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TechForward

DISPATCH

JULY EDITION

COMPUTING, SCIENCE AND HEALTHCARE

are revolutionising medical practices. Advances in computational power and sophisticated algorithms enable the analysis of vast datasets, leading to more accurate diagnoses and personalised treatment plans. AI-driven tools can predict patient outcomes, identify patterns in complex medical data, and assist in drug discovery. As computing technology continues to evolve, its integration with healthcare promises to transform the industry, making it more proactive and tailored to individual needs.

IIITH's TechForward research seminar series is an academia-industry confluence around emerging technologies. The deep insights, directional talks and industry outlooks from accomplished thought leaders at the seminar are compiled monthly in the Tech Dispatch as a ready reckoner for technology directions.

From the Chair's Desk

Welcome to the second edition of the TechForward research seminar series. This initiative aims to bring together academia and industry to exchange ideas in two ways: (i) provide industry with an early peek into new innovations on the academic front, (ii) provide academics with challenging problem definitions to work on. While this seems like a one-way street, it is often not the case. Academics might be able to better articulate an important problem in the industry and research teams in the industry might be involved in development of more cutting-edge solutions.

Unlike other sectors, healthcare presents a unique set of challenges when it comes to technology due to which the ratio of value delivered to innovation created remains one of the lowest. Our two distinguished speakers Prof. Deva Priyakumar and Prof. Sujoy Kar have been trying to surmount these challenges in their own way. Given that healthcare is in equal parts, products and services, we have chosen them to represent two broad sections - drug/pharma and healthcare delivery. While one of them is an academic, the other is a practitioner and both have successfully traversed the boundary between academics and practice. Their talks have been summarised in the Dispatch along with insights from other thought leaders in the field. We hope you find them helpful in your professional journey.

PROF. SARANG DEO

Deputy Dean, Faculty and Research, ISB

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The 2nd edition of TechForward was hosted at ISB campus

Love AI or Hate AI But Biochemists Can't Ignore AI

***Prof Deva Priyakumar** discusses the drug discovery process and sheds light on the role played by computations in making it more efficient.*

The Evolution of Aspirin as Drug

Before delving into how AI supports the drug discovery process, it's essential to understand the evolution of drug discovery as we know it. And no better way to start than with the story of the earliest known drug - Aspirin. It is also one of the most widely consumed drugs today with close to 100 billion pills consumed across the world. Ancient history and written texts reveal that extracts of the bark of the willow tree were used to treat inflammation and fever. Its pain-relieving properties were well known and Hippocrates too recommended willow for fever, pain and even childbirth. Much later in the 19th century, the willow's anti-inflammatory properties were traced to an active ingredient, a compound called salicylic acid. However, it was used sparingly because its long-term usage came to be associated with damage to the stomach in the form of internal bleeding.

A modified form of the compound was created synthetically marking not just the birth of the first official drug known to us but also the genesis of the pharmaceutical industry. It was marketed and patented by Bayer as a non-steroidal anti-inflammatory drug. In fact, in 1918, Aspirin became to Spanish flu what acetaminophen was to the Covid-19 pandemic. With the introduction of competing analgesics like Acetaminophen in 1959 and Ibuprofen in 1969, the monopoly of aspirin as the only pain-relieving drug in the market came to an end. However, there was a gradual revival in its fortunes during the '70s and '80s when aspirin began to be used as a blood thinner for treating vascular diseases like heart attacks and strokes.

Understanding How Aspirin Works

The first step towards an understanding of the drug happened with the discovery of the cyclooxygenases (COX) as the target of non-steroidal anti-inflammatory drugs. Very simplistically, it means that in addition to binding to one particular protein that causes inflammation, it also binds to another that causes gastrointestinal bleeding. It was while looking at the structures of the proteins and understanding their binding affinity that the binding locations were discovered. That explains the discovery of different drugs that could bind to the two different enzymes (COX-1 and COX-2). To summarize the early drug discovery process, it can be pictured in 3 overall stages - the empirical where aspirin began to be used as a pain reliever based on observation or experience, the next stage when there was an understanding of the components of the drug. Incidentally, the market at the time was dominated by the textile and dye industry which had easy access to chemicals. Finally, there was an understanding of not only the drug but also its receptors. An in-depth exploration began at the organism level and moved onto the tissue, cellular and finally the molecular level.

