scanning for OCR systems. Intuitively when the characters packed in a dense manner, the chance for merges are high. The results of percentage of merges and the character density supports this conclusion. The book named *BhagatSingh* has highest page density and the percentage of merges. Thickness of the character directly related to the cuts and merges. When the thickness of the character is low, there will be more cuts. Similarly, if the character spacing is low, there is chance for more merges. Word spacing and Line spacing effects the segmentation at word and line segmentation respectively.

2.9 Quality definitions of document images

We define the quality of the document images in various dimensions. They are the cuts, merges and other degradations in the document, density of the document, character spacing,

word spacing and line spacing, the thickness of the character etc. It is observed that, all the pages in the same book are not having the same level of document quality. The quality of the document vary because of various reasons like, there might be some pages which has some inbuilt degradations in it, which might have happened during the printing or typesetting of the book. Some pages will have more cuts and some might have more merges depending on the lighting adjustments at the scanner etc. These variations results in causes high variation in the recognition accuracy in different pages of the same book.

Depending on the percentage of cuts, merges or noise the words can be put into different qualities. Other than these degradations we consider other qualitative measures mentioned previously to define the quality of a document image.

2.9.1 Word level Degradation

Based on the percentage of degraded words we defined the quality level in words. We define four quality level for words, based on the percentage of degraded words present in the book. A degraded word is, a word with cut, merge or noise present in it. The quality of the book based on words is defined as, if the degraded words are less than 10% of the total words, then the book is put in quality A. Similarly the books with degraded words $10-20\%$ are put in quality B, books with degraded words $20-30\%$ are put in quality B and the books with degraded words more than 30% are put in quality D. Table 2.11 gives the results on these experiments.

		Words			
S.No	Book Name	# Total	# Recognizable	% Degraded	Quality
1	Indulekha	46281	39644	14.34	B
2	ValmikiRamayanam	31360	29339	6.44	A
3	Sarada	32897	26671	18.93	B
4	Sanjayan	4079	3224	20.96	C
5	Hitlerude Athmakadha	16403	14291	12.88	B
6	BhagatSingh	57252	35246	38.44	D
7	Ramarajabahadoor	81021	52047	35.76	D
8	Thiruttu	15654	10553	32.59	D
9	Dharmaraja	95931	65427	31.8	D
10	IniNjanUrangatte	39785	34822	12.47	B
11	ViddhikaluteSwargam	8793	6435	26.82	C
12	Janmadinam	12112	10326	14.75	B

Table 2.11: Word level results computed on all the words (degraded and non-degraded) and non-degraded words in Malayalam books.

2.10 Summary

This chapter proposes a way to generate a large dataset for training and testing the OCR system. We use a DP based method to align the symbols in a word with the given word annotation. We also defined a method to measure the quality of a document based on the degradation of that page rather than the classifier performance. We obtain the symbol level Unigram and Bigram as a byproduct of our approach for word alignment.

Chapter 3

Empirical Evaluation of Character Classification Schemes

3.1 Introduction

Large number of pattern classifiers exist in the literature. Performance of these classifiers depends on the problem, features used and many other problem parameters[2]. A number of comparative studies on classifiers have been found in the literature. STATLOG [38] was considered to be the most comprehensive empirical comparative study for pattern classifiers 10 years back. A recent study focusing on empirical comparison of many recent approaches has been reported by Caruana and Niculescu-Mizil [39]. The best performing classifier in their study was problem dependent, even though some of the classifiers always outperformed most others. Lecun *et. al* [40] reported a comparative study of various convolutional neural network architectures as well as other classifiers for the problem of handwritten digit recognition. Most of the previous studies were limited to relatively small number of classes, and often tested on the UCI [41], NIST or USPS data sets.

Our study on pattern classifiers and various features is primarily focused on character classification issues in Indian scripts, with special emphasis on Malayalam script. Commercial OCR systems are available for Roman scripts. However, character recognition problem in Indian scripts is still an active research area [8, 6]. A major challenge in the development of OCRs for Indian scripts comes from the larger character set, which results in a large class classification problem. Compared to the comparative studies in the literature, we use a huge dataset for the experimental validation.

Scope of this study include (a) applicability of a spectrum of classifiers and features

(b) richness in the feature space (c) scalability of classifiers (d) sensitivity of features to degradation (e) generalization across fonts and (f) applicability across scripts. We can find that all these aspects effect the accuracy of the classifier directly. In Section 3.2 we explain the various parameters used for classifier, features and datasets in this study. Also We briefly explain the theory behind the classifiers and features considered in this section. Readers who are familiar with these methods can skip this section without any lose in continuity. In Section 3.3 we present the various empirical evaluations and the results. The Section 3.4 provides some additional discussions based on other scripts. Finally we give conclusive remarks of this chapter in Section 3.5.

3.2 Problem Parameters

This study considers a spectrum of classifiers and features for the comparison on a huge dataset. In this section we give a brief background of the classifiers and features used for the experiments.

3.2.1 Classifiers

K-Nearest Neighbour (KNN)

One of the most popular classifiers is a nearest neighbour classifier. Its extension to K-nearest neighbor (KNN) is a supervised learning algorithm, where the result of new instance query is classified based on majority of the category of K-nearest neighbors [2]. The purpose of this algorithm is to classify a new object based on attributes and training samples. The classifiers do not use any model to fit and functions based on memory. Given a query point, we find K number of objects or (training points) closest to the query point. The classification is using majority vote among the classification of the K objects. Any ties can be broken at random. K Nearest neighbor algorithm used neighborhood classification as the prediction value of the new query instance.

The popular distance measures used to find the nearest neighbour are Euclidean distance, Mahalanobis distance, City block (Manhattan) distance, Chebyshev distance, Minkowski distance, Canberra distance, Bray Curtis distance etc [2]. We use Euclidean distance based KNN in our experiments.

Approximate Nearest Neighbour (ANN)

Computing exact nearest neighbors in high dimensional space is a very difficult task. There are few methods which can improve the computational requirements compared to a brute-force computation of all distances. However, it has been shown that by computing nearest neighbors approximately, it is possible to achieve significantly faster running times (of the order of 10's to 100's) often with a relatively small actual errors. Many of the ANN algorithms allow the user to specify a maximum approximation error bound, thus allowing the user to control the trade off between accuracy and running time.

The approximate nearest neighbour algorithm we employ here corresponds to [42].

Decision Tree Classifiers(DTC)

Another popular classifier, which classifies samples by a series of successive decisions, is a decision tree. Decision Tree Classifiers (DTC's) are used successfully in many diverse areas such as radar signal classification, character recognition, remote sensing, medical diagnosis, expert systems, data mining and speech recognition, to name only a few [2, 43]. Perhaps, the most important feature of DTC's is their capability to break down a complex decision-making process into a collection of simpler decisions, thus providing a solution which is often easier to interpret. The basic idea involved in any multistage approach is to break up a complex decision into a union of several simpler decisions, hoping the final solution obtained this way would resemble the intended desired solution. The main objectives of decision tree classifiers are: 1. to classify correctly as much of the training sample as possible; 2. generalize beyond the training sample so that unseen samples could be classified with as high accuracy as possible; 3. be easy to update as more training sample becomes available (i.e., be incremental); 4. and have as simple a structure as possible. Then the design of a DTC can be decomposed into following tasks:

1. The appropriate choice of the tree structure.
2. The choice of feature subsets to be used at each internal node.
3. The choice of the decision rule or strategy to be used at each internal node.

We employ a binary decision tree computed using OC1 [44].

Multi-layer Perceptron (MLP)

We also study the performance of neural network classifiers. Multilayer perceptron (MLP) is a feed forward artificial neural network model that maps sets of input data onto a set of

appropriate output [45]. It is a modification of the standard linear perceptron in that it uses three or more layers of neurons (nodes) with nonlinear activation functions, and is more powerful than the perceptron in that it can distinguish data that is not linearly separable, or separable by a hyperplane.

A typical multilayer perceptron (MLP) network consists of a set of source nodes forming the input layer, one or more hidden layers of computation nodes, and an output layer of nodes. The input signal propagates through the network layer-by-layer. The computations performed by such a feed forward network with a single hidden layer with nonlinear activation functions and a linear output layer can be written mathematically as

$$\mathbf{x} = \mathbf{f}(\mathbf{s}) = \mathbf{B}\boldsymbol{\varphi}(\mathbf{A}\mathbf{s} + \mathbf{a}) + \mathbf{b} \tag{3.1}$$

where $\mathbf{s}$ is a vector of inputs and $\mathbf{x}$ a vector of outputs. $\mathbf{A}$ is the matrix of weights of the first layer, $\mathbf{a}$ is the bias vector of the first layer. $\mathbf{B}$ and $\mathbf{b}$ are, respectively, the weight matrix and the bias vector of the second layer. The function $\boldsymbol{\varphi}$ denotes an element wise non-linearity.

The supervised learning problem of the MLP can be solved with the back-propagation algorithm. The algorithm consists of two steps. In the forward pass, the predicted outputs corresponding to the given inputs are evaluated as in Equation 3.1. In the backward pass, partial derivatives of the cost function with respect to the different parameters are propagated back through the network. The chain rule of differentiation gives very similar computational rules for the backward pass as the ones in the forward pass. The network weights can then be adapted using any gradient-based optimization algorithm. The whole process is iterated until the weights have converged.

Experiments were conducted by changing parameters like the number of hidden units, number of epochs, and the momentum term in MLP. Finally, the best results are reported.

Convolutional Neural Networks (CNN)

We explored another popular architecture of neural network classifiers called convolutional neural network (CNN). Convolutional Neural Networks are a special kind of multi-layer neural networks [46, 47]. Like MLPs, they are also trained with a version of the back-propagation algorithm. But they differ in the architecture of the network. Convolutional Neural Networks are designed to recognize visual patterns directly from pixel images with minimal preprocessing. They can recognize patterns with extreme variability (such as handwritten characters), and with robustness to distortions and simple geometric transforma-

tions. CNN exploit the knowledge that the inputs are not independent elements, but arise from a spatial structure. CNN combine three architectural ideas to ensure some degree of shift and distortion invariance: local receptive fields (Units connected to small neighborhoods in previous layer), shared weights(Units in a layer are organized into planes (feature maps) that share a weight vector) and spatial or temporal sub-sampling [48].

Convolutional Neural Networks (CNN) are shown to produce excellent recognition rates for digit recognition problem by Lecun *et. al.* [40]. We use a 5 layers CNN with architecture same as LeNet-5 [40].

Naive Bayes Classifiers (NB)

We also compare with a Naive Bayes (NB) classifier. A Naive Bayes classifier is a simple probabilistic classifier based on applying Bayes' theorem with strong (naive) independence assumptions. Naive Bayes classifiers assume that the effect of a variable value on a given class is independent of the values of other variable. This assumption is called *class conditional independence*. It is made to simplify the computation and in this sense considered to be Naive [2].

Let X be the data record (case) whose class label is unknown. Let H be some hypothesis, such as "data record X belongs to a specified class C." For classification, we want to determine $P(H|X)$ – the probability that the hypothesis H holds, given the observed data record X. $P(H|X)$ is called the posterior probability of H conditioned on X. In contrast, $P(H)$ is the prior probability, or *apriori* probability, of H. The posterior probability, $P(H|X)$, is based on more information (such as background knowledge) than the prior probability, $P(H)$, which is independent of X.

Similarly, $P(X|H)$ is posterior probability of X conditioned on H. $P(X)$ is the prior probability of X. Bayes theorem is useful in that it provides a way of calculating the posterior probability, $P(H|X)$, from $P(H)$, $P(X)$, and $P(X|H)$. Bayes theorem can be stated as:

$$P(H|X) = P(X|H)P(H)/P(X) \tag{3.2}$$

This classifier is known to be mathematically optimal under restricted settings.

Support Vector Machines (SVM)

No empirical evaluation is complete without evaluating the Support Vector Machine (SVM) classifier, at this stage. SVMs have received considerable attention in recent years.

SVMs are a set of related supervised learning methods used for classification and regression [49, 50]. Given a set of points belonging to two classes, a Support Vector Machine (SVM) finds the hyperplane that separates the largest possible fraction of points of the same class on the same side, while maximizing the distance from either class to the hyperplane. SVMs minimize the structural risk - that is, the probability of misclassifying yet-to-be-seen patterns for a fixed but unknown probability distribution of the data. SVMs use the positive and negative samples for a class to find the support vectors, the samples that have high probability of getting misclassified. These support vectors are used to define a decision boundary between the classes such that the margin between the two classes is maximized. Hence it is called a maximum margin classifier. It has high generalization capability [51].

Consider the following two-class classification problem. Given a training dataset if l independently and identically distributed(i.i.d) samples,

$$(x_i, y_i), i = 1, 2, \ldots l, y_i \in (-1, 1), x_i \in \Re^d \tag{3.3}$$

where d is the dimensionality of the dataset. SVM constructs the decision function by finding the hyperplane that has the maximum margin of separation from the closest data points in each class. Such a hyperplane is called an optimal hyperplane. Training an SVM requires solving the following quadratic optimization problem:

Maximize:

$$\sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j K(x_i, x_j) \tag{3.4}$$

subject to the constraints $\alpha_i \geq 0, i = 1, 2, \ldots l$, and $\sum_{i=1}^{l} \alpha_i y_i = 0$ where α_i are the Lagragian multipliers corresponding to each of the training data points x_i.

The decision function is given by:

$$f(x) = sgn(\sum_{i=1}^{l} \alpha_i y_i K(x_i, x)) \tag{3.5}$$

The function K in the equations 3.4 and 3.5, is called the kernel function. It is defined as $K(x, y) = \phi(x)\phi(y)$, where $\phi : \Re^d \longrightarrow H$ maps the data points to a high dimensional(possibly infinite dimensional) space H. For a linear SVM, $K(x, y) = x.y$. While using kernels, we do not need to know the values of the images of the data points in H.

SVMs are basically binary classifiers. In our study, we consider two possible methods of fusing the results of the pair-wise classifiers. First one computes the majority of all the classifiers. We refer to this as SVM-1. The second SVM classifier (SVM-2) integrates the decisions using a decision directed acyclic architecture (DDAG) [51].

3.2.2 Features

In this study, we employ features which are relatively generic. In the context of character classification, this means that the features are highly script-independent. The first class of features are based on moments. We use Central Moments (CM) and Zernike Moments (ZM). They are popular for 2D shape recognition in image processing literature. Another class of feature extraction strategies we used, employ orthogonal transforms for converting the input into a different representation and select a subset of dimensions as effective features. We use Discrete Fourier Transform (DFT) and Discrete Cosine Transform (DCT) as the representative from this class of feature extraction schemes.

A popular class of feature extraction schemes extracts the features by projecting the input (image) into a set of vectors. We consider three candidate algorithms from this class of feature extraction schemes. They are Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA) and Random Projections (RP).

We compare the performance by treating the image itself (IMG) as the feature vector. We also consider an image resulting out of distance transform (DT) as yet another feature. This feature is similar to a fringe map used in [23].

Technical details of many of these feature extraction methods can be found in [52]. There could be numerous other possibilities for feature extraction. However, we have limited our attention to a set of popular and promising feature extraction schemes. One could also think of extracting script specific features to exploit the specific characteristics of the script. However, generating a rich high dimensional feature space with such hand-crafted features could be a difficult task.

In this section we give a brief explanation of the theory behind these features.

Central Moment(CM)

Central moments are moments around the mean of images [53]. We can use these moments to provide useful descriptors of shape. Central moments are calculated by shifting the origin to the center of the image (μ_x, μ_y) as defined below:

$$CM_{i,j} = \sum_{x=0}^{N-1} (x^i - \mu_x)(y^j - \mu_y)w(x, y) \tag{3.6}$$

with the mean $\mu_x = m_{10}/m_{00}$ and $\mu_y = m_{01}/m_{00}$. The normalized central moments are then computed by dividing the result with $\sum_{x=0}^{N-1} w(x, y)$. We experiment with central moment

cm_{02} (F_{11}) that computes squared distance from the y component of the mean μ_y.

$$F_{11} = \sum_{x=0}^{N-1} (y^2 - \mu_y) w(x, y) \tag{3.7}$$

We calculated the raw-vice central moment of the 20×20 scaled binary samples, which resulted to a feature vector length of 20.

Zernike Moments(ZM)

The Zernike moments are a set of complex polynomials inside the unit circle, i.e. $x^2+y^2 = 1$, such that this set completely covers the interior of the unit circle [54]. Zernike moments are defined to be the projection of the image function on these orthogonal basis functions. The basis functions $V_{nm}(x, y)$ are given by

$$V_{nm}(x, y) = V_{nm}(\rho, \theta) = R_{nm}(\rho) e^{jm\theta} \tag{3.8}$$

where n is a non-negative integer, m is non-zero integer subject to the constraints $n - |m|$ is even and $|m| \leq n$, ρ is the length of the vector from origin to (x, y) , θ is the angle between vector ρ and the x -axis in a counter clockwise direction and $R_{nm}(\rho)$ is the Zernike radial polynomial. The Zernike radial polynomial $R_{nm}(\rho)$ are defined as:

$$R_{nm}(\rho) = \sum_{k=|m|, n-k=even}^{n} \frac{(-1)^{((n-k)/2)} \frac{n+k}{2}!}{\frac{n-k}{2}! \frac{k+m}{2}! \frac{k-m}{2}!} \rho^k = \sum_{k=|m|, n-k=even}^{n} \beta_{n,m,k} \rho^k \tag{3.9}$$

Since Zernike moments are defined in term of polar coordinates (r, θ) the Zernike polynomials will have to be evaluated at each pixel position (x, y). Thus the polar from Zernike moments suggests a square-to-circular image transformation.

Among many moment based descriptors, Zernike moments have minimal redundancy (due to the orthogonality of basis functions), rotation invariance and robustness to noise; therefore they are used in a wide range of applications on image analysis, reconstruction and recognition.

We choose the 0 to 12 higher order Zernike moments as our feature set, which resulted to a feature vector length of 47. (We consider both real and imaginary values as features).

Discrete Fourier Transform(DFT)

Discrete Fourier transforms are extremely useful because they reveal periodicities in input data as well as the relative strengths of any periodic components [53, 55]. The sequence

of N complex numbers $x_0, ..., x_{N1}$ is transformed into the sequence of N complex numbers $X_0, ..., X_{N1}$ by the DFT according to the formula:

$$X_k = \sum_{n=0}^{N-1} x_n \exp^{-\frac{2\pi i}{N} kn} \, k = 0, ...N-1 \tag{3.10}$$

In general, the discrete Fourier transform of a real sequence of numbers will be a sequence of complex numbers of the same length.

In mathematics, the discrete Fourier transform (DFT) is a specific kind of Fourier transform, used in Fourier analysis. It transforms one function into another, which is called the frequency domain representation, or simply the DFT, of the original function. But the DFT requires an input function that is discrete and whose non-zero values have a limited (finite) duration. Its inverse transform cannot reproduce the entire time domain, unless the input happens to be periodic. Therefore it is often said that the DFT is a transform for Fourier analysis of finite-domain discrete-time functions. The sinusoidal basis functions of the decomposition have the same properties.

DFT is computed by diving the image into blocks of fixed size and processing them separately to extract local features in each block. Each block is transformed to DFT space and higher rank components are selected. We choose the block size as 5 X 5. This gives us 20 DFT features from a 20 X 20 sample image.

Discrete Cosine Transform (DCT)

A discrete cosine transform (DCT) expresses a sequence of finitely many data points in terms of a sum of cosine functions oscillating at different frequencies[53, 55]. DCTs are important to numerous applications in science and engineering, from lossy compression of audio and images (where small high-frequency components can be discarded), to spectral methods for the numerical solution of partial differential equations. The use of cosine rather than sine functions is critical in these applications: for compression, it turns out that cosine functions are much more efficient (as explained below, fewer are needed to approximate a typical signal), whereas for differential equations the cosines express a particular choice of boundary conditions. In particular, a DCT is a Fourier-related transform similar to the discrete Fourier transform (DFT), but using only real numbers. The DCT is often used in signal and image processing, especially for lossy data compression. The DCT is used in JPEG image compression, MJPEG, MPEG, DV, and Theora video compression.

DCT features are calculated in the same way as DFT features are done. We choose 16 DCT components as our feature set.

Principal Component Analysis(PCA)

Principal Component Analysis (PCA) is derived from Karhunen-Loeve's transformation. Given an s-dimensional feature vector, PCA tends to find a t-dimensional subspace whose basis vectors correspond to the maximum variance direction in the original feature space [2]. This new subspace is normally lower dimensional ($t << s$). If the image elements are considered as random variables, the PCA basis vectors are defined as eigen vectors of the scatter matrix.

Let μ be the mean vectors Σ the covariance matrix of the features in their original space. The eigen vectors and eigen values of the covariance matrix are calculated. Let the eigen vectors be e_1 with a corresponding eigen value λ_1, e_2 with eigen value λ_2 and so on. Choose k eigen vectors having largest eigen values where k is the dimension of the subspace that the features are being mapped to. Now we form a transformation matrix A with these eigen vectors as columns. For a new sample x, the transformed feature vector is calculated as

$$x' = A^{T(x-\mu)} \tag{3.11}$$

We choose 350 as our PCA feature vector length.

Linear Discriminant Analysis (LDA)

Fishers linear discriminant analysis is a feature extraction method that projects high-dimensional data onto a line and performs classification in this one dimensional space [2]. The projection maximizes the distance between the means of the two classes while minimizing the variance within each class. LDA finds the vectors in the underlying space that best discriminate among classes. For all samples of all classes the between-class scatter matrix S_B and the within-class scatter matrix S_W are defined. The goal is to maximize S_B while minimizing S_W, in other words, maximize the ratio $\frac{\det|S_B|}{\det|S_W|}$. This ratio is maximized when the column vectors of the projection matrix are the eigen vectors of $(S_W^{-1} \times S_B)$. We choose the LDA feature vector length as 350.

Random Projections (RP)

In random projection (RP), the original d-dimensional data is projected to a k-dimensional ($k << d$) subspace through the origin, using a random $(k \times d)$ matrix R whose columns have unit lengths [56]. Using matrix notation where $X_{d \times N}$ is the original set of N d-dimensional observations,

$$X^{RP}_{k\times N} = R_{k\times d} X_{d\times N} \tag{3.12}$$

is the projection of the data onto a lower k-dimensional subspace. The key idea of random mapping arises from the Johnson-Lindenstrauss lemma [57]: if points in a vector space are projected onto a randomly selected subspace of suitably high dimension, then the distances between the points are approximately preserved.

RP is computationally very simple: forming the random matrix R and projecting the $d \times N$ data matrix X into k dimensions is of order $O(dkN)$, and the data matrix X is sparse with about c nonzero entries per column, the complexity is of the order $O(ckN)$. We choose 350 RP features for the experiments.

Raw Pixel (IMG)

We also compare the performance by treating the binarized image (IMG) as the feature vector. This does not result in any dimensionality reduction. Avoiding any explicit feature extraction assumes that the data do not vary significantly in appearance. We obtained 400 IMG features from the samples scaled to the size 20 X 20.

Distance Transform(DT)

For the benchmarking, we also consider an image resulting out of distance transform (DT) as yet another feature. This feature is similar to a fringe map [58]. A distance transform, also known as distance map or distance field, is a representation of a digital image. The choice of the term depends on the point of view on the object in question: whether the initial image is transformed into another representation, or it is simply endowed with an additional map or field.

The map supplies each pixel of the image with the distance to the nearest obstacle pixel. A most common type obstacle pixel is a boundary pixel in a binary image. In this case also, we choose the feature vector length as 400.

Datasets We employ binary character images from documents in multiple languages for the study. The script used for experiments are Malayalam, Telugu and English. We work on an annotated corpus mentioned in the previous Chapter 2.1. Examples of character images from the the datasets are given in the Figure 3.1. Around 5% of the datasets are randomly picked for training, and the rest is used for testing. The number of classes in this

Figure 3.1: Examples of character images of Malayalam Script, used for the experiments

experiment is 205, 72 and 350 respectively for Malayalam, English and Telugu. Malayalam dataset is more than $5,00,000$ samples, collected from 5 different books.

3.3 Empirical Evaluation and Discussions

3.3.1 Experiment 1: Comparison of Classifiers and Features

In the first experiment, we compare the performance of different classifiers and features on the Malayalam data and the error rates are presented in the Table 3.1. The aim of the study is to find a set of features and classifiers from the literature whose combination perform the best on the character recognition problem. The classifiers considered for the study are MLP, KNN, ANN, SVM-1, SVM-2, NB and DTC. We also compared the results with CNN, which resulted in an error rate of 0.93%. Reader may note that feature extraction is embedded in the CNN, and can not be compared as in Table 3.1.

For MLP, the reported results are with the number of nodes in the hidden layer 60, number of epochs 30 and momentum 0.6. For both KNN and ANN, Euclidean distance is used, and the results are reported with $K = 5$. Here SVM results are reported with linear kernel. For SVM experiments we used SVM^{light} implementation. All the images are scaled to a common size of 20×20 pixels. Five percentage of samples from each class are randomly selected as training set and the classifier is tested on the rest 95% of the data.

The Malayalam data, described in the previous section, is used for this experiment. A series of feature extraction schemes starting from moments to linear discriminant analysis

Feat	Dim.	MLP	KNN	ANN	SVM-1	SVM-2	NB	DTC
CM	20	12.04	4.16	5.86	10.04	9.19	11.93	5.57
DFT	16	8.35	8.96	9.35	7.88	7.86	15.33	13.85
DCT	16	5.43	5.11	5.92	5.25	5.24	8.96	7.89
ZM	47	1.30	1.98	2.34	1.24	1.23	3.99	8.04
PCA	350	1.04	1.14	2.39	0.37	0.35	4.83	5.97
LDA	350	0.55	0.52	1.04	0.35	0.34	3.20	4.77
RP	350	0.33	0.50	0.74	0.34	0.34	3.12	8.04
DT	400	1.94	1.27	1.98	1.84	1.84	4.28	2.20
IMG	400	0.32	0.56	0.78	0.32	0.31	1.22	2.45

Table 3.1: Error rates on Malayalam dataset.

is used for the study. Please refer to the previous section for the acronyms used in the Table 3.1. These feature extraction schemes are language/script independent.

It can be seen that SVM classifiers outperformed all other classifiers because of their high generalization capability. KNN also performs moderately well, with a very high classification time. The DTC and NB performed the worst of all. In cases of certain features, KNN had performance comparable to SVM. However, this was obtained with significantly higher computational requirement.

Observation: We observe that SVM classifier outperform other classifiers. A class of feature extraction techniques, based on the use of raw image and its projection onto an uncorrelated set of vectors resulted in the best performance.

3.3.2 Experiment 2: Richness in the Feature space

One other important observation from the previous experiment is that, the classification accuracy can be improved using a large number of features. For a set of feature extraction techniques (LDA, PCA, RP, DCT, DFT), we varied the number of features used and conducted the classification experiment on the Malayalam data. Results are presented in Figure 3.2. It is observed that the error rates rapidly decreases with the increase in number of features initially and then remain more or less constant. When the number of features is small, LDA outperforms PCA. This is because LDA has more discriminative power than PCA. However, with a large number of features PCA, LDA, RP etc. performs more or less similarly, which implies that as the feature space become larger, the discriminative power of the feature may increase.

We used the SVM-2 classifier for the experiments, which performed the best in the previous feature-classifier combination study. RP was performing the best with 350 dimensional feature vector (with error rate 0.34%), where LDA and PCA also performed more than 99% accuracy (with error rate 0.35% and 0.37% respectively).

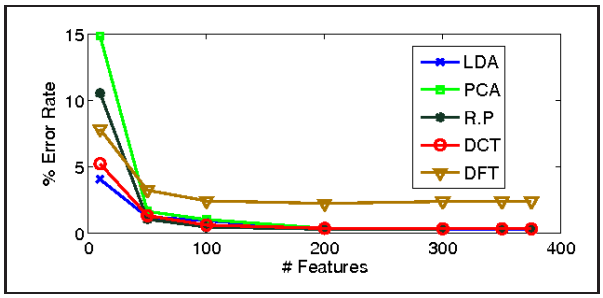


Figure 3.2: Richness in feature space.

Observation: We observe that for better performance, a rich feature space is required for large class problems. If the feature space is rich, they could also become discriminative for most classifiers. It may be noted, with a large feature vector computed using a statistical technique, character classification problem can be solved with reasonable success.

3.3.3 Experiment 3: Scalability of classifiers

We now look into a relatively un-noticed aspect of pattern classifiers – scalability to the number of classes. The classifier performance has a great effect on number of classes involved. We conduct the experiments with increasing the number of classes from 10 to 200. The classes are selected randomly from a set of 200 classes. At the first step, 10 classes are randomly selected from 200 classes. The classifier is trained with 5% of samples from each of these 10 classes, and tested of the rest 95% of the samples of these 10 classes. To continue the experiment with more number of classes, another set of 10 classes are selected from 190 classes and added to the initial set of 10 classes. Now from the set of 20 classes 5% of samples from each class, are randomly selected for training and the classifier will be tested on rest 95% of the samples of these 20 classes. The experiment is continued for all the 200 classes. The experiments are conducted multiple times, and finally the average accuracies are reported in Figure 3.3.

It is observed that the performance of all the classifiers goes down as the number of classes increases. Most of the publicly available multi-class datasets (eg. UCI data sets) have total number of classes in few tens. One of the challenges in character recognition in Indian languages is to design classifiers that can scale to hundreds of classes [8].

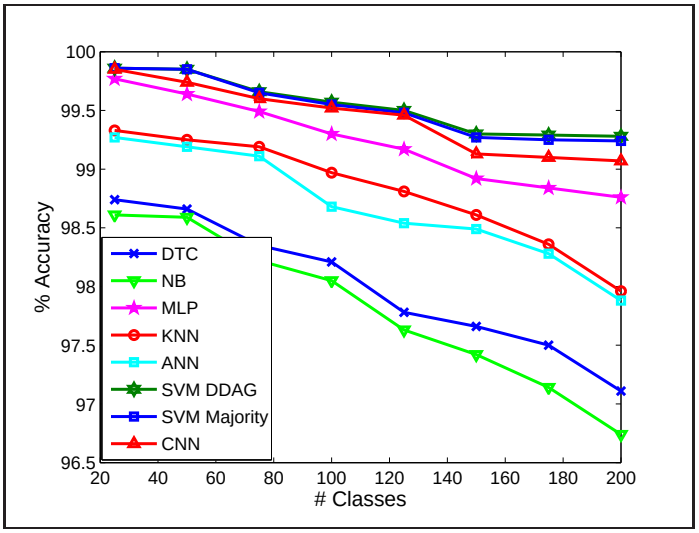


Figure 3.3: Scalability: Accuracy of different classifiers Vs. no. of classes.

Observation: Out of all the classifiers considered, we observe that the SVM classifiers (SVM-1 and SVM-2) degrade gracefully when the number of classes increases. The second best class of classifiers is the Neural network classifiers.

3.3.4 Experiment 4: Degradation of Characters

Characters in real documents are often degraded. We now investigate the performance of various feature extraction schemes for degradation. Study on the effects of degradation in the classification accuracy is important in any classification problem. The effect of noise in the component image may change the features extracted from the image.

Degradation models are developed to simulate the various artifacts seen in real-life documents. We used the degradation models in [59] for the systematic studies. The salt and pepper type of noise is caused by errors in data transmission and scanning. It is distributed all over the image flipping white pixels to black (i.e. pepper) if it is a background and black pixels to white (i.e. salt) if it is a foreground. Degradation caused by erosion of boundary pixels effects the image by changing either black pixels to white or vice verse. It happens mostly at the boundary of the image due to the imperfections in scanning. We use the degradation model proposed by Zheng and Kanungo [59], which states that black and white pixels are swapped according to some probabilities directly related to the distance from the boundary pixel. The Degradations- 1, 2 and 3 are modeled by varying the level of degradations explained above.

On a similar line, we also modeled ink blobs, cuts and shear to analyze the performance of the features [34]. The occurrence of cuts in a document image breaks continuity of the shape of characters (or components) by changing pixel values into background (white). Such degradation occurs due to paper quality, folding of paper and print font quality. These noises corrupt a size of $n \times m$ pixels at a time by flipping black pixels into white. Blobs occur due to large ink drops within the document image during printing, faxing and photocopying. The existence of these noise pixels merge separate characters or components, thereby distorting character readability. The shear gives an italic effect on the character images. This effect is modeled by the affine transform of character image with five degree.

Some examples of the degraded images from the dataset is shown in Figure 3.4(d).

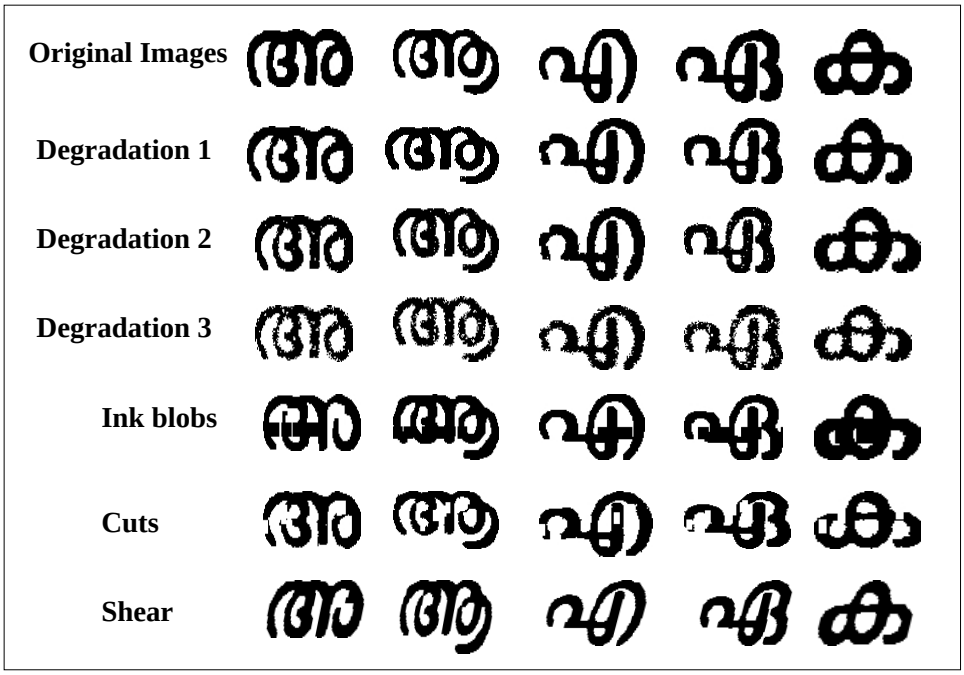


Figure 3.4: Examples of various degraded characters.

Out of a wide spectrum of features studied, our observation has been that the statistical features are more robust compared to structural features. In presence of excessive degradation, when the characters gets cut into multiple parts, most of the feature extraction schemes have difficulty. This problem will have to be understood as a segmentation problem. Structural features like number of loops, junctions etc. were found to be highly sensitive to degradations.

Statistical features are reasonably insensitive to the small degradations (D-1, D-2 and

D-3) as shown in Table 3.2. These degradations are primarily three different levels of boundary erosion. Features like distance transforms (DT) which works well with the clean images fails drastically in the presence of ink blobs as well as cuts in the symbols. With shear, performance of all the features reduces. But the performance degradation with PCA, LDA, RP and raw image (IMG) are much better than the other features in the study.

Feature	D-1	D-2	D-3	Blob	Cuts	Shear
CM	9.45	9.46	10.97	16.28	12.33	30.07
DFT	7.89	7.93	7.98	26.70	8.73	18.90
DCT	5.71	5.72	6.07	19.80	7.93	16.46
ZM	1.96	1.98	2.10	8.41	4.35	17.75
PCA	0.30	0.31	0.32	2.17	0.64	8.59
LDA	0.39	0.39	0.40	2.01	0.61	7.32
DT	1.75	1.98	2.21	10.33	5.07	12.34
RP	0.48	0.67	1.04	3.61	0.71	6.75
IMG	0.32	0.33	0.33	2.78	0.66	6.84

Table 3.2: Error rates of degradation experiments on Malayalam Data, with SVM-2.

Observation: Our observation is that statistical features like LDA are better suited to address the degradations in the data set. Shear is a challenging degradation to address. Traditional feature extraction schemes need modifications to obtain acceptable performance on shear.

3.3.5 Experiment 5: Generalization Across Fonts

This study mainly points towards the performance variation of classifier schemes with minor variations in the font. We included 5 popular fonts in Malayalam (MLTTRevathi, MLTTKarthika, MLTTMalavika, MLTTAmbili and MLTTKaumudi)in this study. The experiment is conducted by training the classifier with samples from 4 different fonts and test on the fifth font. We use SVM-2 as the classifier and LDA features. The results are reported in Table 3.3. The one dataset(S1) is without any degradation, and the second one(S2) is with degradation. It can be observed that better generalization across fonts can be obtained by adding degradation to the training data. Also note that, this observation need not applicable to a completely different and fancy font. This experiment is limited to popular fonts which are often used for publishing.

Observation: Generalization across similar type fonts can be achieved by adding some degradation to the training data.

	Font-1	Font-2	Font-3	Font-4	Font-5
S1	98.15	95.49	92.52	94.27	92.22
S2	98.97	97.14	95.22	94.59	94.65

Table 3.3: Error rates on different fonts, without degradation in training data (S1) and with degradation in training data.

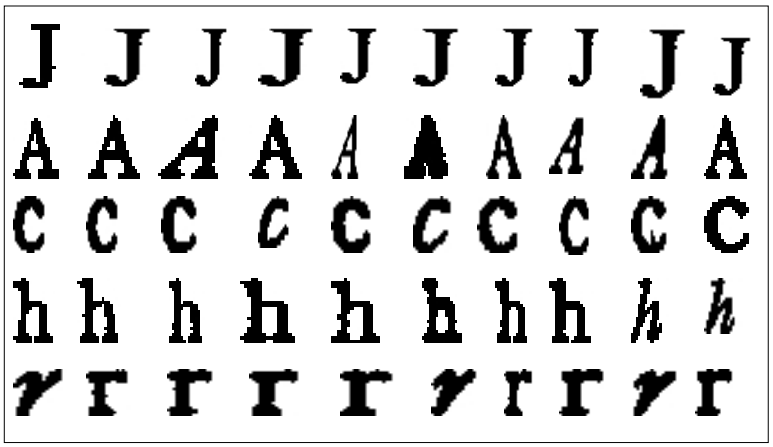


Figure 3.5: Examples of character images from English dataset.

3.3.6 Experiment 6: Applicability across scripts

Now, we demonstrate that the observations of the previous experiments are also extend-able to other scripts. For this, we consider, the Telugu and English data. We use around 50000 real character images for Telugu and English experiments. They are obtained from scanned document images for the experimentation. The English dataset composed of 72 classes and Telugu dataset of 350 classes. Examples of sample images from English and Telugu datasets are given in the Figure 3.5 and Figure 3.6. In all our experiments, SVM-2 classifier had shown the best results and we present the results of this SVM-2 classifier in Table 3.4.