The Drug Discovery Process

When there's a disease that needs to be treated, identifying pathways involved in it - whether it is an infection or a non-communicable disease - is the first step. The next is target identification which refers to the process of identifying molecular targets for compounds to bind to and is at the heart of the drug discovery process. It is when the actual drug design begins. To test whether the binding takes place, trials are conducted 'in vitro' and 'in vivo'. When the trials are successful, a marketable drug can be produced. The failure rate of this process is extremely high and so are the corresponding costs involved.

AI In Drug Discovery Cycle

Every time you ingest a pill, it travels to the digestive system where it is absorbed before getting distributed or spread throughout the body, metabolised or processed by the body into subsequent compounds, and finally excreted. In effect, any drug molecule that is discovered needs to possess the above-mentioned properties. In the drug discovery process, once the target protein molecule has been identified, it comes down to shortlisting molecules that can bind to the target. In the initial stages, this means beginning with a large library of drug-like molecules where each shortlisted molecule is painstakingly evaluated. This is where computational methods play a big role. It's more about rejecting bad candidates for binding than about finding the right ones. Physics-based methods to predict molecular properties are time-consuming and very expensive. Due to these limitations, AI algorithms are being used at every stage of the drug discovery cycle. The first HIV drug that targeted the protease owes its success to significant contribution from computational technologies. Over the last few years, AI is playing an increasing role not just in the initial stages of drug discovery but throughout the pipeline - from identifying the target or analysing biological pathways right down to predicting clinical trial outcomes.

The number of startups using AI for drug discovery has only grown exponentially over the last few years. However, scientists are still hesitant about embracing technology because AI is a big black box for them. The hesitancy arises from not knowing how it works. However, we have started to explore these methods in the following situations.

When Physics is well known but is inefficient: One of the first steps in the drug discovery pipeline is to take a large database of drug-like molecules and then screen them. It essentially means shortlisting all the molecules with the properties of absorption, distribution, metabolism and excretion. Machine learning models make this process more efficient. The exercise refers to choosing the top hits from the library that fulfil the conditions laid down. In this case, we typically start with zero data, or begin evaluations with minimal data explicitly generated to acquire compounds that are more useful in treating the particular disease. The percentage of effort put in is inversely proportional to the returns you get when you use computational methods.

For problems not yet solved by Physics-based methods: One of the trickiest parts of drug discovery is predicting protein structures which will help in determining binding affinity. We have come a long way in the understanding of protein folding during the last few decades, however it is still elusive through exclusive physics-based methods. ML has provided the best answer yet in form of Alphafold.

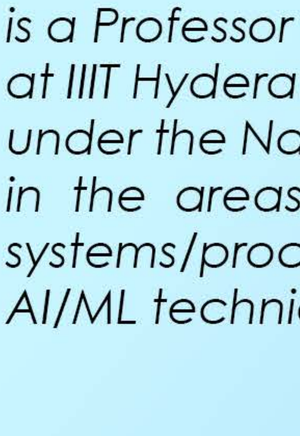
When the solution is known, but it's hard to code: It needs an expert to figure out how to make a drug-like molecule starting from available reagents. However, given the large number of possible synthetic methodologies, it is hard to make rules so that a code could be written. We use reinforcement-based learning to figure out given a compound, what is the pathway one should take, or steps to be followed to make the same compound in a lab.

Essentially, the ML model is working backwards in this case from a target compound to develop multiple pathways.

Inverse Problems: Typically in drug discovery, you begin with a molecule and proceed to ask if it fulfils the 4 properties. But in this case, you begin with the 4 properties you want in a molecule and use them as inputs in a machine learning model. You cannot use Physics-based methods to handle these questions. A Generative AI model will respond by generating molecules based on the criteria used as inputs. We have also used GPT architecture to generate new molecules with specific properties of interest.

Summary

AI and ML have established themselves as the fourth paradigm in scientific research with these methods proving to be an excellent addition to the chemist's toolkit. Their use in bridging the human-machine intelligence gap will revolutionise the way we do Science. That said, there are bottlenecks in the adoption of AI for drug discovery such as lack of datasets, inherent biases, interpretability of models, generalizability and so on.