We conducted experiments with 2 different image sizes, 20×20 and 40×40 pixels. The images of size 40×40 resulted in better accuracy than the 20×20. This is because the character in Telugu have relatively more complex shapes than English and Malayalam. With increase in image size, the feature space becomes further rich and possibly more discriminative.

Observation: We observe that our conclusions on character classification are highly script /language independent.

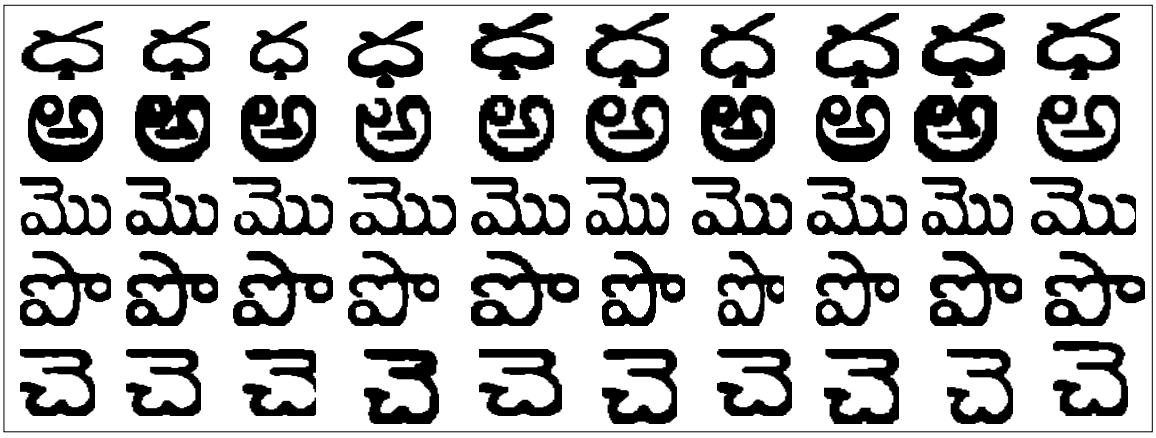


Figure 3.6: Examples of character images from Telugu dataset.

3.4 Discussion

We present some more results of our experiments with Bangla and Kannada datasets. The Bangla dataset consists of 17022 of samples of 49 classes. The 49 classes includes the basic character set of Bangla script. Examples of samples from Bangla dataset are given in Figure 3.7. The Kannada dataset included an exhaustive set of symbols in Kannada script. It includes 283 classes and 74767 samples. Examples from Kannada dataset are given in the Figure 3.8.

We conducted experiments with SVM-2 classifier and used the features IMG, LDA, PCA, and RP. The experiments are conducted with changing the ratio of changing training and testing samples. We selected the train-test ratio of 5:95, 10:90, 20:80 and 40:60. The training samples are randomly selected from the dataset and the rest of the samples used for testing. We used a scale size of 20×20. The experimental results are given in the Table 3.4.

It can be noted that for all the features as the training ratio (size of the training set) increases the accuracy of the classifier also increases. But it can also be noted that, even by selecting 5% of training data, the accuracies are relatively high, or in other words, even with 5% of training data, the results are comparable to 40% of training data. This gives an evidence of the high generalization capacity of SVM classifiers.

In this chapter, we have tried to provide the low-level details of the experiments and implementation. However, some fine aspects which are widely known in the community have been avoided. The absolute values of error rates may not mean that the OCR problem for

Feature	Telugu		English	
	20×20	40×40	20×20	40×40
CM	20.78	12.32	7.25	6.48
ZM	8.45	5.48	2.04	1.12
DCT	9.67	2.71	2.14	1.04
DFT	15.71	6.71	5.37	3.31
PCA	4.62	2.93	0.86	0.46
LDA	2.56	1.67	0.29	0.23
RP	2.49	1.66	0.28	0.23
DT	3.48	3.17	0.98	0.87
IMG	3.18	2.84	0.28	0.23

Table 3.4: Experiments on various scripts, with SVM-2.

Figure 3.7: Examples of character images from Bangla dataset.

these scripts can expect these performances. These rates are obtained on isolated segmented characters. To improve the accuracies beyond whatever we have reported here, one may have to tune the parameters, fuse the features and employ better image processing and segmentation algorithms. That is not the objective of this work.

The cost we need to pay for a richer feature space is the additional computations in pattern classification. An alternate way of achieving this is using kernels as in SVM. Our experience is that, one can obtain very high classification rates and efficient classification

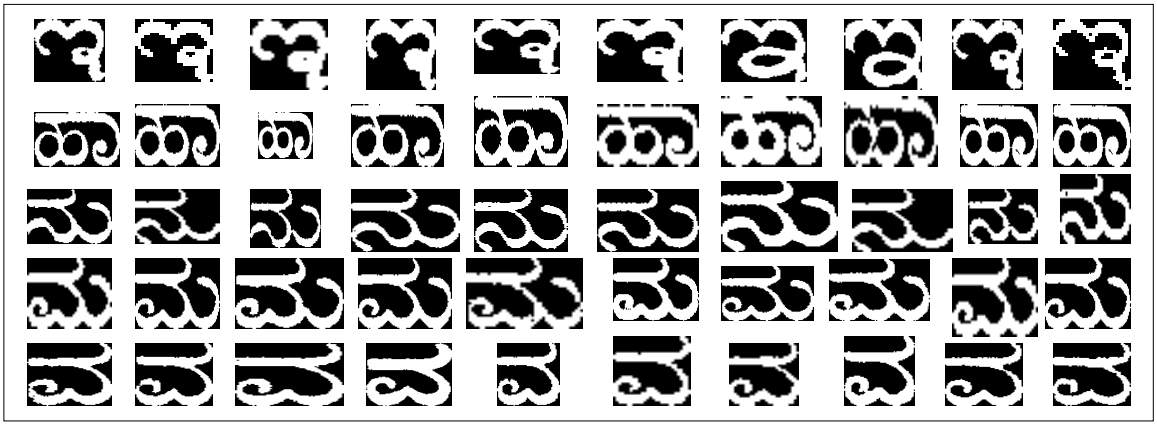


Figure 3.8: Examples of character images from Kannada dataset.

Language	# Classes	# Samples	Feat	Dim.	Train:Test Ratio			
					5:95	10:90	20:80	40:60
Bangla	49	17022	IMG	400	95.99	97.00	97.45	97.83
			PCA	350	95.78	96.84	97.41	97.66
			LDA	350	96.26	97.01	97.43	97.66
			RP	350	96.08	97.01	97.44	97.66
Kannada	283	74767	IMG	400	96.60	97.76	98.23	98.67
			PCA	350	96.21	97.63	98.17	98.59
			LDA	350	96.47	97.69	98.24	98.62
			RP	350	96.40	97.66	98.20	98.63

Table 3.5: Experiments with Bangla and Kannada datasets.

on our state of the art desktop computers.

3.5 Summary

In this chapter, we present the results of our empirical study on character classification problem focusing on Indian scripts. The dimensions of the study included performance of classifiers using different features, scalability of classifiers, sensitivity of features on degradation, generalization across fonts and applicability across five scripts etc. We have demonstrated that with a rich feature space, the problem is solvable with an acceptable performance using state of the art classifiers like SVMs.

Some of the interesting results of our experiments are summarized below. SVM classifiers are found to outperform other classifiers throughout the experiments. The naive Bayes and decision tree classifiers are the poorly performing ones. Statistical features with a rich feature space performed well across the classifiers. A large feature space derived with the statistical feature extraction schemes, and a classifier with high generalization capability are found to be the ideal candidates for solving character classification problems in Indian languages.

Chapter 4

Design and Efficient Implementation of Classifiers for Large Class Problems

4.1 Introduction

Multiclass pattern classifiers have significant applications in many real-life problems. Traditional pattern recognition literature aims at designing optimal classifiers for two class classification problems [2]. However, most of the practical problems are multi-class in nature. When the number of classes increase, problem becomes challenging, both conceptually as well as computationally. Large class classification problems often appear in object recognition, bio-informatics, character recognition, biometrics, data-mining etc.

The analysis of scalability of classifiers presented in Subsection 3.3.3, shows that many of the popular classifiers fail to scale to large number of classes. Our study reveal that classifier systems with multiple modular classifiers scale well. Our empirical studies and theoretical results provide convincing evidences to support the utility of SVM (multiple pair-wise) classifiers for solving the problem. In addition to this, recent comparative studies have argued that Support Vector Machine (SVM) based classifiers provide the best results on a wide variety of data sets [60, 39].

However, a direct use of multiple SVM classifiers has certain disadvantages. One of the disadvantage comes in terms of storage and computational requirements. SVMs were originally designed for binary (two-class) classification [61]. Direct extension of SVM to multiclass classification is not attractive due to the complexity of the associated optimization

task [62]. Therefore, multiclass problem using SVMs is usually solved as several independent binary classification problems.

Several techniques for solving a multiclass problem using binary SVMs are available [63, 64]. Preferred methods for doing this are: 1-Vs-1 method implemented by max-wins (majority voting) [62] and Directed Acyclic Graph (DAG) based SVM [51]. While both these methods achieve similar classification accuracies, DAG-SVM is computationally efficient compared to majority voting. The architecture of DAG to solve a four-class problem is shown in Figure 4.1. Each node is an independent trained binary-SVM classifier designed for a specific pair of classes. Each of these classifiers take decision based on the associated support vectors (s_i) it has, using $f(x) = \sum_i \alpha_i y_i K(x, s_i) + b$. Here, x is the test sample, α_i is the Lagrangian and y_i is the predictions corresponding to the s_i. A node contains an array A of scalar values $(\alpha_i \cdot y_i)$ (we refer this product as A_i) and another array V of support vectors (SVs). Support Vectors are of dimension D, where D is the feature dimension. Clearly, the storage and computational complexity of each node is proportional to the number of SVs it has. Since there are NC_2 pairwise classifiers, to solve a N class problem the storage and computational complexity of the final classifier becomes high for many practical applications.

There are well established methods that reduce the complexity of SVMs, generally by reducing the number of SVs. Some of them are *exact* simplification methods while others aim at *approximate* reductions. Burges [65] introduced a method for determining a reduced set of vectors from the original SVs. This reduced set method achieved 90% reduction rate with small impact on generalization. T.Downs *et al.* [66] presented an exact simplification method that gave 65% average reduction on different data sets. Clearly, the application of these methods at each node lead to an overall reduction in size of the multiclass solution.

However, the overall reduction is only the average of reductions obtained at the nodes, that need not be the best for a multiclass problem. We propose a new data structure for multiclass solutions, that exploits the redundancies in a multiclass scenario (while traditional methods focused on binary-SVMs). In our case, as the number of classes, N, increases the reduction becomes more and more significant. We also propose efficient methods to minimize the storage and computational complexity of SVMs for the classification purpose. We extend our algebraic simplification method for simplifying hierarchical classifier solutions. Experimental validations on large class (of the order of hundreds) data sets show that our proposed implementation is scalable even with minimum computational resources.

Also, the optimal design for multiclass SVM classifiers is a research area. The success of SVM methods lies in the choice of most suitable kernel for a particular problem. But

there is no pre-designed method to find the best kernel for a problem. We address these issues by efficiently designing a Decision Directed Acyclic Graph (DDAG) classifier with SVM pair-wise classifiers as nodes in the graph. We argue that, in a large class problem most of the pairs of classes are linearly separable. Therefore, we choose linear kernel for the pair-wise SVMs in the DDAG.

In the Section 4.2 we discussed the use of a multiclass data structure which is best suited to store the support vectors(SVs) for large class problems. In the Section 4.3 we propose an algebraic solution to reduce the number of support vectors in a hierarchical manner. In this thesis we have given more attention to the classification module present in the OCR architecture. In the Section 4.4, we discuss about the character classification scheme used for designing the OCR system.

4.2 Multiclass Data Structure(MDS)

In this section, we introduce our Multiclass data structure (MDS) for efficiently storing and accessing SVs. MDS for a N-class problem is shown in Figure 4.2. It consists of two major components. First one is a set of nodes, each of which represents a *modified* IPI node. (IPI (Independent Pairwise Implementation) represents the nodes in a naive implementation.) Second one is a list of vectors L, containing *reduced* set of SVs for the multiclass problem. The effectiveness of our solution basically comes from the following change in the node structure. The first scalar array A in the node is retained as such, while the second array of vectors that stored the SVs in the original node (Figure 4.1) are replaced with a scalar array $INDEX$ in MDS. This second array now stores the index positions of the corresponding SVs, that are moved to list L.

IPI ideally treats the set of SVs that belong to a particular binary classifier to be *independent* of SVs that belong to other binary classifiers. Hence it stores the SVs of each binary classifier at the corresponding node. MDS breaks the independence assumption and maintains a single list (L) of all SVs, thereby allowing component binary classifiers to point a single instance of the *shared* SVs. Thus it brings a true and exact multiclass reduction, exploiting the redundancies in a multiclass scenario. This helps in scaling the solution for large classes as explained below.

Table 4.1 summarizes the analysis of space required by IPI and MDS implementation. Though MDS adds an extra storage ($S \times i$) for indexing, it is negligible considering the amount of reduction in the storage of SVs for large class problems. Our experiments show that for a 300-class problem R is only 1% of S. As N increases, the space reduction

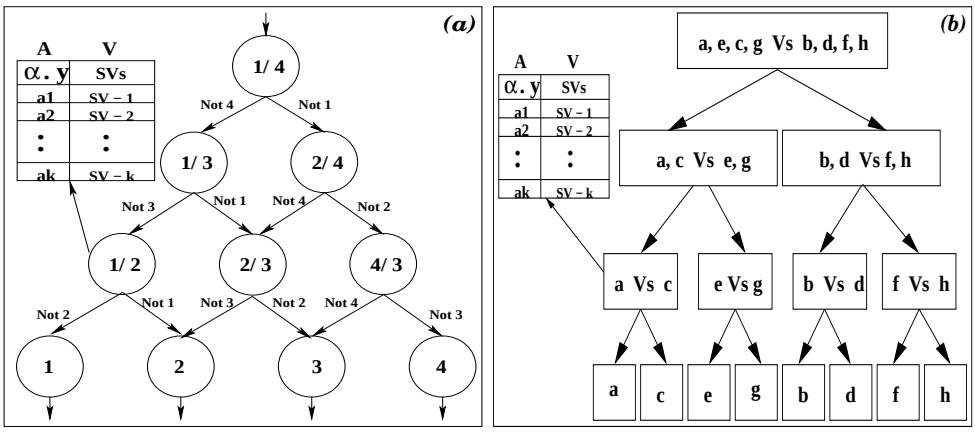


Figure 4.1: (a)DAG with independent binary classifiers. (b) BHC architecture

Space requirement of IPI in bytes:	
Storage of SVs :	$S \times D \times d$
Storage of A_i values :	$S \times d$
Total size:	$S \times D \times d + S \times d$
Space requirement of MDS in bytes:	
Storage of SVs :	$R \times D \times d$
Storage of A_i values :	$S \times d$
Extra space for indexing :	$S \times i$
Total size:	$R \times D \times d + S \times (d + i)$

Table 4.1: Space complexity analysis. Let S be the total number of SVs in all the nodes in Figure 4.1, R be the number of SVs in the list L of Figure 4.2 and D is the dimensionality of the feature space. Also let d be sizeof(double), i be sizeof(integer).

approaches $\frac{S-R}{S}$, since the space requirement of A and $INDEX$ are negligible compared to that of support vectors.

Though the $\frac{N(N-1)}{2}$ pairwise classification problems are independent, we observe that many of these classifiers share support vectors. This is because of the fact that SVs are the samples on the class boundaries. Therefore, even if the number of classes increase, the unique support vectors in the solution increase only marginally. This is the primary reason for obtaining very high reduction in space requirement. Figure 4.3 shows that as many binary classifiers as there are in the decomposed solution, the dependency among them will also be high for any type of kernel. That is, the number of *shared* SVs is more. Hence, as we combine the SVs of the binary classifiers into a unique reduced set, we can see that the reduced set converges only with SVs from a fraction of binary classifiers.

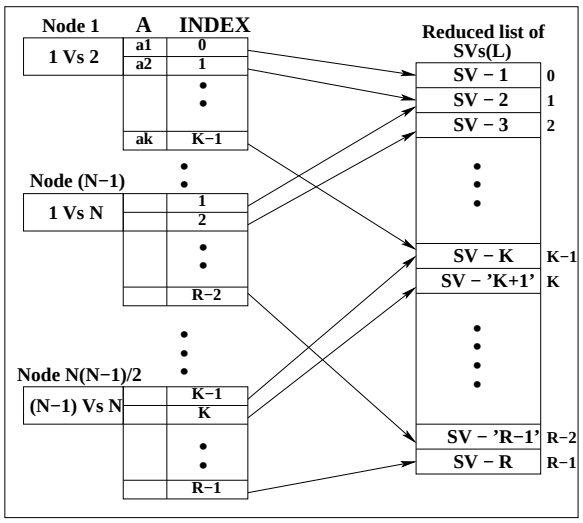


Figure 4.2: Multiclass data structure. Support vectors are stored in a single list (L) uniquely.

Algorithm 4 shows the computations performed by a binary SVM for classifying a sample. To decide the class of a given test sample x, $f(x) = \sum_i \alpha_i y_i K(x, s_i) + b$ must be computed for the binary classifiers that fall along the evaluation path. The costly part of this computation is the evaluation of the kernel function $K(x, s_i)$ for each support vector s_i. So if the same vector s_i is used in more than one of those binary SVMs, we compute the $K(x, s_i)$ only once and reuse it at other places. Algorithm 4 uses MDS to implement this with, $KERNEL$ to store $K(x, s_i)$ and associated $FLAG$ for indication.

In the proposed implementation, we need to maintain a unique list of support vectors. This is done by incrementally inserting the non-redundant SVs into L. Though it adds little extra time during training, there are notable benefits as well such as the number of write and read File I/O operations is reduced from order of S to R for creating the model file (training phase) and loading it in memory (during classification) respectively. Also the cost of adding and accessing a SV to and from the list is constant.

We achieve significant reduction in space and testing time with minimal extra computation during the training. In the proposed implementation, we only need to maintain a unique list of support vectors. This is done by incrementally inserting the non-redundant SVs into L. Apart from that, the number of write and read File I/O operations is reduced from order of $S \cdot D$ to $R \cdot D$ for creating (training phase) the model file and loading it in memory (during classification) respectively.

There are two components to the added cost. One comes from creating the list of reduced SVs and the second is from building the index associated with each node. The upper bound

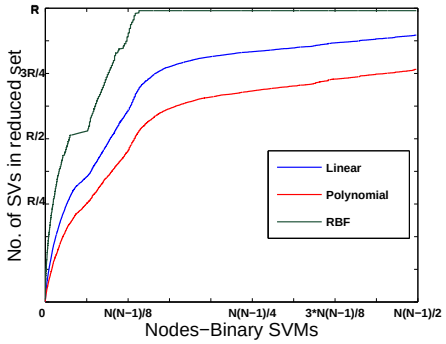


Figure 4.3: Dependency analysis. R is the total number of SVs in the reduced set for RBF kernel.

for the former is $O(S \cdot R \cdot D)$ and for the later it is $O(S)$. However, practically both the list and the index are built *online* as the SVs are added – leaving the training time comparable to DAG. Also note that the cost of adding and accessing a SV to and from the list are constant. Apart from that, the number of write and read File I/O operations is reduced from order of $S \cdot D$ to $R \cdot D$ for creating (training phase) the model file and loading it in memory (during classification) respectively, ignoring the I/O cost for INDEX which is negligible.

Algorithm 4 SVM_CLASSIFY(Node, Sample)

```
1: for i = 1 to (Node→NumOfSVs) do
2:    index ← (Node → INDEX[i])
3:    if FLAG[index] = 0 then
4:       KERNEL[index] ← K(Sample, L[index])
5:       FLAG[index] ← 1
6:    end if
7:    Add KERNEL[index] × (Node → A[i]) to D
8: end for
9: Add (Node → b) to D
10: RETURN sign of D
11: END SVM_CLASSIFY
```

N	Kernel Type	No. of SVs			Classification Time		
		S	R	Red.(%)	S	R	Red.(%)
10	Linear	983	334	**66.02**	1.680	1.420	**15.47**
	Poly.	1024	216	**78.91**	1.750	1.100	**37.14**
	RBF	8123	701	**91.37**	12.200	3.840	**68.52**
50	Linear	25172	2428	**90.35**	6.768	2.924	**56.80**
	Poly.	25706	1575	**95.86**	4.226	2.422	**42.68**
	RBF	211948	3382	**98.40**	37.364	15.126	**59.52**
100	Linear	74855	3950	**94.72**	8.288	3.559	**57.06**
	Poly.	79963	2945	**96.31**	6.854	3.567	**47.95**
	RBF	606058	4937	**99.18**	58.220	21.386	**63.27**
150	Linear	178857	6495	**96.37**	11.439	5.834	**48.98**
	Poly.	190832	5025	**97.37**	12.759	6.523	**48.88**
	RBF	1431019	7721	**99.46**	88.565	34.490	**61.05**
200	Linear	290716	7506	**97.42**	15.985	6.684	**58.19**
	Poly.	306619	6095	**98.01**	16.394	7.737	**52.81**
	RBF	2114043	8623	**99.59**	380.450	36.490	**90.40**
250	Linear	411732	7899	**98.08**	18.840	7.275	**61.38**
	Poly.	429006	6760	**98.42**	20.290	7.855	**61.28**
	RBF	2672340	8773	**99.67**	397.320	37.904	**90.46**
300	Linear	552622	8175	**98.52**	21.092	8.114	**61.53**
	Poly.	566709	7127	**98.74**	21.269	8.474	**60.16**
	RBF	3260961	8923	**99.73**	458.280	38.105	**91.69**

Table 4.2: MDS Vs IPI on Character Recognition data set.

4.2.1 Discussions

In all our experiments, SVM^{light} [67] implementation was used as binary classifier. For polynomial kernel degree=3 and for RBF kernel gamma=1 are chosen as parameters. There are multiclass SVM implementations available from libraries such as $LIBSVM$, $SVM^{multiclass}$, and SVM^{Torch}. LIBSVM [68] provides 1-Vs-1 method implemented using DAG architecture. However, the benefit of DAG is not efficiently used in minimizing the evaluation of kernel functions in LIBSVM. Its data structure for storing the A_i values is inefficient, since it has to store zero even if a SV does not belong to a binary-SVM. Also, LIBSVM doubles the storage space for each SV - by storing the feature indices along with the values

(though it could help in case the SVs are highly sparse). While these implementations are concerned about relatively simple multiclass problems (20 or 30-classes), we worry about problems with hundreds of classes.

SVM^{light} computes a single linear weight vector $w = \sum_i \alpha_i y_i s_i$ for linearly separable problems. So the binary classifier stores only w and need not require the SVs for classification. Therefore the multiclass solution stores only $\frac{N(N-1)}{2}$ linear weights and uses $(N-1)$ of them for classifying a sample. Though this linear weight method gives better space reduction for 10 and 50-class problems, MDS has better reduction for large classes, since $R < \frac{N \cdot (N-1)}{2}$ for $N >= 100$ in Table 4.2. However, $R > (N-1)$ for all $N = 10 \cdots 300$, hence linear weight method has faster classification rate always. (The serious limitation of the linear weight method is that it is not applicable to non-linear kernels). We conducted our experiments were on UCI data sets [41] and our own Indian language OCR data sets.

In our experiments, we report the number of SVs that were found in IPI (S) and compare it with the number of reduced SVs (R) obtained using MDS implementation. We also report the reduction in average classification time (per sample in milliseconds) that is obtained by reusing the computation of $K(x, s_i)$. The accuracy in all our experiments is preserved exactly.

Table 4.3 shows the results against two UCI data sets. The reduction in SVs for linear and polynomial kernels are observed to be closer, while RBF kernel gives higher reduction rate. Because RBF solution picks more samples as SVs in IPI, that leads to more redundancy among the SVs from the binary solutions. Also, comparing the results from PenDigits and Letters data sets shows that the reduction rate increases with increase in number of classes, irrespective of the type of kernel used.

Experiments with large class character recognition data sets were performed to test the scalability of our proposed implementation. A few examples from the dataset are shown in the Figure 4.4. The results are shown in Table 4.2 for different number of classes N, with 100 samples per class for training. We obtain a maximum of around 98.5% of reduction in SVs and 60% reduction in classification time for linear and polynomial kernels on the 300-class data set. The time reduction is lesser than the reduction in SVs obtained, since classifying a sample involves only $N-1$ binary classifiers and not all the $\frac{N \cdot (N-1)}{2}$.

As one can see, the reduction in SVs gradually increases as N goes from 10 to 300. The reduction rate in classification time also shows similar increment except on RBF kernel for $N >= 200$. The reason for the sharp increase in the exceptional cases comes from S being very large, hence the classifier model (having the SVs) does not fit into main memory space (on a 2GB machine). We found that the virtual memory swap space was used, that

Figure 4.4: Sample characters from the recognition dataset. These are characters present in Malayalam script.

made the classification process slower in IPI. However, MDS implementation exploits the redundancy among these SVs, thereby giving a reduced set of SVs R with more than 99% reduction. Thus the model file in MDS no more requires the swap space. This observation clearly shows that the MDS implementation is scalable for large class problems even if the available resources are less.

Data set Name	Kernel Type	No. of SVs		
		IPI(S)	MDS(R)	Red.(%)
PenDigits (10-class)	Linear	5788	2771	**52.13**
	Poly.	3528	1777	**49.63**
	RBF	67450	7494	**88.89**
Letters (26-class)	Linear	113249	15198	**86.58**
	Poly.	80553	12961	**83.91**
	RBF	482975	18666	**96.14**

Table 4.3: MDS Vs IPI on UCI data sets.

4.2.2 SVM simplification with linear kernel

When we know that our data is linearly separable in the input space, the kernel mapping - $K(x, s_i)$ is simply the dot product $x.s_i$. Hence we can compute and store single vector $w = \sum_{i=1}^{r} \alpha_i y_i s_i$. Therefore the decision surface becomes $f(x) = x.w + b$. That is, the binary classifier replaces a set of SVs with a single linear weight vector(w) of dimension D. Thus it saves both storage space and classification time.

For a $N - class$ problem using above simplification, we need to store only $N\dot{(}N-1)/2$ linear weight vectors. And for classifying a sample vector (x), $(N-1)$ vector inner-products needs to be calculated using DAG. However the above simplification is not applicable for non-separable problems, where we need to apply non-linear kernel mapping to feature space in which the problem becomes linearly separable. (Also replacing the support vectors is against the philosophy of SVM).

No. of Classes	Size of Lin. Wt.s File	Size of Reduced SV File	Reduction in Size(%)
10	156K	1.1M	-85.81
50	4.0M	7.8M	-48.71
100	16M	14M	12.50
150	36M	23M	36.11
200	64M	27M	57.81
250	99M	30M	69.69
300	143M	33M	76.92

Table 4.4: Linear weights Vs MDS on OCR data-sets

The results of the model file size the file with MDS and the one using linear weight are compared in Table 4.4. Though for 10-class and 50-class, we get negative reduction in the size of the model file with MDS; It performs better than linear weights when $\frac{N\cdot(N-1)}{2}$ becomes larger than R (number of reduced set of SVs). But for classification, linear weights always took lesser time in our experiments. This is because we can observe from Table 4.2, that $R > (N-1)$ for linear kernels for all N (but remember that linear weight is not applicable to other kernels).

4.3 Hierarchical Simplification of SVs

Downs *et al.* [66] introduced a method called Exact Simplification for recognizing and eliminating unnecessary SVs in SVMs. The method reduces a given set of SVs by finding those SVs that are linearly dependent of other SVs in the feature space and removing them from the solution. Suppose we have a support vector solution that has r SVs that determine the decision surface

$$f(x) = \sum_{i=1}^{r} \alpha_i y_i K(x, s_i) + b. \tag{4.1}$$

Now suppose that SV x_k is linearly dependent on other SVs in the feature space, *i.e.*, $K(x, s_k) = \sum_{i=1, i \neq k}^{r} c_i K(x, s_i)$, where the c_i are scalar constants. Then the solution can be simplified as $f(x) = \sum_{i=1, i \neq k}^{r} \overline{\alpha_i} y_i K(x, s_i) + b$, where $\overline{\alpha_i}$ are the updated Lagrangians that keeps the solution otherwise unchanged.

A direct extension of this exact simplification to any hierarchical multiclass SVM solutions is to apply the reduction method on each of the component classifiers. This reduces each component classifier by removing a subset of SVs, leaving only the linearly independent SVs in their corresponding solutions. However, the obtained reduction from each component classifier need not be the best for the overall multiclass solution. At the same time, the method cannot further eliminate any SVs since all of them are now linearly independent within a component solution.

We can eliminate SVs further from the solutions of the component classifiers, if we break the linear independence. This is possible if we add new vectors to each component solutions. Suppose we have a component classifier that has a reduced set of SVs I that are linearly independent. We could add a new set of vectors to I to get an extended set of vectors E. If the extended set of vectors are no longer linearly independent, then we can further reduce the component classifier by eliminating many SVs. Note that while we are eliminating a subset of SVs from I, we have already added some new vectors to the solution to get the benefit. The addition of new vectors is justifiable and do not bring any extra cost when we add the SVs that belong to component classifiers that are up in the hierarchy in a decision path to the one at a lower level for reducing the later. Since the kernel computations $K(x, s_i)$ for those SVs once computed at any component classifier higher in the decision path are reusable anywhere down the decision path.

The hierarchical simplification involves two steps as given in Algorithm 5. The algorithm also simplifies a multiclass solution *exactly*, by reducing the number of SVs as explained below.

Suppose a component classifier X has its solution of the form Equation 4.1. Let V denote the set of SVs in the solution. *Step* 1 of the algorithm reduces V to a subset I of SVs and the solution becomes

$$f(x) = \sum_{i=1, s_i \in I}^{r} \overline{\alpha_i} y_i K(x, s_i) + b \tag{4.2}$$

Step 2 of the algorithm now adds a set of SVs A that are picked up from any of the component classifiers above X in the decision path. Let $A = a_1, a_2, ..., a_k$ be the SVs with

Algorithm 5 Hierarchical Exact Simplification(HC: Hierarchical Classifier)

Step 1: Individual component reduction.
for each component classifier (node) $'X'$ in HC **do**
  Reduce $'X'$ using Exact Simplification method.
end for
Step 2: Reduction across component classifiers.
for each decision path $'P'$ in HC **do**
  for each internal node $'X'$ in $'P'$ **do**
    Extend the set of SVs in $'X'$.
    Identify the linearly dependent SVs $\in X$ and eliminate them.
  end for
end for

corresponding Lagrangians $\alpha_{a_1}, \alpha_{a_2}, ..., \alpha_{a_k}$ that are added to I. The exact simplification method is now applied on the extended set $E = I \cup A$. Let a set of SVs $R \subseteq I$ are recognized as linearly dependent on other SVs $\in E$ in the feature space, *i.e.* for each $s_k \in R$, $K(x, s_k) = \sum_{s_i \in (I-R)} c_i K(x, s_i) + \sum_{a_j \in A} c_j K(x, a_j)$ where the c_i and c_j are scalar constants.This allows the algorithm to eliminate the SVs $\in R$ from E resulting in a reduced set $\overline{V} = (I - R) \cup A$. Hence the final solution for X is of the form

$$f(x) = \sum_{\substack{i=1 \\ s_i \in (I-R)}}^{r} \overline{\overline{\alpha_i}} y_i K(x, s_i) + \sum_{j=1}^{k} \overline{\alpha_{a_j}} y_{a_j} K(x, a_j) + b \tag{4.3}$$

Note that the lagrangians of the SVs $\in A$ are now updated as per the exact simplification method. However this updated values are only used in computing the solution for X, leaving the original lagrangians at the corresponding component classifiers intact.

Dataset (# Class)	#Dim.	Reduction(%)		
		Step 1	*Step* 2	Overall
PenDigits (10)	16	85.42	71.49	95.84
Letters (26)	16	94.87	17.78	95.60
OptDigits(10)	64	59.25	54.92	81.63
Vowel(11)	10	76.89	68.90	92.81

Table 4.5: Reduction in classification time (using linear kernel).

Table 4.5 shows the computational advantage obtained by applying Algorithm 5 on standard datasets. The extended set in *Step* 2 was obtained by adding all the SVs from nodes

that are higher in a decision path to a particular node to reduce the later and the procedure was repeated iteratively. Note that the computational advantage comes with an additional storage requirement of modified Lagrangian values. The reductions obtained are problem dependent in both the steps as also observed by Downs *et al.* [66] in their experiments.

4.4 OCR and Classification

In this section we are explaining the classification scheme used in the design of our OCR. Figure 4.5 shows the basic architecture of an optical character recognition system. A more detailed figure is given in Chapter 1 (Refer Figure 1.1). In this work we have given attention to the classification module. Here we explain the design and implementation details of the classification scheme used for our OCR.

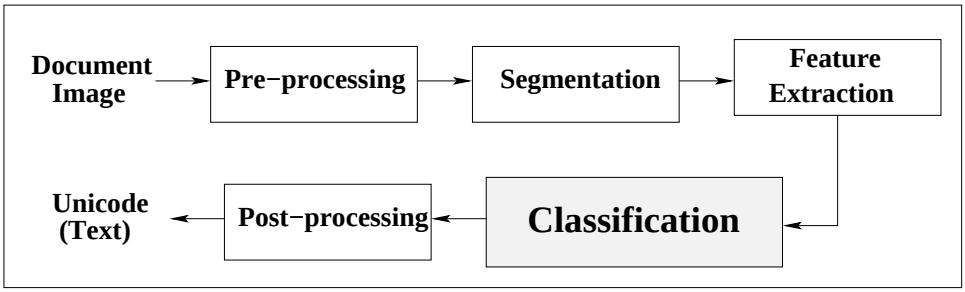


Figure 4.5: Basic architecture of an OCR system. In this work we have given attention to classification module.

The design approach to classifiers can be based on two different philosophies. The first one uses complex classifier models such as neural networks for direct classification of a sample into one of the N classes possible, resulting in an efficient classifier that is trainable. The second approach uses the divide an conquer strategy, where an ensemble of simple binary classifiers are integrated to form the final N-class classifier. Our classifier needs to handle a large number of classes, with close similarities between certain component pairs. Hence we prefer the latter approach for our OCR classification, as the individual classifiers can be independently trained and analyzed for improving the overall performance.

One could choose from a large set of classification algorithms for the binary classifiers. We have experimented with a variety of algorithms and found that Support Vector Machines (SVMs) offer the best performance for this problem in most cases. It's success comes out of its capability to maximize the margin and thereby enhancing the generalization in classifier design. Thus SVM differs from the neural network based approaches which, in a way,

maximizes the empirical accuracy rates measured on the training data. SVMs, built on statistical learning theory, maximizes the generalization and hence shown superior results. The objective function which SVM minimizes is convex and there by guaranteeing a global minima (unlike Neural network based approaches, which often gets trapped in local minima) with a set of additional constraints. Final solution to the classification is expressed in terms of some of the training samples (support vectors) and the decision rule is expressed in terms of dot products of inputs with support vectors. This helps in using the kernel methods and deriving nonlinear decision boundaries.

However, in this work, we decided to explicitly increase the feature dimensions (mildly) and make the data more separable for pairwise classification and thereby to avoid the floating point operations required for kernel. This makes the computations efficient. Far more than that, this allow a compact representation of the decision boundary. Thus our final SVM classifier stores the decision boundaries directly rather than storing the support vectors as in most popular implementations. This makes our SVM classifier, memory and time efficient compared to the popular implementations.

DDAG is SVM's one of the fastest combination strategies for multiclass classification [51]. In DDAG the modular classifiers are arranged in a hierarchical manner. The advantages of hierarchical modular classifiers are :

1. Simpler classifiers compared to multiclass methods.
2. Uses lesser space compared to other ensemble methods.
3. Highly flexible because of its modularity, and hence node level training is possible.
4. Approach is scalable to large class problems.

All the $\frac{N\cdot(N-1)}{2}$ pair-wise classifiers are combined in a DDAG to create the classification module in the OCR architecture. Figure 4.6 shows the DAG architecture for the Malayalam OCR design. We have considered 205 classes/symbols in this design.

Given an input sample x for classification, it is first presented to the root node of the DDAG for decision. The decision that happens at each node of the classifiers is not which class the sample belongs to, but which class the sample *does not* belongs to. One of the classes is rejected as a feasible class at the root node and the sample thus reach the root node of the left or right sub-DAG, which does not contain the rejected class. Another class rejection takes place at this root and the sample follows an edge leading to one of the sub-DAGs of the current root node. This way, the sample rejects $N-1$ classes before it reaches the leaf node of the DAG. The sample x is assigned the label corresponding to the

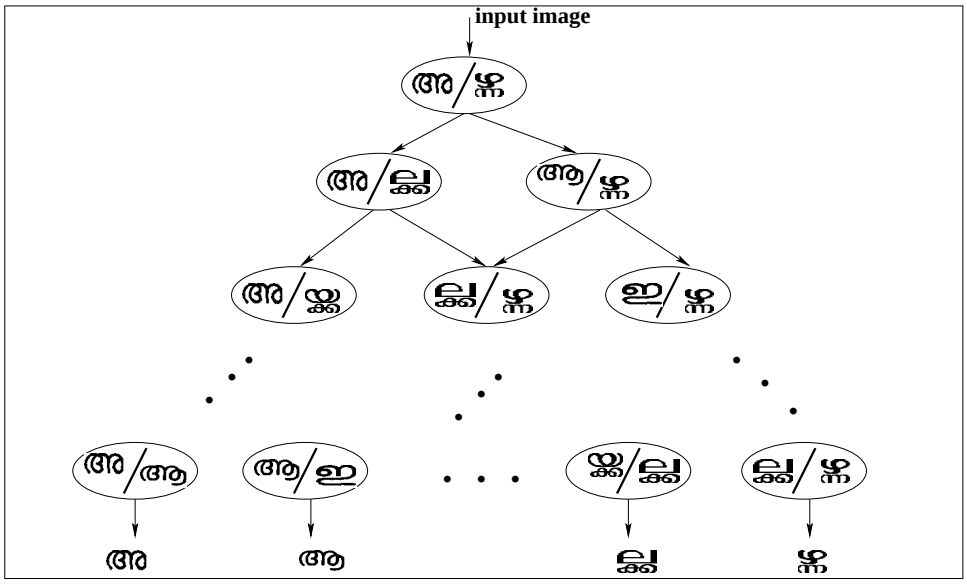


Figure 4.6: DDAG architecture for Malayalam OCR.

leaf node it reached. It can be observed that the number of binary classifiers built for a N class classification problem is $\frac{N\cdot(N-1)}{2}$. The DDAG design for Malayalam OCR contains a total of 20910($205*204/2$) nodes. However, for each test case only 204 nodes are evaluated.

4.5 Summary

In this chapter we have presented an efficient data structure for implementing multiclass solutions. This data structure is applicable to any multiclass classification technique that builds the solution on binary SVMs. We had shown that our data structure reduces both space and time complexity significantly on multiclass problems. We are presently exploring algebraic reduction schemes on the list L. We also explained the design strategies used for classification module in our OCR design. The experimental results and the performance evaluation of the OCR system is discussed in the next chapter.