PROF DEVA PRIYAKUMAR

IIIT HYDERABAD

is a Professor and Head of the Center for Computational Natural Sciences and Bioinformatics at IIIT Hyderabad. He is also the Project Director of IHub-Data, the Technology Innovation Hub under the National mission for Interdisciplinary Cyber Physical Systems. His research interests lie in the areas of applying computational methods for studying chemical and biological systems/processes. Recently, his group has made significant contributions in applying modern AI/ML techniques for molecular science research.

Transforming Healthcare With AI

Dr. Sujoy Kar walks us through the elements that constitute Clinical AI while explaining how Apollo Hospitals embraces responsible AI practices for clinical adoption.

Artificial intelligence, machine learning and deep-learning in particular is empowering the use of labelled clinical data – 'big' in terms of volume, variability, velocity or scalability - with significantly enhanced computing power and cloud storage. In clinical practice and public health, this is making initial steps to have an impact with better clinical outcomes.

The Building Blocks Of Clinical AI : 9 Steps

It is important to start with Ideation of Clinical AI in terms of attitude, behaviour, expectations, experience of Users (principles of Design Thinking) and what one would like to deliver as a better proposition. Ideation phases bring together multidisciplinary teams - clinical consultants, nurses, and other healthcare workers who look at the current clinical practice guidelines and identify where an AI tool would help augment their respective roles. Data Hygiene is the second and most pivotal step. This is challenging due to many reasons, not the least because of the way in which it has been collected, stored and retrieved. Approval from local Ethics Committees with appropriate clinical AI protocol and consents for prospective use from patients are critical. Modelling with development cohorts following appropriate data quality and mitigating bias is the fourth important step. This is often followed by External Validation with consortium members, whose data quality, normalisation and federated learning processes are in place. On the sixth step, we go through the important peer-reviewed publishing process, followed by API generation integrating the algorithm with clinical pathways (decided by the multidisciplinary team). Our eighth step involves securing Intellectual Property, ISO 13485 Certification and Regulatory Approvals, which naturally paves the way towards integration and prospective use of these APIs in clinical workflows.

EASE Framework is an Apollo Hospitals Concept

Heterogenous Perception among Clinicians and Responsible AI

Healthcare professionals may have varying views on the impact of AI. Some perceive it as a valuable tool for improving patient outcomes while others may be sceptical and apprehensive about its accuracy. This is in many ways reflective of the data, AI methodologies and interpretation – which can provide sense of a "Black Box". Hence, building trust pipelines, which sequentially flow from the Model to the Clinician and to the Patient, is imperative for AI Adoption.

At Apollo Hospitals, responsible AI practices are at the core of clinical adoption. The EASE *(https://doi.org/10.1007/s40012-023-00381-2)* Framework brings in 18 aspects of ethical considerations, adoption, sustainability and explanability in design, development and deployment of Clinical AI.

Current Workstreams

At Apollo Hospitals, we work on 6 different work streams - conversational AI, disease progression models, images and signals, augmented pathways with AI, throughput optimization, and genomics. In disease progression models, we have models that can identify cardiovascular diseases, liver fibrosis, pre-diabetes, chronic obstructive pulmonary disease (COPD), chronic kidney disease (CKD) and a pipeline of longitudinal clinical pathways (with their outcomes).

Building Data Consortiums

External consortiums are difficult to build but absolutely essential for clinical AI, with their significance in each phase of design, development and deployment. These consortiums include the industry, academia and healthcare and digital health platforms. In the near future, secured and confidential computing methodologies will drive these consortiums.

Access to Data for Research and Innovation

In the ideation phase that was mentioned earlier, we can have academic institutions join hands with our clinical consultants, have workshops within the organisation, identify the clinical need, apply to the Ethics Committee, get their approval upon which access is provided through Apollo Azure Tenant's secured computing. This is where anonymised, normalised data is hosted for an approved research purpose.

Conclusion

Rightful adoption of AI practices in healthcare requires skilling and training people about AI in healthcare. It also involves training them about understanding the implications and interpreting some of the results.