Chapter 5

Performance Evaluation

5.1 Introduction

We have conducted extensive experiments to validate the OCR modules and overall performance on the corpus pages (mentioned in Section 2.8). This chapter provides some of our conclusions and observations based on these experiment. For measuring the performance of the OCR, we have taken measures like (i) Accuracy, (ii) Edit distance between two UNICODE strings (iii) Substitution errors, which provide a more factual distance in the case of Indian scripts.

We use the edit distance based performance metric for the evaluation of document image recognition. The same metric is used to evaluate, the accuracies at different levels such as, symbol level, Unicode level, Akshara level, word level and Page level. Different levels of these analysis gives different aspects of OCR. Refer Section 2.5 for the definition of symbol, Unicode and Akshara.

The lowest level is symbol level edit distance. This gives direct information about the number of symbols misclassified. Symbols are the base for the classifier design. Therefore, accuracy calculated at the symbol level gives direct information about the strength and generalization capacity of a classifier. The confusion matrix obtained by symbol level annotation, misclassifications occurred during classification. This is a very valuable information to redesign the classifier. The modular classifiers can be retrained to get better classification accuracy.

The next level of performance metric is Unicode level. Once the classifier classifies all the symbols, the class labels have to be converted to the corresponding Unicode. As we have explained in chapter 2, the isolated symbols may or may not be a meaningful character.

Sometimes, a Unicode might be composed of more than one symbol. On the other hand, there will be more than one Unicode corresponding to one symbol. The second case is more popular. Examples of this type is a huge set of composite/conjunct characters. When we measure the Unicode level accuracy, it is important to reorder the symbol labels in a meaningful manner. This is important because of the fact that, the symbols in the text may or may not occur in the order it has to be represented in Unicode. Therefore, compared to the total number of symbols the the total number of Unicode is usually higher in a document page of Indian languages. The major change in the representation of Unicode and symbols are the places of occurrence of *matras*. In symbol representation, *matras* may come before, after, on top, or bottom of a character. But in Unicode representation there is a unique way of representing *matras*. In Unicode, matras come after the consonant character. In this way, the Unicode level performance metric covers, the classification errors and the reordering errors in the OCR. This measure is generally higher than the symbol level edit distance.

Next level of performance metric is *Akshara* level edit distance. An *Akshara* is the basic unit of a language. An *Akshara* can be composed of multiple symbols or multiple Unicodes. This metric is important from a linguistic point of view. In a document page, the total number of *Aksharas* will be much lesser compared to the total number of symbols or Unicode. This is because, the matras will not be counted as a part of the character to which it is attached. Akshara level edit distance gives a combined measure of error caused by mis-classification and reordering. The Akshara level edit distance is a more meaningful error metric compared to Unicode. As our basic unit is an *Akshara*, this measure of error gives a higher value of error compared to symbol and Unicode level results.

The next level of performance metric is word level. The word level error is calculated as, total number of words with at least one error in the word to total number of words. The word level accuracy depends on the length of the word. In this case, Languages with small words have advantage over the languages with average word length higher. In addition to the misclassification and reordering errors, the word level and the line level segmentation errors will be reflected in this measure.

We have considered page level error as the highest level of error metric. This is the average error across the pages in a book.

5.1.1 Performance Metrics

Many different metrics can be used for evaluation of OCR output. Any evaluation requires comparison of the OCR output with annotation. Results presented in the following section

calculates error in terms of Edit distance. Edit distance between two strings can be computed with the help of Dynamic programming. Our approach for evaluation is as explained below. A true word sequence in the annotated corpus correspond to the Unicode sequence $C =< C_1, C_2, C_3...C_n >$. Correspondingly, OCR systems output Unicode sequence is given by $O =< O_1, O_2, O_3...O_n >$. We can define character error rate (CER) in the following way:

$$CER = \frac{CharEditDistance(C, O)}{|C|} \tag{5.1}$$

We could also use substitution error in place of edit distance. Number of substitutions can be calculated by analyzing the optimal alignment path by backtracking the Dynamic programming cost matrix. Symbol level evaluation is done using a similar approach on class Ids or Unique Symbol Identifiers. Language specific annotation at sub-word level is used for achieving this. Also word level statistics are computed by considering the word boundaries available in the annotated data.

To compare the output of our OCR with the text in the corpus, we first concatenate all the lines in a page to get a long string. Thus we get two long strings, one the result of our OCR, and the other from the corpus. Now we dynamically compare both the strings. Concatenation of all the lines in a page is necessary to eliminate the error when line segmentation error (over segmentation or under-segmentation of lines) is present.

5.2 Experiments and Results

5.2.1 Symbol and Unicode level Results

The results of symbol and Unicode level error rates on various books are given in the Table 5.1. Symbol level error is calculated on symbols which are recognizable. That is, we have eliminated not included the symbols with cuts/ merges in this calculation. As we have already discussed in the previous section symbol level accuracy gives an exact measure of strength of the classifier.

$$Symbol\ Error\ Rate = \frac{No.\ of\ Misclassified\ and\ Recognizable\ Symbols}{Total\ No.\ of\ Recognizable\ Symbols} \tag{5.2}$$

But in the Unicode results is an overall result on the book. In other words, this error include the error caused by cuts and merges also. As the final output of the OCR system has to be in Unicode format, it is important to have an error metric at Unicode level.

$$Unicode\ Error\ Rate = \frac{No.\ of\ Misclassified\ Unicode}{Total\ No.\ of\ Unicode} \tag{5.3}$$

S.No	Book Name	Symbols		Unicode	
		# Total	Error.(%)	# Total	Error.(%)
1.	Indulekha	321470	1.70849	423884	4.80698
2.	ValmikiRamayanam	228188	0.94001	293822	2.82732
3.	Sarada	235791	2.76384	299056	3.92275
4.	Sanjayan	28661	3.34585	35668	4.59709
5.	Hitlerude Athmakadha	125658	1.23403	163863	2.95065
6.	BhagatSingh	458016	3.11732	489534	6.39824
7.	Ramarajabahadoor	216744	2.12732	268653	4.38768
8.	Thiruttu	117403	3.88202	143582	5.71832
9.	Dharmaraja	897449	2.35065	947419	5.82614
10.	IniNjanUrangatte	277257	1.71141	315259	3.74576
11.	ViddhikaluteSwargam	62396	3.34805	74719	6.89868
12.	Janmadinam	86269	2.41994	108881	4.98745

Table 5.1: Symbol level and Unicode level error rates on Malayalam books.

Now we analyze the Unicode and Symbol level results based on the cuts, merges and other distortion for the book Indulekha. Table 5.2 shows the cuts, merges, and other noise details of the book *Indulekha*. We can notice that the sum of cuts, merges, noise and symbol level classification error comes out to be 4.179951, and the total Unicode level error is 4.80698. These numbers almost matches, but the Unicode level error rate is a bit higher than the total error rate calculated from the results. This increase in the error rate at Unicode level is due to the fact that, one symbol level misclassification may results in more than one Unicode level error. This happens when a conjunct character get misclassified. There are some rare occasions where the reverse effect happens. That is one Unicode error constitute to more than one symbol error. But these scenario occurs rarely compared to the occurrence of conjunct characters in the language. Thus the Unicode error will be always higher than the symbol level results.

When a conjunct character got misclassified, we count one error in the symbol level. But a set of different scenarios can happen. Consider a conjunct character which has 3 components. Mostly it is composed of a basic character + a *halant* another basic character. If this conjunct character got misclassified to another entirely different conjunct character character, it contributes two errors in Unicode. In this case, both the base characters are wrong and only the middle *halant* is correct. Another scenario, the first or second base character is correct, only one of them got wrong. This will contribute, one error in Unicode. Yet another situation is a conjunct character getting misclassified to a base character.

Name of the Book	Indulekha
Total No. of Symbols	321470
Total No. of Unicode	423884
Symbol level classification error	1.70849
Cuts	1.57091
Merges	0.45852
Noise	0.44203
Total (Cut, Merge, Noise & Misclassification)	**4.17995**
Unicode level edit distance	**4.80698**

Table 5.2: Symbol level and Unicode level error rates on Malayalam books.

This will contribute, one misclassification error and two *delete* error, a total of three edit distance. In the above situation suppose this conjunct character misclassified to a basic character which is one of the constituent basic characters of the same conjunct character. This case will contribute two *delete* error, and thus two edit distance.

Consider a case where the reverse scenario happens, i.e., a basic character gets misclassified to a conjunct character. Here, if the basic character matches with one of constituent characters of the conjunct character this error will contribute two *insert* errors and thus two edit distance. Otherwise, this will contribute one misclassification and two *inserts*, a total of three edit distance.

Using the dynamic programing technique we also calculated the percentage of substitution, inserts or deletes that contributed the total edit distance for the Unicode. Table 5.3 gives the result of these experiments. These numbers gives an approximate match with the calculation we have done already.

S.No	Book Name	Edit-Dist	Substitution	Inserts	Deletes
1.	Indulekha	4.80698	2.13179	2.00354	0.98761
2.	ValmikiRamayanam	2.82732	1.49772	0.79015	0.65425
3.	Sarada	3.92275	2.10003	1.22171	0.89911
4.	Sanjayan	4.59709	2.31822	1.09669	1.57666
5.	Hitlerude Athmakadha	2.95065	1.35846	0.70114	0.94703
6.	BhagatSingh	6.39824	3.94839	3.18630	1.19315
7.	Ramarajabahadoor	4.38768	2.57491	1.95001	0.80074
8.	Thiruttu	5.71832	4.92912	2.53587	1.26341
9.	Dharmaraja	5.82614	1.43978	1.68051	1.30065
10.	IniNjanUrangatte	3.74576	1.89763	0.75756	1.19759
11.	ViddhikaluteSwargam	6.89868	2.45957	1.29882	2.75755
12.	Janmadinam	4.98745	1.80187	0.82338	2.24626

Table 5.3: Unicode level error rates classified to errors due to substitution, inserts and deletes, on Malayalam books scanned with 600dpi resolution.

Table 5.4 gives the results of the same set of experiments conducted on Malayalam books scanned with 300dpi resolution. There are slight change in the results obtained from those with 600dpi images. These difference arises from various stages of OCR. The changes in degradation is caused by the pre-processing stages.

S.No	Book Name	Edit-Dist	Substitution	Inserts	Deletes
1.	Indulekha	5.49112	2.76686	1.65368	1.07058
2.	ValmikiRamayanam	2.23806	1.06743	0.71968	0.45095
3.	Sarada	4.36719	2.49340	1.10736	0.76634
4.	Sanjayan	4.31030	2.15515	1.09428	1.06087
5.	Hitlerude Athmakadha	3.08706	1.49422	0.75763	0.83520
6.	BhagatSingh	8.07345	4.00433	2.86220	1.20692
7.	Ramarajabahadoor	5.43921	2.60320	1.95734	0.87866
8.	Thiruttu	6.36529	3.27384	1.95957	1.13189
9.	Dharmaraja	6.41670	3.05483	1.63581	1.72606
10.	IniNjanUrangatte	3.75548	2.02939	0.62600	1.10009
11.	ViddhikaluteSwargam	5.59839	2.37324	0.94056	2.28458
12.	Janmadinam	4.20989	1.95101	0.69517	1.56370

Table 5.4: Unicode level error rates classified to errors due to substitution, inserts and Deletes, on Malayalam books scanned with 300dpi resolution.

5.2.2 Word level Results

The word level accuracy details of the books are given in the Table 5.5. The word level accuracy of a book is calculated using the following formula:

$$Word\ level\ Accuracy = \frac{No.\ of\ Correct\ Words}{Total\ No.\ of\ Words} \tag{5.4}$$

If all the Unicode in a word are correctly classified and correctly ordered, then that word is considered as a correct word. To know the effect of degradations in word level accuracy we have calculated the word accuracy in recognizable words using the formula:

$$Word\ level\ Accuracy = \frac{No.\ of\ Correct\ and\ Recognizable\ Words}{Total\ No.\ of\ Recognizable\ Words} \tag{5.5}$$

Other than classification, many other factors effect the word level accuracy. The first thing is, word level segmentation. There might be under-segmentation or over-segmentation of the words. The factors that effect the segmentation errors in word level are the strength of the segmentation algorithm, the thresholds used in the implementation of the algorithm, the quality of printing and scanning, etc. In the case of under-segmentation, two or more words will be segmented as a single word. This will add to the errors, even if all the symbols in

S.No	Book Name	Words			
		# Total	(%) Accuracy	# Recognizable	(%) Accuracy
1	Indulekha	46281	80.7091	39644	94.2211
2	ValmikiRamayanam	31360	90.3000	29339	94.2200
3	Sarada	32897	72.1008	26671	88.9318
4	Sanjayan	4079	70.6301	3224	89.361
5	Hitlerude Athmakadha	16403	81.3205	14291	93.3385
6	BhagatSingh	57252	51.3291	35246	80.1253
7	Ramarajabahadoor	81021	53.8404	52047	83.8127
8	Thiruttu	15654	59.7419	10553	88.6193
9	Dharmaraja	95931	51.8310	65427	86.5825
10	IniNjanUrangatte	39785	81.8273	34822	93.4897
11	ViddhikaluteSwargam	8793	63.1866	6435	86.3403
12	Janmadinam	12112	77.2705	10326	90.6353

Table 5.5: Word level results computed on all the words (degraded and non-degraded) and non-degraded words in Malayalam books.

those words have been classified correctly. On the other hand, over-segmentation segments out a single word into multiple words. In our calculation we are adding only one error in this case. Another thing that effects the word level accuracy is the wrong ordering of the Unicode after classification. The importance of ordering of the components, in the case of Indian languages, is described previously. Incorrect grammar rules used in the implementation or printing cause a disaster in this case.

The definition of a correct word is, the word with all the Unicode are correctly classified. If at least one of these Unicode is incorrect, that word is considered as an erroneous one. To study the pattern of errors in the word error distribution, we studied the number of errors in the words. The results are presented in the Table 5.6. Note that a considerable percentage of the word error is caused by a single error in a word. In the book *Indulekha*, out of 19.29% of word error, 6.9% errors are caused by words with single error, and 4.69% of error caused by words with 2 errors.

This study opens the possibility of language models based post-processing. For example using Unigram and Bigram models it may be possible to correct a word with a single error, if we could identify the correct location of the error in the word.

5.2.3 Page level Results

The average page level error rates of a book is calculated using the formula:

$$Average\ Page\ Error\ Rate = \frac{\sum Error\ Rates\ in\ all\ the\ Pages}{Total\ No.\ of\ Pages} \tag{5.6}$$

S.No	Book Name	Total Words	(%) Words with		
			0 Error	1 Error	2 Errors
1	Indulekha	46281	19.2909	6.90564	4.69523
2	ValmikiRamayanam	31360	9.7000	2.71365	4.12946
3	Sarada	32897	27.8992	9.17713	7.75451
4	Sanjayan	4079	29.3699	6.47217	9.70826
5	Hitlerude Athmakadha	16403	18.6795	8.90691	5.35268
6	BhagatSingh	57252	48.6709	12.4278	13.4620
7	Ramarajabahadoor	81021	46.1596	8.39412	13.1238
8	Thiruttu	15654	40.2581	4.22895	16.6092
9	Dharmaraja	95931	48.1690	13.1679	14.9682
10	IniNjanUrangatte	39785	18.1727	6.11788	6.33153
11	ViddhikaluteSwargam	8793	36.8134	8.43853	6.96008
12	Janmadinam	12112	22.7295	8.99934	5.30053

Table 5.6: Words with one and two errors and non-degraded words in Malayalam books.

We studied the results on the distribution of errors across pages. This is presented in Table 5.7. This table describes the percentage of pages with different error rates. This provides an objective method to quantitatively label the quality of the pages. Similar studies were also conducted to know the error rates of words with one or more errors.

S.No	Book Name	Total Pages	Error Rate	(%) Pages with Error			
				$(\leq 2\%)$	$(2-5\%)$	$(5-10\%)$	$(>10\%)$
1.	Indulekha	235	4.80	0.42	70.63	26.38	2.55
2.	ValmikiRamayanam	170	2.82	31.76	57.64	4.11	6.47
3.	Sarada	155	3.92	6.41	75.00	14.74	3.20
4.	Sanjayan	35	4.59	5.55	55.55	30.55	5.55
5.	Hitlerude Athmakadha	86	2.94	3.44	89.65	2.29	3.44
6.	BhagatSingh	282	7.39	0	29.92	52.46	16.90
7.	Ramarajabahadoor	141	4.38	7.80	68.79	20.56	2.83
8.	Thiruttu	86	5.71	2.32	52.32	30.23	15.11
9.	Dharmaraja	419	5.85	0.23	56.53	33.96	8.78
10.	IniNjanUrangatte	162	3.74	4.61	66.15	11.28	1.02
11.	ViddhikaluteSwargam	68	6.73	0	33.33	57.97	7.24
12.	Janmadinam	93	4.97	0	69.89	20.43	9.67

Table 5.7: Page level accuracies and Unicode level error distribution across pages.

5.2.4 Comparison with Nayana

We compare our results with that of Nayana, a Malayalam OCR available in public. Results on randomly selected pages from books are shown in Table 5.8. Superiority of our results possibly comes out of the segmentation and classification algorithms. Since we do not have

access to the internals of the Nayana OCR, our results are superficial (black box).

Book Code	No. of Pages	Edit Distance		Substitution	
		Nayana	Our OCR	Nayana	Our OCR
ValmikiRamayanam	7	13.03	2.04	4.28	0.97
Sanjayan	10	34.48	2.76	19.18	1.03
Hitlerude Athmakadha	8	13.96	2.66	4.9	1.05
BhagatSingh	6	9.72	2.63	3.97	1.31
Indulekha	10	13.55	2.32	5.62	1.08
Dharmaraja	9	10.33	2.52	4.19	1.31
Thiruttu	10	13.44	3.91	6.17	2.11
Ramarajabahadoor	10	12.19	3.02	4.05	1.41
IniNjanUrangatte	9	9.49	1.91	4.23	1.02
ViddhikaluteSwargam	3	13.73	4.72	4.86	1.51
Janmadinam	5	15.98	3.89	5.2	1.47
Tot/Ave	87	15.34	2.81	6.64	1.28

Table 5.8: Comparison with Nayana.

5.3 Quality level Results

5.3.1 Results on Scanned Quality A documents

To validate methods and implementations, we decided to scan and test the OCR on some of the fonts and sizes. One of our observation was that the Microsoft word and fonts used introduced too many merges in these documents and this effects the overall performance. Since our objective was to demonstrate the symbol level accuracy and its extension to Unicode over non-degraded pages, we minimized such word-processor/font induced errors and did an evaluation. The experimental results are briefly summarized in Table 5.9.