DR. SUJOY KAR
APOLLO HOSPITALS

is the Chief Medical Information Officer and Vice President at Apollo Hospitals, India. He is responsible for designing, developing and deploying over dozens of clinical APIs at Apollo Hospitals. His current and ongoing research interests are in the adoption of AI in healthcare, digital health platforms and design thinking in healthcare.

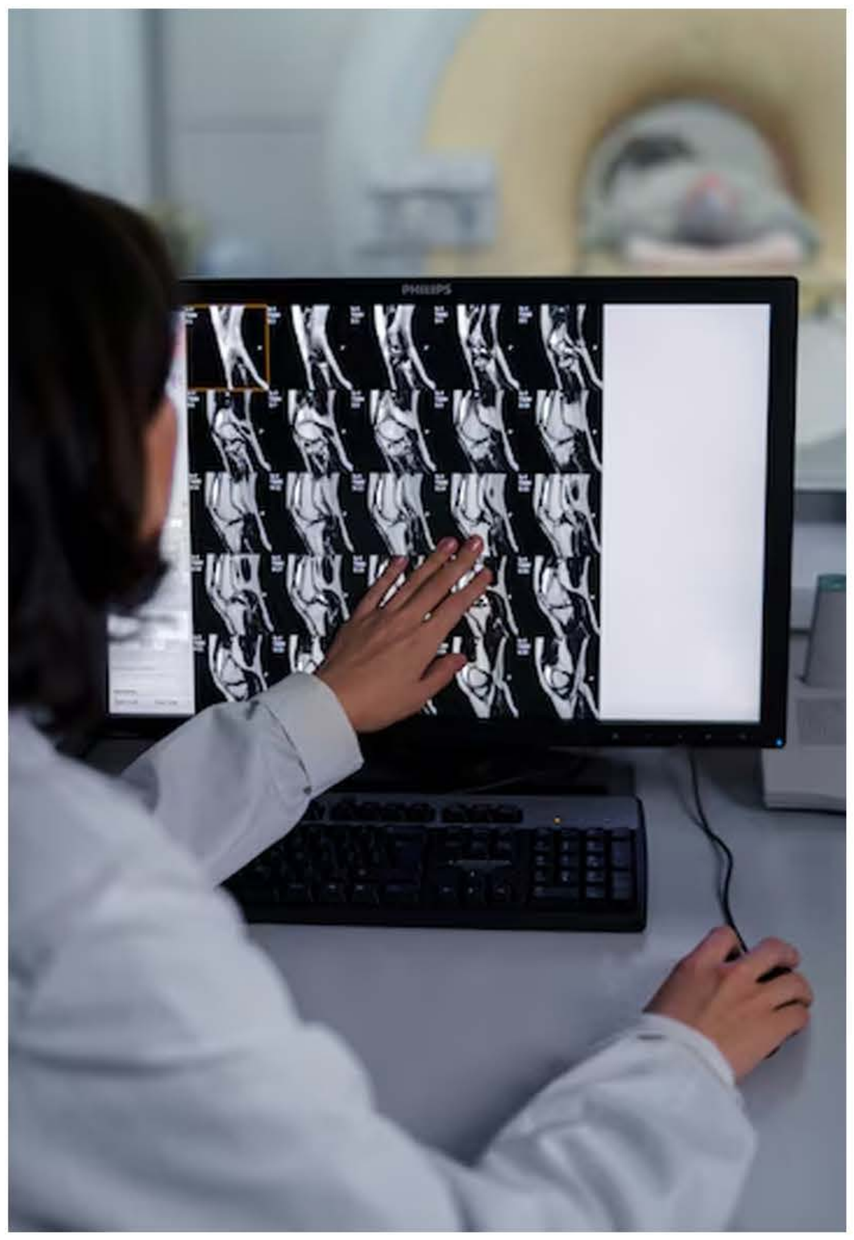
AI In Medical Imaging: A Diagnostic Enabler

From assisting experts in healthcare diagnosis based on images alone, AI-assisted radiology is evolving to include multiple evidence-based reports, observes Prof. Jayanthi Sivaswamy

Images have been a key part of diagnosis in healthcare for long. From the X-ray that is routinely used to screen the chest (for a variety of diseases) and the breast (for cancer), to ultrasonography for assessing the health of a foetus or the abdomen, heart, etc, to MRI/CT for detecting strokes and haemorrhages, a wide range of imaging options are employed.

Ease Of Digital Imaging and Availability of Expert Diagnosis: A Mismatch

The advent and widespread use of digital computers spurred even film-based imaging such as in X-ray to go digital, facilitating not only easy storage but also processing by computers. Visual exams of the retina by ophthalmologists and of biological specimens on slides by pathologists also have digital footprints now, due to advances in digital cameras and their easy availability. This enabled telemedicine as digital images taken at one location can be easily transmitted to an expert far away for either real time or off-line consultation. However, there is a bottleneck. The increasing ability to image is however highly mis-matched with the availability of medical expertise needed to read and interpret the images. Systems that automatically process medical images are expected to offer a solution to address this gap as well as increase efficiency in clinical workflow by providing assistance to experts. Machine learning from images is a key methodology enabling this automated processing.



Evolution Of AI in Medical Imaging

The goal of AI systems designed to process images has become increasingly ambitious. Initially it was to primarily assist experts in diagnosis. The earliest approval given by the Federal Drug Authority or FDA for such an automated solution in breast cancer screening was in 1998 as a second reader. I.e., a human expert had to first read the mammogram and record their decision on the presence of cancer; only after this were they allowed to access the view of the AI system and possibly modify their original decision. With increasing maturity of technology and proven performance, standalone systems are also part of the goal especially in screening for diseases.

AI-assisted medical device is a broad category where ML algorithms are part of a medical device. An example is a wearable sensor paired with a special software running on a mobile phone for monitoring epilepsy. There has been a rising number of regulatory approvals in this category. In the last 5 years, the Federal Drug Authority or FDA in USA has also issued approvals for another special category, namely, software as a medical device or SaMD. This has been predominantly in the image-based area of Radiology, with 531 approvals given in 2023 which is an impressive 77% of all approved medical devices.

Many of the FDA-approved-SaMDs are targeted at aiding clinical workflow and emergency medicine. Examples of the first kind are those proposed for detecting stroke / intracranial bleeding, cancers of the lung, liver and breast, and cardiovascular analysis; examples of the second are devices for detecting pneumothorax or collapsed lung, rapid triaging of time-sensitive cases and wrist fracture. Devices have also been approved for use in improving general workflow in areas like neurology and ophthalmology. The latter has the distinction of being the first area in which a fully standalone device was approved for detecting diabetic retinopathy - a sight-threatening condition if untreated.

Deep Learning In Image Computing

The recent uptick in SaMD for Radiology is due to the developments in machine learning in general and computer vision in particular. Machine learning underwent a paradigm shift to deep learning (DL) which focuses on intelligent processing of general images. The hallmark of DL is that learning is done by neural networks which are computational schemes inspired by networks found in our brain; the learning is done directly from data unlike features in traditional machine learning where the features were generally handcrafted based on the task at hand and extracted from the data. The paradigm shift led to huge success in Computer vision, paving way for numerous everyday applications from biometrics-based secure access to smartphones and airport terminals to driverless cars. These advances also spurred data driven methodologies to be adopted in medical image computing for automating specific tasks resulting in SaMD.

The initial success of AI-assisted Radiology led to so much exuberance that some experts even predicted a doomsday for radiologists. However, the last five years have shown that this is only hyperbole. This is due to multiple reasons, a fundamental issue being the data driven nature of DL-based systems and the complexity of the practice of medicine.

What is the model learning?

A research study done in our group at IIITH looked at this question for Pneumonia which is a disease affecting the lungs. It can be caused by fungal, bacterial and viral infections each requiring very different type of treatments. Typically, chest X-rays are used along with other lab tests for the differentiation. During COVID 19, numerous papers were published to detect COVID-pneumonia from X-rays; they reported very high detection accuracy. When we queried the algorithm on which part of the chest X-ray image was the basis for a positive decision, regions outside the lungs were shown in many cases! This does not instil confidence to adopt such a model in a clinical workflow since it appears to perform a task well but by learning something from the image data that is not anatomically grounded. An alternate design that forces the model to learn the right things was proposed by us. Since COVID-pneumonia occurs typically in the peripheral regions of the two lungs, by modifying that region we could even demonstrate the model changing its decision.