Font Name	Font Size							
	8		10		12		14	
	E(%)	S(%)	E(%)	S(%)	E(%)	S(%)	E(%)	S(%)
Amibili	2	0.9	1.92	0.88	2.71	0.52	4.99	0.82
Karthika	2.87	1.52	0.7	0.28	1.1	0.44	0.73	0.45
Lohit	3.86	1.29	2.27	1.11	2.51	1.56	3.29	1.75
Nila	2.43	1.22	1.53	0.54	1.54	0.59	2.01	0.6
Revathi	2.57	1.12	0.57	0.24	1.08	0.53	0.74	0.3

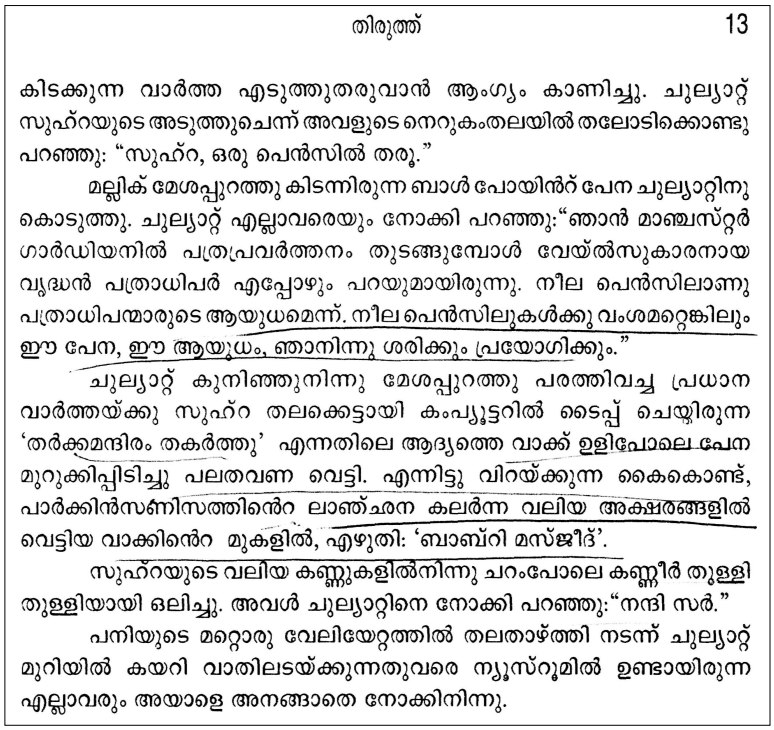
Table 5.9: Results on Scanned Quality A documents, in various fonts., E = Edit distance , S = Substitution error

One of our observation by testing on 5 fonts and 4 sizes (total of 20 variations) is that our OCR extends reasonably well across these collections. However, we find that when the

size increases significantly, our scaling/normalization routines are not able to cope up with it completely.

5.4 Qualitative Results/Examples

Example 1: This example (See Figure 5.1) shows a case where the recognition rate become very low, because of the segmentation error at line level. In this page some of the lines are underlined with ink. In the segmentation algorithm, we used the number of black pixels as a threshold to detect different lines. This caused under-segmentation to those lines. So this page gives a huge error rate of 26.84% and a substitution error of 10.85%.



തിരുത്ത് 13

കിടക്കുന്ന വാർത്ത എടുത്തുതരുവാൻ ആംഗ്യം കാണിച്ചു. ചുല്യാറ്റ് സുഹ്റയുടെ അടുത്തുചെന്ന് അവളുടെ നെറുകംതലയിൽ തലോടിക്കൊണ്ടു പറഞ്ഞു: "സുഹ്റ, ഒരു പെൻസിൽ തരൂ."

മല്ലിക് മേശപ്പുറത്തു കിടന്നിരുന്ന ബാൾ പോയിൻറ് പേന ചുല്യാറ്റിനു കൊടുത്തു. ചുല്യാറ്റ് എല്ലാവരെയും നോക്കി പറഞ്ഞു:"ഞാൻ മാഞ്ചസ്റ്റർ ഗാർഡിയനിൽ പത്രപ്രവർത്തനം തുടങ്ങുമ്പോൾ വേയ്ൽസുകാരനായ വൃദ്ധൻ പത്രാധിപർ എപ്പോഴും പറയുമായിരുന്നു. നീല പെൻസിലാണു പത്രാധിപന്മാരുടെ ആയുധമെന്ന്. നീല പെൻസിലുകൾക്കു വംശമറ്റെങ്കിലും ഈ പേന, ഈ ആയുധം, ഞാനിന്നു ശരിക്കും പ്രയോഗിക്കും."

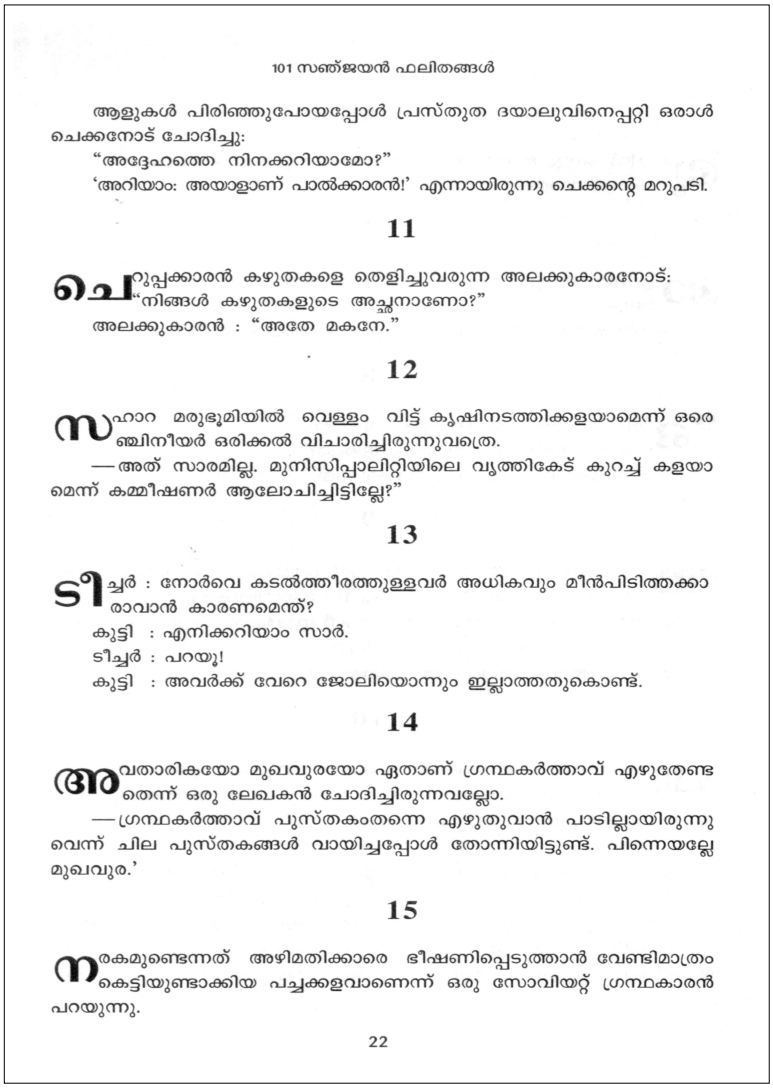
ചുല്യാറ്റ് കുനിഞ്ഞുനിന്നു മേശപ്പുറത്തു പരത്തിവച്ച പ്രധാന വാർത്തയ്ക്കു സുഹ്റ തലക്കെട്ടായി കംപ്യൂട്ടറിൽ ടൈപ്പ് ചെയ്തിരുന്ന 'തർക്കമന്ദിരം തകർത്തു' എന്നതിലെ ആദ്യത്തെ വാക്ക് ഉളിപോലെ പേന മുറുക്കിപ്പിടിച്ചു പലതവണ വെട്ടി. എന്നിട്ടു വിറയ്ക്കുന്ന കൈകൊണ്ട്, പാർക്കിൻസണിസത്തിൻെറ ലാഞ്ഛന കലർന്ന വലിയ അക്ഷരങ്ങളിൽ വെട്ടിയ വാക്കിൻെറ മുകളിൽ, എഴുതി: 'ബാബ്റി മസ്ജീദ്'.

സുഹ്റയുടെ വലിയ കണ്ണുകളിൽനിന്നു ചരംപോലെ കണ്ണീർ തുള്ളി തുള്ളിയായി ഒലിച്ചു. അവൾ ചുല്യാറ്റിനെ നോക്കി പറഞ്ഞു:"നന്ദി സർ."

പനിയുടെ മറ്റൊരു വേലിയേറ്റത്തിൽ തലതാഴ്ത്തി നടന്ന് ചുല്യാറ്റ് മുറിയിൽ കയറി വാതിലടയ്ക്കുന്നതുവരെ ന്യൂസ്റൂമിൽ ഉണ്ടായിരുന്ന എല്ലാവരും അയാളെ അനങ്ങാതെ നോക്കിനിന്നു.

Figure 5.1: A Sample Page from the book *Thiruttu* which has segmentation error at line level.

Example 2: Another example (See Figure 5.2) where the recognition rate is low, because of line segmentation error. In this case the drop caps at the starting of each paragraph causes problem in the threshold of line segmentation. Even though we have set conditions for drop caps, in this particular case, the big character touched with the small characters makes them a single connected component.



101 സഞ്ജയൻ ഫലിതങ്ങൾ

ആളുകൾ പിരിഞ്ഞുപോയപ്പോൾ പ്രസ്തുത ദയാലുവിനെപ്പറ്റി ഒരാൾ ചെക്കനോട് ചോദിച്ചു:
"അദ്ദേഹത്തെ നിനക്കറിയാമോ?"
'അറിയാം: അയാളാണ് പാൽക്കാരൻ!' എന്നായിരുന്നു ചെക്കന്റെ മറുപടി.

11

ചെറുപ്പക്കാരൻ കഴുതകളെ തെളിച്ചുവരുന്ന അലക്കുകാരനോട്:
"നിങ്ങൾ കഴുതകളുടെ അച്ഛനാണോ?"
അലക്കുകാരൻ : "അതേ മകനേ."

12

സഹാറ മരുഭൂമിയിൽ വെള്ളം വിട്ട് കൃഷിനടത്തിക്കളയാമെന്ന് ഒരെഞ്ചിനീയർ ഒരിക്കൽ വിചാരിച്ചിരുന്നുവത്രെ.
—അത് സാരമില്ല. മുനിസിപ്പാലിറ്റിയിലെ വൃത്തികേട് കുറച്ച് കളയാമെന്ന് കമ്മീഷണർ ആലോചിച്ചിട്ടില്ലേ?"

13

ടീച്ചർ : നോർവെ കടൽത്തീരത്തുള്ളവർ അധികവും മീൻപിടിത്തക്കാരാവാൻ കാരണമെന്ത്?
കുട്ടി : എനിക്കറിയാം സാർ.
ടീച്ചർ : പറയൂ!
കുട്ടി : അവർക്ക് വേറെ ജോലിയൊന്നും ഇല്ലാത്തതുകൊണ്ട്.

14

അവതാരികയോ മുഖവുരയോ ഏതാണ് ഗ്രന്ഥകർത്താവ് എഴുതേണ്ടതെന്ന് ഒരു ലേഖകൻ ചോദിച്ചിരുന്നവല്ലോ.
—ഗ്രന്ഥകർത്താവ് പുസ്തകംതന്നെ എഴുതുവാൻ പാടില്ലായിരുന്നുവെന്ന് ചില പുസ്തകങ്ങൾ വായിച്ചപ്പോൾ തോന്നിയിട്ടുണ്ട്. പിന്നെയല്ലേ മുഖവുര.'

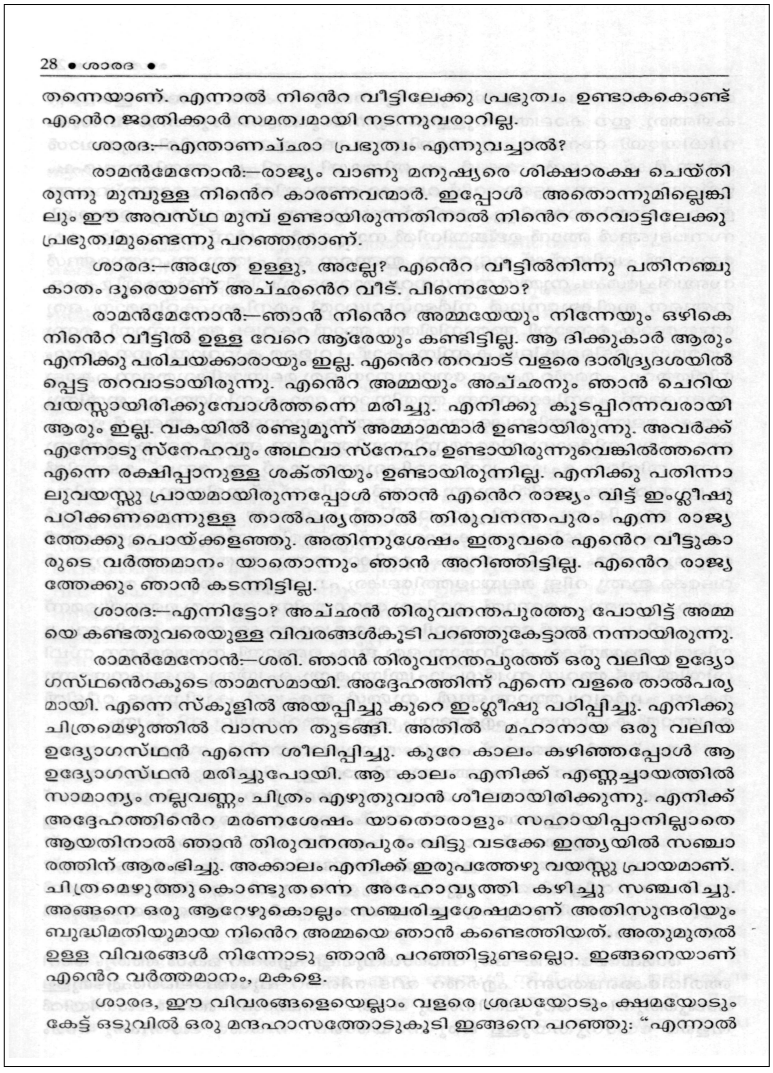
15

നരകമുണ്ടെന്നത് അഴിമതിക്കാരെ ഭീഷണിപ്പെടുത്താൻ വേണ്ടിമാത്രം കെട്ടിയുണ്ടാക്കിയ പച്ചക്കളവാണെന്ന് ഒരു സോവിയറ്റ് ഗ്രന്ഥകാരൻ പറയുന്നു.

22

Figure 5.2: A Sample Page from the book *Sanjayan* which has segmentation error at line level.

Example 3: A sample page from the book *Sarada* is given in the Figure 5.3. This page has backside reflections and degradations. This page gives us an error rate of 5.61%.



28 • ശാരദ •

തന്നെയാണ്. എന്നാൽ നിന്റെ വീട്ടിലേക്കു പ്രഭുത്വം ഉണ്ടാകകൊണ്ട് എന്റെ ജാതിക്കാർ സമത്വമായി നടന്നുവരാറില്ല.

ശാരദ:—എന്താണച്ചാ പ്രഭുത്വം എന്നുവച്ചാൽ?

രാമൻമേനോൻ:—രാജ്യം വാണു മനുഷ്യരെ ശിക്ഷാരക്ഷ ചെയ്തിരുന്നു മുമ്പുള്ള നിന്റെ കാരണവന്മാർ. ഇപ്പോൾ അതൊന്നുമില്ലെങ്കിലും ഈ അവസ്ഥ മുമ്പ് ഉണ്ടായിരുന്നതിനാൽ നിന്റെ തറവാട്ടിലേക്കു പ്രഭുത്വമുണ്ടെന്നു പറഞ്ഞതാണ്.

ശാരദ:—അത്രേ ഉള്ളു, അല്ലേ? എന്റെ വീട്ടിൽനിന്നു പതിനഞ്ചു കാതം ദൂരെയാണ് അച്ചന്റെ വീട്. പിന്നെയോ?

രാമൻമേനോൻ:—ഞാൻ നിന്റെ അമ്മയേയും നിന്നേയും ഒഴികെ നിന്റെ വീട്ടിൽ ഉള്ള വേറെ ആരേയും കണ്ടിട്ടില്ല. ആ ദിക്കുകാർ ആരും എനിക്കു പരിചയക്കാരായും ഇല്ല. എന്റെ തറവാട് വളരെ ദാരിദ്ര്യദശയിൽപ്പെട്ട തറവാടായിരുന്നു. എന്റെ അമ്മയും അച്ചനും ഞാൻ ചെറിയ വയസ്സായിരിക്കുമ്പോൾത്തന്നെ മരിച്ചു. എനിക്കു കൂടപ്പിറന്നവരായി ആരും ഇല്ല. വകയിൽ രണ്ടുമൂന്ന് അമ്മാമന്മാർ ഉണ്ടായിരുന്നു. അവർക്ക് എന്നോടു സ്നേഹവും അഥവാ സ്നേഹം ഉണ്ടായിരുന്നുവെങ്കിൽത്തന്നെ എന്നെ രക്ഷിപ്പാനുള്ള ശക്തിയും ഉണ്ടായിരുന്നില്ല. എനിക്കു പതിന്നാലുവയസ്സു പ്രായമായിരുന്നപ്പോൾ ഞാൻ എന്റെ രാജ്യം വിട്ട് ഇംഗ്ലീഷു പഠിക്കണമെന്നുള്ള താൽപര്യത്താൽ തിരുവനന്തപുരം എന്ന രാജ്യത്തേക്കു പൊയ്ക്കളഞ്ഞു. അതിന്നുശേഷം ഇതുവരെ എന്റെ വീട്ടുകാരുടെ വർത്തമാനം യാതൊന്നും ഞാൻ അറിഞ്ഞിട്ടില്ല. എന്റെ രാജ്യത്തേക്കും ഞാൻ കടന്നിട്ടില്ല.

ശാരദ:—എന്നിട്ടോ? അച്ചൻ തിരുവനന്തപുരത്തു പോയിട്ട് അമ്മയെ കണ്ടതുവരെയുള്ള വിവരങ്ങൾകൂടി പറഞ്ഞുകേട്ടാൽ നന്നായിരുന്നു.

രാമൻമേനോൻ:—ശരി. ഞാൻ തിരുവനന്തപുരത്ത് ഒരു വലിയ ഉദ്യോഗസ്ഥന്റെകൂടെ താമസമായി. അദ്ദേഹത്തിന് എന്നെ വളരെ താൽപര്യമായി. എന്നെ സ്കൂളിൽ അയപ്പിച്ചു കുറെ ഇംഗ്ലീഷു പഠിപ്പിച്ചു. എനിക്കു ചിത്രമെഴുത്തിൽ വാസന തുടങ്ങി. അതിൽ മഹാനായ ഒരു വലിയ ഉദ്യോഗസ്ഥൻ എന്നെ ശീലിപ്പിച്ചു. കുറേ കാലം കഴിഞ്ഞപ്പോൾ ആ ഉദ്യോഗസ്ഥൻ മരിച്ചുപോയി. ആ കാലം എനിക്ക് എണ്ണച്ചായത്തിൽ സാമാന്യം നല്ലവണ്ണം ചിത്രം എഴുതുവാൻ ശീലമായിരിക്കുന്നു. എനിക്ക് അദ്ദേഹത്തിന്റെ മരണശേഷം യാതൊരാളും സഹായിപ്പാനില്ലാതെ ആയതിനാൽ ഞാൻ തിരുവനന്തപുരം വിട്ടു വടക്കേ ഇന്ത്യയിൽ സഞ്ചാരത്തിന് ആരംഭിച്ചു. അക്കാലം എനിക്ക് ഇരുപത്തേഴു വയസ്സു പ്രായമാണ്. ചിത്രമെഴുത്തുകൊണ്ടുതന്നെ അഹോവൃത്തി കഴിച്ചു സഞ്ചരിച്ചു. അങ്ങനെ ഒരു ആറേഴുകൊല്ലം സഞ്ചരിച്ചശേഷമാണ് അതിസുന്ദരിയും ബുദ്ധിമതിയുമായ നിന്റെ അമ്മയെ ഞാൻ കണ്ടെത്തിയത്. അതുമുതൽ ഉള്ള വിവരങ്ങൾ നിന്നോടു ഞാൻ പറഞ്ഞിട്ടുണ്ടല്ലൊ. ഇങ്ങനെയാണ് എന്റെ വർത്തമാനം, മകളെ.