Recently, a group in MIT showed that often, the models that predict chest diseases also end up being highly accurate in predicting demographics which is not possible for radiologists. The latter actually signals a deeper problem, namely, model's bias across race and gender, i.e. the model learns "demographic short cuts" to perform chest diagnosis whose accuracy is uneven across demography.

Can the model explain its decision for a particular image?

Interpretability/explainability of decisions by DL-based AI models is another major concern as it has affected the rate of adoption of AI models in clinical settings. I.e. the number of publications in the area has grown exponentially (to be in several thousands) whereas the number of solutions gaining approvals is a few hundreds and grows at a very slow rate. The Interpretability/explainability is more natural in clinical diagnosis because it is largely multiple evidence-driven. In contrast, most AI models for diagnosis rely only on an image. This scene was largely due to research groups working in silos (ex. vision, natural language processing). However, this is changing.

At IIITH, our group worked on the explainability issue using both multi-modal and only image data. In the first problem, radiology reports (text) associated with an image were leveraged to train a model to diagnose pneumothorax from chest X-rays. Pneumothorax can be very small or large regions of lung collapse. Our design enabled a model to predict pneumothorax by accurately extracting the contour of the pneumothorax region if present; the contour serves as a visual explanation for the decision. In the second problem, a differential diagnosis of malignant melanoma using only images was attempted. Clinicians use multiple information to arrive at a diagnosis. These include a lesion's appearance with respect to others, location in the body, gender and population-level prevalence. We also designed a clinical-flow-inspired model which performs a lesion-focused analysis and integrates patient and population-level information to finally arrive at a prediction for malignant melanoma. The design specifically allowed interpretability of the final decision by showing how the decision changed with addition of various information.

The Future Scenario

In the future, AI-models need to and are likely to have the capability of mimicking clinical conditions in terms of not only considering multiple sources of information such as lab tests, images, etc., at multiple time points to arrive at robust decisions but also be bias-free and clinically acceptable. Population-specific data is needed to train models to be deployed largely in one geography. Many efforts are on in India, to collect brain data for the Indian population. At IIITH, our interest in brain imaging led us to collect brain scans (MRI) of healthy adults between the age of 20 to 80. This was used to model the structural changes in the brain that occur due to the ageing process. Such normative information is helpful among various things, in the prediction of any cognitive decline, Alzheimer's disease, etc. at an early stage.

In short, AI in healthcare is here to stay. It's current role as an assistant to the expert is expected to sustain for long. However, it is likely that in the near future, the role will extend to be a partial /full replacement in non-critical areas.

PROF. JAYANTHI SIVASWAMY
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is Raj Reddy Professor at IIITH. Trained as Electrical Engineer, she has been working in the medical image computing field for over 15 years. She has extensive experience in developing computer aided diagnostic (CAD) solutions to help screen for eye diseases, lung cancer and Covid based on images from different modalities Besides CAD, her current work focusses on understanding population-based differences in aging of the human brain and developing VR-based solution for anatomy education.

How AI Is Revolutionising Diagnosis Of Sleep Disorders

***Prof S. Bapi Raju** lists out IIITH's innovations in detection of sleep disorders through automatic classification of sleep stages, thereby providing an in-depth sleep analysis.*

Importance of Sleep Quality Assessment

A nutritious diet and adequate exercise are cornerstones of good health. But good quality sleep is crucial too for overall health, impacting physical, cognitive, and emotional well-being. Quality sleep supports muscle growth, tissue repair, and immune function, while poor sleep is linked to higher risks of cardiovascular diseases, diabetes, and obesity. Cognitively, sleep aids memory consolidation, problem-solving, and decision-making, with deprivation impairing concentration, slowing reactions, and contributing to long-term cognitive decline and neurodegenerative diseases like Alzheimer's. Emotionally, inadequate sleep increases stress, anxiety, and depression, exacerbating mental health issues and reducing resilience to daily stressors. For example, insomnia heightens anxiety and depression, creating a harmful cycle. Poor sleep also affects performance and safety, contributing to drowsy driving - a major cause of road accidents, as well as decreased productivity and increased errors in professional settings. Therefore, accurate sleep quality assessment is essential for diagnosing and managing sleep disorders like insomnia, sleep apnea, and narcolepsy, which can lead to chronic health issues if untreated. Advanced diagnostic tools are needed to efficiently and accurately monitor sleep quality, enabling timely and effective interventions and ultimately improving quality of life and health outcomes.