ശാരദ, ഈ വിവരങ്ങളെയെല്ലാം വളരെ ശ്രദ്ധയോടും ക്ഷമയോടും കേട്ട് ഒടുവിൽ ഒരു മന്ദഹാസത്തോടുകൂടി ഇങ്ങനെ പറഞ്ഞു: "എന്നാൽ

Figure 5.3: A Sample Page from the book *Sarada* which has backside reflections and degradations.

5.5 Annotation correction

The document image annotation is a semi-automatic process. The bounding boxes of the word images are mapped with the corresponding typed content, and this information is stored in the database [33]. Since the typing is a manual process, the typed content may be error prone even after careful proof reading. Some situations are, there is a typing mistake in the document itself and the content is typed correctly, the author has used some slang language or some combination of the *aksharas* which the Unicode does not support etc. In this section, we are proposing an annotation correction scheme with the help of a high-performing OCR.

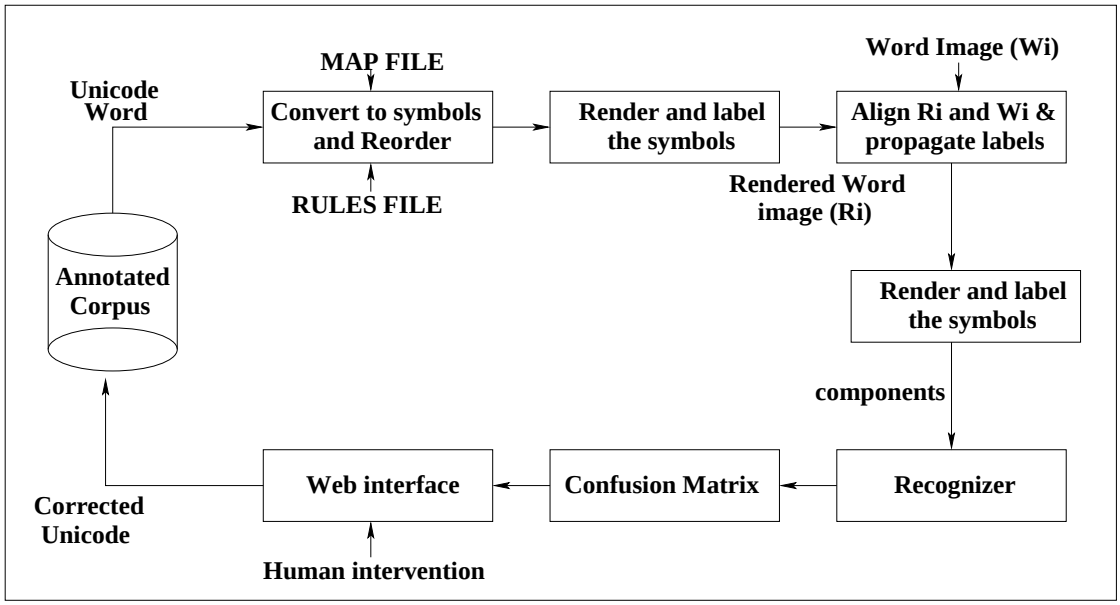


Figure 5.4: Procedure for annotation correction with the help of Recognizer.

The block diagram overall process is given in the Figure 5.4. This is an extension of the symbol level annotation explained in chapter 2. As, we have already explained, confusion matrix is a byproduct of symbol level annotation. In the confusion matrix, the diagonal elements represents the correct classification of the symbol. In the other words this happens, when the classification of the symbol is correct and the typed content is also correct. The non-diagonal elements can occur because of many reason. The first one is, a misclassification by the OCR. The second situation is, the OCR recognizes the symbol correctly, but the content is typed wrongly. And the third condition is, both the content is typed wrongly and the OCR mis-classifies the symbol. The second and the third condition require a correction

of the typed content in the database. We provide a web-interface to correct this data. If the error is caused because of the first reason, we keep the content without any change.

With the help of a very high performing OCR, we can do this correction process very fast. Consider an OCR with 95% symbol level accuracy (using the non-corrected annotated data). In a document image of average 1000 symbols, this gives, 50 errors. In this case we need to look at only 50 symbols instead of 1000 symbols. This way we can save 95% of the time of annotation correction compared to a naive method, that is looking at each symbol/word in the document image. Considering at word level, With the help of an OCR with 60% of word level accuracy, compared to a naive process, 60% of the time can be saved.

A disadvantage of this method is, according to the above mentioned process, we are not recognizing the symbols with cuts and merges. Thus, we are not correcting the errors that occurred at a symbol which has a cut or a merge. To avoid the errors due to this, while correcting the text, we can also look into the symbols with cuts or merges. Consider a document page having with 2% cuts and 1% merge out of 1000 symbols. In this case, With the help of an OCR with 95% of accuracy, we if add the symbols, which are cut into multiple pieces or symbols with merges, for annotation correction, this will add up to 8 % of symbols. That is, 80 symbols out of 1000. Still we can save 93 % of the time compared to the naive process.

Another disadvantage of this method is, it can not detect errors, if the typed content is wrong, and the OCR has misclassified the symbol, and the OCR output and the typed content is same.

5.6 Summary

In this chapter we analyzed the performance of our OCR with various view points. We used character edit distance and the substitution error as the error metrics. We conducted experiments on real document images scanned from twelve Malayalam books, which comes out to be more than 2000 pages. We achieved an average edit distance of 4.75 and substitution error of 2.37 on these real document images, at Unicode level. We also achieved high accuracy compared to the state of the art OCR available in public.

Chapter 6

Recognition of Books using Verification and Retraining

6.1 Character Recognition

Optical character recognition (OCR) is a well researched and mature area in the literature [69, 70]. Most, if not all, of these studies focused on recognition of isolated pages or words. With the emergence of digital libraries, in recent years, recognition of a complete book (or a document image collection) has become important [71, 72, 73]. For machine understanding and language processing of digitized document images, it is important to convert them into a textual form using an OCR. We argue that the recognition of a book, as a large collection of symbols, is considerably different from that of a word or a page. This is due to the fact that books provide rich additional information that could be used for improving the recognition rates of character classifiers and OCRs.

The heart of a typical OCR system is a pattern classifier, with very high performance to recognize isolated symbols. Any error at this stage can get propagated, if not avalanched, into the next phase. A classifier is often trained offline using labeled samples in multiple fonts and styles. With unseen fonts/styles, the performance may deteriorate. When it comes to the recognition of a large collection, such as a book, traditional OCRs may repeat similar mistakes across pages. Or else an OCR designed for isolated pages need not *learn* to improve the performance over time. The advantage of books from a recognition point of view is that, books are often typeset in a single font and style. This implies that, we can use the first few pages to obtain better performance over the rest of the collection.

We enhance the recognition/classification rates of our Book-OCR by *verification* and

retraining. New training data is introduced into the system without any manual intervention. This is done with the help of a dynamic programming based verification module. We employ an automatic learning framework to get more training samples with the help of a verification module. Thereafter, we employ these samples to improve the performance of the classifier by retraining. Our primary contribution is a novel procedure that is specially suited for the recognition of books. We obtain an average performance improvement of around 14% in classification accuracies. We obtain performance enhancement at the cost of additional computations during the verification and retraining.

The experiments are conducted on samples from five annotated books in Malayalam script. Malayalam is an Indian-language, which has rich literary heritage. At present there is no robust commercial OCR system available for this language. Languages like English employ a dictionary to correct errors in the recognition phase. However, dictionary based post-processing techniques are not feasible for highly inflectional languages like Malayalam.

A verification scheme based on a dictionary based approach was introduced in [72]. Recently, another step towards the whole book recognition is reported in [73], using mutual entropy based model adaptation, which uses linguistic constraints to calculate the posterior probabilities of word classes. There are also attempts to enhance the accuracy without using an explicit language model [74] for languages where traditional post-processing is challenging. However, they are applicable only when one simultaneously recognizes a larger collection. In our implementation, we replace the conventional post-processor with a verification scheme.

6.2 Overview of the Book Recognizer

We present a novel and practical approach, for the recognition of symbols from a large collection of documents. Our method employs a data-driven adaptation method to enhance the performance, specific to a particular collection. Training the system with the samples from the same collection to be recognized, is an obvious method to improve the performance of the system. However, collecting the samples from the same environment and labeling them, each time when a new book needs to be recognized, is impractical. We propose an automatic procedure for getting labeled samples and allowing the system to adapt to the same. This is achieved with the help of a high performance verification module, which acts as a post-processor in the system.

The input to the recognizer is a word image. We assume that preprocessing and segmentation of document images up to word level is available. The overall working of the system

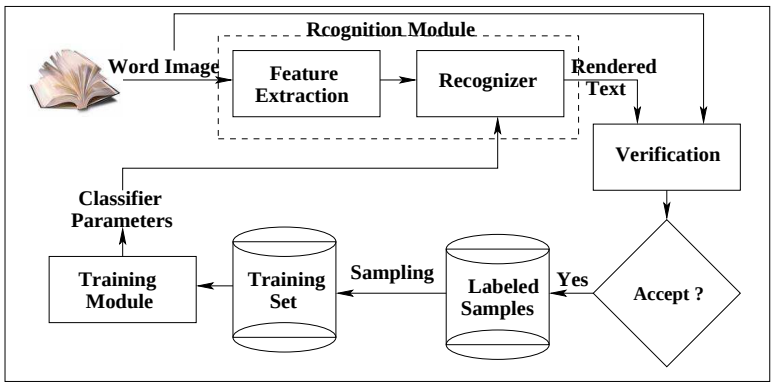


Figure 6.1: Overview of the proposed book recognition scheme.

is as follows. The base recognizer parses the connected components in the word image and identifies the sequence of symbols to be recognized. The recognizer classifies each symbol and returns a class-id associated with it. The class labels are converted back to a Unicode representation. Note that for the Indian scripts, the basic symbols we employ are different from the Unicode[8]. Verification module validates the recognized word *visually*. (Note that a typical post processor validates using a language model.) At this stage, a new set of automatically labeled samples are generated (more details in the next section). In the next iteration, a subset of the labeled samples(depending on the sampling rate chosen) are added to the training set and the classifier is re-trained with the modified set. We repeat the process until, the required accuracy is achieved or the performance improvement in an iteration is less than a threshold. The procedure is summarized in Algorithm 6. Retraining the system in this manner, creates a new improved classifier. We use this new multi-class classifier for further recognitions. This process is repeated until we get required accuracy for the classifier. The overview of the recognition process is shown in Figure 6.1.

With the availability of huge computational power, machine learning techniques are finding new applications in document image analysis [70]. In this work we give more importance to the effectiveness in terms of accuracy of the system than the time consumed for retraining and recognition. At this stage, it is possible to assume that the machines used for recognizing books have enough computational power to do some additional computations so that the performance improves.

Sampling is an important aspect of building the training set. The sampling scheme employed in the system randomly selects the samples from the labeled samples database, and add to the training set. The sampling rate can be specified by the user. While generating more training data, we give priority to the samples which got misclassified initially and

Algorithm 6 Algorithm for adaptation in book recognizer.

1: Input: Word images from the books.
2: Find the connected components(symbols).
3: Recognize each symbol using the classifier and get the class-id.
4: Map the class-ids to Unicode(text) and render the text to obtain a word image.
5: Verification module takes the input word image and the rendered word image to matches both with a dynamic programming based algorithm.
6: The matched samples from the original word image are stored in a labeled images database.
7: The samples are randomly selected from the database (according to the sampling rate selected) and added to training set.
8: Train the classifier with new samples and use this new classifier for further classification.
9: Repeat the steps 2-7 until the required accuracy is achieved or the performance improvement is less than a threshold.

correctly classified in subsequent iterations. This is done by restricting the sampling from newly labeled samples in the labeled samples database at each iteration.

6.3 Verification Scheme

A dynamic programming (DP) based verification module acts as the post-processor for our system. In contrast to the conventional post-processing methods based on the dictionary look-up, our method uses an image based matching technique for verification. The input of the verification module is a word image and the corresponding Unicodes from the recognizer. The output Unicodes are rendered to get an image, which is matched with the input word image. The output of the verification module is a set of labeled samples from the word image. Note that the purpose of the verification module is to provide labeled data for retraining the classifier in the next iteration and thus improving the performance of the recognition module. We need to make sure that correct samples are selected in the training set.

In the DP table, each cell is filled with the matching cost of connected components in the rendered and original word image. In our DP table, diagonal elements represent the *one-to-one* matching of the symbols from the original image and corresponding rendered image. Consider a simple case, where the input word image does not have any cut or merge. In this case a high score in the diagonal element refers to a mismatch and a low score refers

to the match, as shown in Figure 6.2. A match in a diagonal cell refers to the correct classification in the recognition and the mismatch refers to the misclassification.

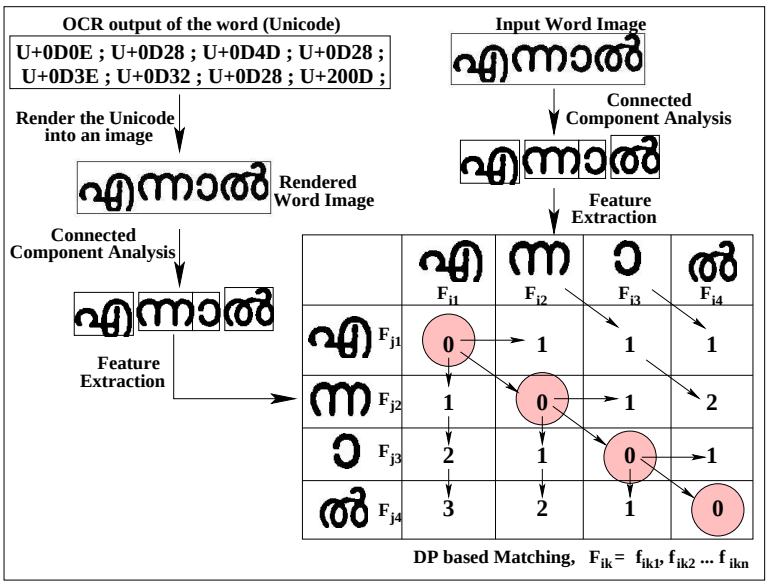


Figure 6.2: An Example of a dynamic programming based verification procedure. Word image is matched with an image rendered out of the recognized text.

Though the focus of this work is not to recognize the degraded characters with cuts and breaks, our verification algorithm identifies such samples, and avoid them in the sampling process. A cut or merge results in the non-diagonal path in the dynamic programming. In the case of cuts, two or more image components may correspond to one rendered component. The DP that we employed is different from the popular DP algorithm (used for string matching) in the following aspects: (a) We obtain cuts and merges instead of deletions and insertions in a normal DP algorithm. (b) The matching is done in the image domain to find the match scores in DP. (c) The computation of matching cost is different for non-diagonal elements. Algorithm 7 gives the details of the DP based word matching process.

The verification module uses simple and structural features. This module performs well, even if the characters are similar. In our implementation, we assume that a character can get cut only into two pieces and the merges can happen only between two characters.

Algorithm 7 Algorithm for Verification as post-processor.

1: Input: Word image and the corresponding text from the Recognizer.
2: Render the text to get a word image.
3: Find the connected components of both original and rendered word images.
4: Create the Dynamic Programming based Cost table, by matching the symbols.
5: Fill the cost values in the table $C(i, j)$ as,

$$C(i,j) = \min \begin{cases} C(i-1, j-1) + MC(S_i, K_j) \\ C(i-1, j) + MC((S_{i-1}, S_i), K_j) \\ C(i, j-1) + MC(S_i, (K_{j-1}, K_j)) \end{cases}$$

where, $MC(S_i, K_j)$ is the matching Cost of symbol S_i in the text(rendered as image) with symbol K_j in the original image.
Matching Cost will be 0 if the two symbols matches, otherwise matching cost will be 1.
6: Get the matching String by reconstructing the path, by following the minimum cost path.
7: Output the text that caused the minimum path as recognized text.

6.4 Results and Discussions

We have conducted our experiments on five Malayalam books. For the automatic evaluation of performance, all these books are annotated *apriori*. The annotation is done as a part of a larger activity [33]. The quality of the images in the corpus vary widely. These books contain more than $500,000$ symbols to recognize.

Book title	# Pages	# Words	# Symbols
Book 1	96	11,404	74, 774
Book 2	119	20,298	147,652
Book 3	84	10,585	83,914
Book 4	175	21,292	152,204
Book 5	94	12,111	92,538

Table 6.1: Details of the books used for the experiments.

In this work, our focus is on improving the classification accuracy of these symbols rather than recognizing degraded images. Malayalam has 56 basic alphabets in its character set, in addition to a large number of conjunct characters. We have considered a total of 205 classes for our experiments, which includes, all the basic alphabets, popular conjunct characters, punctuations, numerals etc. Table 6.1 summarizes the details of the books used for the experiments.

Input to our system is a set of binary document images. After word-level segmentation, the connected components are identified in each of the word images. They form the basic symbols for classification. The symbols are then scaled to 20×20 pixels size keeping the

aspect ratio unchanged. We then use PCA for the feature extraction. The scaled image is converted into a $1D$ array of 400 pixel values which is mapped to the PCA feature space of length 350. Pair-wise SVM classifiers with linear kernel is employed as the basic classifier. The initial classifier is trained with five popular fonts. The books used for the experimentation are typeset in fonts somewhat different from that used for training.

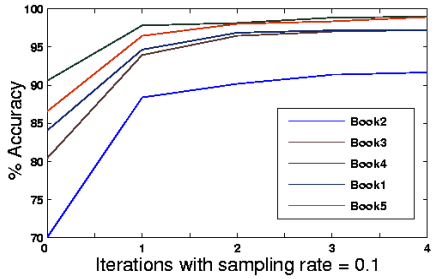


Figure 6.3: Improvement in the performance of a book, with sample rate = 0.1.

Our experimental results on different books are shown in the Figure 6.3. The performance improvement obtained in the books depends on the quality of the book. This is why the maximum accuracies obtained vary across the books. With sampling rate 0.1 in one case (Book 3:*Thiruttu*), we obtain a performance improvement of 21.66% (from 70.02 to 91.68) and in another case (Book 4:*ValmikiRamayanam*) we obtained 8.43% (from 90.58 to 99.01). The average percentage improvement is 13.61. In each iteration we recognize the complete book.

# Iteration	0.01	0.05	0.1	0.3
0	80.42	80.42	80.42	80.42
1	93.28	94.33	93.96	93.94
2	96.46	96.80	96.47	95.35
3	97.41	97.59	97.01	96.28
4	97.52	97.69	97.26	96.46

Table 6.2: % Accuracies obtained with varying sampling rate for the Book 3:*Thiruttu*.

It is observed that, in the first iteration the performance improvement of the classifier is significantly high. As the iteration progresses the rate of improvement decreases. Even though the SVM classifier is considered as a strong and stable classifier, addition of these training samples practically results in significant change in the decision boundaries. The sampling rate also affects the learning rate of the system. We conducted the experiments by varying sampling rate. It was felt initially that if the sampling rate is high the OCR

will learn fast. However, in our experiments the change in learning rate with the change in the sampling rate was marginal (Refer Table 6.2). This is because additional samples of the same font/style do not improve the classifier significantly. This also means that, we can select a low sampling rate and reduce the training time.

Figure 6.4(a) shows a character that is correctly classified after improvement. In Figure 6.4(b) the character is distorted and so that even after improvement the classifier is not able to recognize this case. In Figure 6.4(c) there is cut in the character so that each component is classified as different classes. Similarly Figure 6.4(d) shows a failure case occurred because of merge. One of the holes in the character shown in Figure 6.4(e) is filled, so that it is recognized as another character.

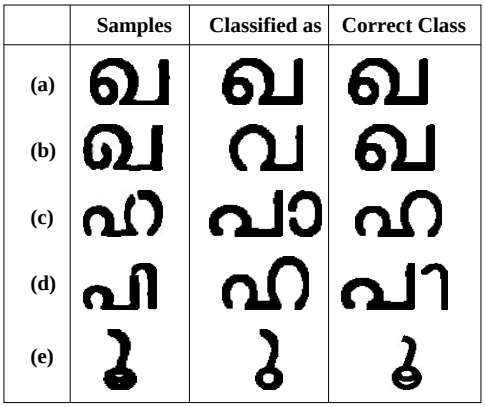


Figure 6.4: Examples of characters tested.

It is observed that, in the first iteration the performance improvement of the classifier is very high, reaching to high 90's, and as the number of iterations increases, the improvement decreases, where the recognition process terminates. The model obtained at this stage is the best updated knowledge we can come up for the given book (or document image collection).

6.5 Summary

In this Chapter, we propose a novel system for adapting a classifier for recognizing symbols in a book. We employed a verification module as a post-processor for the classifier, and make use of an automatic learning framework for the continuous improvement of classification accuracy. We obtain an average improvement of 14% in classification accuracy. This demonstrates that the proposed approach is promising for the recognition of books.

Chapter 7

Conclusions

7.1 Summary and Conclusions

This thesis proposes a classifier system for effectively and efficiently solving the character recognition problem, when the character set is very large(in the order of hundreds). The major contributions of this thesis are: (1). Large dataset generation. (2). Approaches to solve large class problems. (3). Performance evaluation on a huge dataset (Malayalam books).

We generated a large dataset for training and testing the OCR system, using a DP based approach. we conducted empirical study on character classification problem focusing on Indian scripts. The dimensions of the study included performance of classifiers using different features, scalability of classifiers, sensitivity of features on degradation, generalization across fonts and applicability across five scripts etc. We have demonstrated that with a rich feature space, the problem is solvable with an acceptable performance using state of the art classifiers like SVMs.

This data structure is applicable to any multiclass classification technique that builds the solution on binary SVMs. We had shown that our data structure reduces both space and time complexity significantly on multiclass problems. We explain an OCR architecture based on SVM pair wise classifiers with DDAG architecture.

We carried out our classification experiments on a character recognition data set, with more than 200 classes and 10 million examples. We tested our system on real document images scanned from twelve Malayalam books, which comes out to be more than 2000 pages. We achieved an average error rate of 4.75 on these books. We conduct extensive experiments to study the implications of various parameters in design of computationally

efficient and yet effective classifier. We also extend our classifier to continuously improve the performance by providing feedback and retraining the classifier.

7.2 Future Scope

This work opens up many interesting problems in document understanding in the Indian language context.

- Extend the features and classifier to support more fonts and old lipi characters.
- More script specific techniques at pre-processing stage.
- A strong post-processor based on language models. Also, a strong word recognizer as a part of post-processor will improve the system.
- Degradation handing: To handle the spurious noise, cuts and merges in the characters.

Bibliography

[1] A. K. Jain, R. P. W. Duin, and J. Mao, "Statistical pattern recognition: A review," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 22(1), 2000, pp. 4–37. 1

[2] R. O. Duda, P. E. Hart, and D. G. Stork, *Pattern Classification*. Wiley-Interscience Publication, 2000. 1, 42, 43, 44, 46, 51, 64

[3] G. Nagy, "At the frontiers of ocr," *Proceedings of IEEE*, vol. 80, pp. 1093–1100, July 1992. 5

[4] C. Y. Suen, S. Mori, S. H. Kim, and C. H. Leung, "Analysis and recognition of asian scripts - the state of the art," in *ICDAR '03: Proceedings of the Seventh International Conference on Document Analysis and Recognition*, Washington, DC, USA, IEEE Computer Society, 2003, p. 866. 5

[5] H. Fujisawa, "Forty years of research in character and document recognition: An industrial perspective," *PR*, vol. 41, pp. 2435–2446, August 2008. 5

[6] V. Govindaraju and S. Setlur, *Guide to OCR for Indic Scripts: Document Recognition and Retrieval*. Springer Publishing Company, Incorporated, 2009. 5, 42

[7] B. B. Chaudhuri, "On OCR of a printed indian script," in *Digital Document Processing: Major Directions and Recent Advances, B. B. Chaudhuri (ed.), Springer-Verlag London Ltd*, 2007, pp. 99–119. 5, 8

[8] U. Pal and B. B. Chaudhuri, "Indian script character recognition: a survey," *Pattern Recognition*, vol. 37, no. 9, 2004. 5, 42, 55, 96

[9] V. Bansal and R. Sinha, "A devanagari ocr and a brief overview of ocr research for indian scripts," in *Proceedings of STRANS01, held at IIT Kanpur*, 2001. 5

[10] V. Bansal and R. M. K. Sinha, "A complete OCR for printed Hindi text in Devanagari script," in *Proc. of the 6th International Conference on Document Analysis and Recognition (ICDAR)*, 2001, pp. 800–804. 5, 6

[11] B. B. Chaudhuri and U. Pal, "An OCR system to read two Indian language scripts: Bangla and Devanagari (Hindi)," in *Proc. of the 4th International Conference on Document Analysis and Recognition (ICDAR)*, 1997, pp. 1011–1015. 5, 8

[12] B. B. Chaudhuri and U. Pal, "A complete printed Bangla OCR system," *Pattern Recognition*, vol. 31, no. 5, pp. 531–549, 1997. 5, 6

[13] U. Pal and A. Sarkar, "Recognition of printed Urdu script," in *Proc. of the 7th International Conference on Document Analysis and Recognition (ICDAR)*, 2003, pp. 1183–1187. 5, 6

[14] V. Bansal and R. M. K. Sinha, "A Devanagari OCR and a brief overview of OCR research for Indian scripts," in *Proc. of the Symposium on Translation Support Systems*, 2000. 6

[15] U. Pal and B. Chaudhuri, "Printed Devanagiri Script OCR System," *Vivek*, vol. 10, no. 2, pp. 12–24, 1997. 6

[16] G. S. Lehal and C. Singh, "A complete OCR system for Gurmukhi script," in *Structural, Syntactic and Statistical Pattern Recognition, T. Caelli, A. Amin, R.P.W. Duin, M. Kamel and D. de Ridder (Eds.), Lecture Notes in Computer Science*, 2002, pp. 344–352. 6, 7

[17] G. S. Lehal and C. Singh, "A Gurmukhi script recognition system," in *Proc. of the 15th International Conference on Pattern Recognition (ICPR)*, 2000, pp. 557–560. 6

[18] S. Antanani and L. Agnihotri, "Gujarati character recognition," *Proc. of the 5th International Conference on Document Analysis and Recognition (ICDAR)*, pp. 418–421, 1999. 6, 7

[19] S. Mohanty and H. K. Behera, "A complete OCR development system for Oriya script," in *Proc. of symposium on Indian Morphology, phonology and Language Engineering*, 2004. 6, 7

[20] B. B. Chaudhuri, U. Pal, and M. Mitra, "Automatic recognition of printed Oriya script," in *Proc. of the 6th International Conference on Document Analysis and Recognition (ICDAR)*, 2001, pp. 795–799. 6

[21] K. H. Aparna and V. S. Chakravarthy, "A complete OCR system development of Tamil magazine documents," in *Tamil Internet, Chennai, Tamilnadu, India*, 2003. 6, 7

[22] C. V. Lakshmi and C. Patvardhan, "A complete multi-font OCR systems for printed Telugu text," in *Language Engineering Conference*, 2002. 6

[23] A. Negi, C. Bhagvathi, and B. Krishna, "An OCR system for Telugu," in *Proc. of the 6th International Conference on Document Analysis and Recognition (ICDAR)*, 2001, pp. 1110–1114. 6, 7, 48

[24] P. Rao and T. Ajitha, "Telugu script recognition - A feature based approach," in *International Conference on Document Analysis and Recognition (ICDAR)*, 1995, pp. 323–326. 6

[25] V. N. Manjunath, P. S. Aradhyal, G. H. Kumar, and S. Noushathl, "Fisher linear discriminant analysis based technique useful for efficient character recognition," in *Proc. of the 4th International Conference on Intelligent Sensing and Information Processing*, 2006, pp. 49–52. 6

[26] T. Ashwin and P. Sastry, "A font and size-independent ocr system for kannanda documents using svm," in *Sadhana*, vol. 27, 2002. 6

[27] K. Jithesh, K. G. Sulochana, and R. R. Kumar, "Optical character recognition (OCR) system for Malayalam language," in *National Workshop on Application of Language Technology in Indian Languages*, 2003. 6, 7

[28] G. Prathap, "Indian language document analysis and understanding," *Special Issue of Sadhana*, vol. 27, 2002. 7

[29] T. V. Ashwin and P. S. Sastry, "A font and size independent OCR system for printed Kannada documents using support vector machines," *Special Issue of Sadhana*, vol. 27, pp. 35–58, 2002. 7

[30] C. V. Jawahar, M. N. S. S. K. P. Kumar, and S. S. R. Kiran, "A Bilingual OCR for Hindi-Telugu Documents and its Applications," in *Proc. of the International Conference on Document Analysis and Recognition (ICDAR)*, 2003, pp. 408–412. 8

[31] M. N. S. S. K. P. Kumar and C. V. Jawahar, "Design of hierarchical classifier with hybrid architectures," in *Proc. of 1st Int. Conf. on Pattern Recognition and Machine Intelligence (PReMI)*, 2005, pp. 276–279. 8

[32] T. K. Chalasani, A. M. Namboodiri, and C. V. Jawahar, "Support vector machine based hierachical classifieds for large class problems," in *proceedings of International Conference on Advances in Pattern Recognition (ICAPR)*, 2007. 8

[33] C. V. Jawahar and A. Kumar, "Content-level annotation of large collection of printed document images," in *International Conference on Document Analysis and Recognition (ICDAR)*, 2007, pp. 799–803. 15, 92, 99

[34] M. Meshesha and C. V. Jawahar, "Matching word images for content-based retrieval from printed document images," *Int. J. Doc. Anal. Recognit.*, vol. 11, no. 1, pp. 29–38, 2008. 17, 57

[35] A. Balasubramanian, M. Meshesha, and C. V. Jawahar, "Retrieval from document image collections," in *In: Proc. DAS*, Springer, 2006, pp. 1–12. 31

[36] T. M. Rath and R. Manmatha, "Word image matching using dynamic time warping," *Computer Vision and Pattern Recognition, IEEE Computer Society Conference on*, vol. 2, p. 521, 2003. 31

[37] T. M. Rath and R. Manmatha, "Features for word spotting in historical manuscripts," in *ICDAR '03: Proceedings of the Seventh International Conference on Document Analysis and Recognition*, Washington, DC, USA, IEEE Computer Society, 2003, p. 218. 31

[38] R. King, C. Feng, and A. Shutherland, "Statlog: comparison of classification algorithms on large real-world problems," *AAI*, vol. 9, pp. 259–287, June 1995. 42

[39] R. Caruana and A. Niculescu-Mizil, "An empirical comparison of supervised learning algorithms," in *proceedings of International Conference on Machine Learning (ICML)*, 2006. 42, 64

[40] Y. e. Lecun, "Learning algorithms for classification: A comparison on handwritten digit recognition," in *Neural Networks: The Statistical Mechanics Perspective*, 1995, pp. 261–276. 42, 46

[41] A. Asuncion and D.J.Newman. "UCI machine learning repository,",". WWW page, 2007. 42, 71

[42] S. Arya and H.-Y. A. Fu, "Expected-case complexity of approximate nearest neighbor searching," in *proceedings of Symposium on Discrete Algorithms*, 2000, pp. 379–388. 44

[43] T.-S. Lim, W.-Y. Loh, and Y.-S. Shih, "An empirical comparison of decision trees and other classification methods," Tech. Rep. 979, Madison, WI, 30 1997. 44

[44] S. K. Murthy, S. Kasif, S. Salzberg, and R. Beigel, "Oc1: A randomized algorithm for building oblique decision trees," tech. rep., 1993. 44

[45] S. Haykin, *Neural Networks - A Comprehensive Foundation, 2nd ed.* Prentice-Hall, Englewood Cliffs, 1998. 45

[46] L. Bottou, C. Cortes, J. Denker, H. Drucker, I. Guyon, L. Jackel, Y. LeCun, U. Muller, E. Sackinger, P. Simard, and V. Vapnik, "Comparison of classifier methods: a case study in handwritten digit recognition," in *Proc. of the International Conference on Pattern Recognition (ICPR)*, vol. II, Jerusalem, IEEE, October 1994, pp. 77–82. 45

[47] Y. LeCun, L. D. Jackel, L. Bottou, A. Brunot, C. Cortes, J. S. Denker, H. Drucker, I. Guyon, U. A. Muller, E. Sackinger, P. Simard, and V. Vapnik, "Comparison of learning algorithms for handwritten digit recognition," in *proceedings of International Conference on Artificial Neural Networks*, Paris, EC2 & Cie, 1995, pp. 53–60. 45

[48] A. Caldern, S. Roa, and J. Victorino, "Handwritten digit recognition using convolutional neural networks and gabor filters," in *INTERNATIONAL CONGRESS ON COMPUTATIONAL INTELLIGENCE*, 2003. 46

[49] N. Cristianini and J. Shawe-Taylor, *An Introduction to Support Vector Machines and Other Kernel-based Learning Methods.* Cambridge University Press, March 2000. 47

[50] T. M. Mitchell, *Machine Learning.* New York: McGraw-Hill, 1997. 47

[51] J. Platt, N. Cristianini, and J. Shawe-Taylor, "Large margin dags for multiclass classification," in *proceedings of Advances in Neural Information Processing Systems*, 2000, pp. 547–553. 47, 65, 77

[52] O. Trier, A. Jain, and A. Taxt, "Feature extraction methods for character recognition - a survey.," in *Pattern Recognition 29,*, 1996, pp. 641–662. 48

[53] W. Gonzalez, *Digital Image Processing.* Massachusetts: Addison Wesley, 1992. 48, 49, 50

[54] A. Khotanzad and Y. H. Hong, "Invariant image recognition by zernike moments," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 12, no. 5, pp. 489–497, 1990. 49

[55] I. Popivanov and R. J. Miller, "Similarity search over time series data using wavelets," in *Proc. of the 18th Int. Conf. on Data Engineering*, 2002, pp. 212–221. 49, 50

[56] E. Bingham and H. Mannila, "Random projection in dimensionality reduction: applications to image and text data," in *KDD '01: Proceedings of the seventh ACM SIGKDD international conference on Knowledge discovery and data mining*, New York, NY, USA, ACM, 2001, pp. 245–250. 51

[57] W. Johnson and J. Lindenstrauss, "Extensions of lipshitz mapping into hilbert space.," *In Conference in modern analysis and probability*, vol. 26 of Contemporary Mathematics, pp. 189–206, 1984. 52

[58] R. Brown, "The fringe distance measure: An easily calculated image distance measure with recognition results comparable to gaussian blurring," *SMC*, vol. 24, pp. 111–115, 1994. 52

[59] Q. Zheng and T. Kanungo, "Morphological degradation models and their use in document image restoration," in *proceedings of International Conference on Image Processing (ICIP)*, 2001, pp. 193–196. 56

[60] R. Caruana and A. Niculescu-Mizil, "Data mining in metric space: An empirical analysis of supervised learning performance criteria," in *Knowledge Discovery and Data Mining*, 2004. 64

[61] V. Vapnik, "The nature of statistical learning theory," in *second ed. Springer Verlag*, 1999. 64

[62] N. Cristianini and J. Shawe-Taylor, *An Introduction to Support Vector Machines and Other Kernel-based Learning Methods*. 2000. 65

[63] C.-W. Hsu and C.-J. Lin, "A comparison of methods for multiclass support vector machines," in *IEEE Transactions on Neural Networks*, vol. 13, 2002, pp. 415–425. 65

[64] K.-B. Duan and S. S. Keerthi, "Which is the best multiclass svm method? an empirical study," in *proceedings of Multiple Classifier Systems(MCS)*, June 2005, pp. 278–285. 65

[65] C. J. C. Burges, "Simplified support vector decision rules," in *proceedings of International Conference on Machine Learning (ICML)*, vol. 13, 1996. 65

[66] T. Downs, K.E.Gates, and A. Masters, "Exact simplification of support vector solutions," *Journal of Machine Learning Research*, vol. 2, pp. 293–297, 2001. 65, 73, 76

[67] T. Joachims, "Making large-scale svm learning practical," in *Advances in Kernel Methods - Support Vector Learning,MIT-Press*, 1999. 70

[68] C.-C. Chang. "Libsvm,",". http://www.csie.ntu.edu.tw/~cjlin/libsvm/, 2008. 70

[69] Y. Xu and G. Nagy, "Prototype extraction and adaptive ocr," *IEEE Trans. on Pattern Analysis and Machine Intelligence (PAMI)*, vol. 21, no. 12, pp. 1280–1296, 1999. 94

[70] C. L. Liu and H. Fujisawa, "Classification and learning methods for character recognition :Advances and remaining problems," in *Neural Networks and Learning in Document Analysis and Recognition*. 2008, pp. 139–161. 94, 96

[71] K. P. Sankar, V. Ambati, L. Pratha, and C. V. Jawahar, "Digitizing a million books: Challenges for document analysis," in *International Workshop on Document Analysis Systems (DAS)*, 2006, pp. 425–436. 94

[72] M. Meshesha and C. V. Jawahar, "Self adaptable recognizer for document image collections," in *proceedings of Pattern Recognition and Machine Intelligence*, 2007, pp. 560–567. 94, 95

[73] P. Xiu and H. S. Baird, "Whole-book recognition using mutual-entropy-driven model adaptation," in *Document Recognition and Retrieval XV. Proc. of SPIE*, 2008. 94, 95

[74] V. Rasagna, A. Kumar, C. V. Jawahar, and R. Manmatha, "Robust recognition of documents by fusing results of word clusters," in *ICDAR '09: Proceedings of the 2009 10th International Conference on Document Analysis and Recognition*, Washington, DC, USA, IEEE Computer Society, 2009, pp. 566–570. 95

Appendix A

Character Lists

A.1 Malayalam Class List

The classlist used for the experiments in Malayalam script is shown in the Figure A.1 and A.2. We have chosen 205 classes in our experiments.

Figure A.1: Malayalam symbols used for experiments.

Figure A.2: Malayalam symbols used for experiments, continued.

Appendix B

Publications Related to This Work

The work done during my masters has been disseminated to the following conferences:

1. Neeba N.V, C.V Jawahar, **Empirical Evaluation of Character Classification Schemes**, *The seventh International Conference on Advances in Pattern Recognition (ICAPR '09)*, Feb . 4-6, 2009, Kolkotta, India. [PDF].

2. Neeba N.V, C.V Jawahar, **Recognition of Books by Verification and Retraining**, *The nineteenth International Conference on Pattern Recognition (ICPR '08)*, Dec. 8-11,2008, Florida, USA. [PDF].

3. P.Ilayaraja, Neeba N.V, C.V Jawahar, **Efficient Implementation of SVM for Large Class Problems**, *The nineteenth International Conference on Pattern Recognition(ICPR '08)*, Dec. 8-11,2008, Florida, USA. [PDF].

We have also written a book chapter:

- Neeba N.V, A.M Namboodiri, C.V Jawahar and P.J Narayanan, **Recognition of Malayalam documents,** *Guide to OCR for Indic Scripts, Pages 125-146, 2009.*