Role of AI in Diagnosing Sleep Disorders

Sleep is typically divided into several distinct stages that cycle throughout the night, each characterised by unique brain wave patterns and physiological activities. These stages are essential for various cognitive and biological functions, including memory consolidation, emotional regulation, and physical restoration. The sleep cycle broadly consists of non-rapid eye movement (NREM) sleep and rapid eye movement (REM) sleep. NREM sleep is further subdivided into three stages, namely, N1 (light sleep), N2 (deeper sleep), and N3 (deep or Slow-Wave Sleep (SWS)). Using the electrophysiological signals (EEG), different sleep stages such as awake, N1, N2, N3, and REM need to be identified either manually or through an algorithm. Sifting through typical 8-hour sleep lab data manually and scoring various stages is tedious and error-prone. Recent advancements in artificial intelligence (AI) offer promising new avenues to diagnose and manage sleep disorders. Deep learning (DL), a subset of AI, has shown exceptional potential in automating sleep stage classification, a task traditionally performed through labour-intensive manual scoring of polysomnography (PSG) or sleep study data (see Figure 1 for a typical sleep lab setup). DL models, particularly those employing supervised and unsupervised learning techniques can analyse large datasets to identify patterns and classify sleep stages with high precision.

Figure 1: A participant undergoing sleep polysomnography in a sleep laboratory (captured at NIMHANS Hospital, Bangalore, during the curation of the iSLEEPS dataset).

Supervised and Unsupervised Learning Approaches

Supervised Learning involves training DL models on annotated datasets where the correct output is known. These models learn from labelled examples and can make accurate predictions on new, unseen data. For sleep stage classification, supervised models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been widely used. These models have demonstrated improvements in accuracy and efficiency over traditional methods, reducing the need for human intervention and enabling quicker, more reliable diagnoses (see Figure 2 for CNN-based classification results in the form of a hypnogram).

Unsupervised Learning does not rely on labelled data. Techniques such as clustering and anomaly detection find patterns in the data without predefined labels, making them particularly useful for exploring large datasets where manual annotation is impractical. Self-supervised learning, a form of unsupervised learning, has also been successfully applied to EEG data for sleep staging tasks.

Innovations in Sleep Stage Classification

At IIITH, we have been working on both supervised as well as unsupervised learning algorithms for classifying sleep stages. mulEEG or multi-view self- supervised learning is a an unsupervised learning method that leverages complementary information from multiple views to enhance representation learning (see Figure 3). Our approach outperforms existing multi-view baselines and supervised methods in transfer learning for sleep-staging tasks. Additionally, it significantly enhances training efficiency with an 8x speed increase. We have also come up with an EOG-based wearable solution. EOG or electrooculography measures electrical activity of the eyes to track their movement and position. Current wearable solutions for sleep monitoring that utilise sensors for parameters like heart rate variability (HRV), respiratory rate, and movement, face challenges in accuracy and reliability compared to traditional PSG. These devices often struggle with consistent data quality across diverse populations and environments, hindering precise sleep stage classification necessary for diagnosing sleep disorders. To address these issues, our EOG and electrode-based mask combines non-intrusive monitoring with multi-channel data collection, providing real-time feedback.

In addition to this, IIITH is collaborating with the NIMHANS Neurology Department to create an Indian SLEEP Stroke dataset (iSLEEPS hosted at IHub-Data, IIIT-H). It marks a significant advancement in sleep research particularly addressing the scarcity of annotated datasets in India. The dataset includes sleep data of 100 ischemic stroke patients, most of whom suffer from sleep disorders, featuring comprehensive polysomnography (PSG) recordings and detailed clinical annotations. By adhering to strict ethical guidelines and ensuring patient privacy through anonymization, the iSLEEPS provides a robust foundation for developing AI models tailored to the Indian population. This initiative facilitates global collaboration in sleep medicine, enabling researchers to develop more accurate diagnostic tools and therapeutic strategies, identify unique patterns and risk factors specific to the Indian population, and ultimately enhance the global understanding of sleep health.

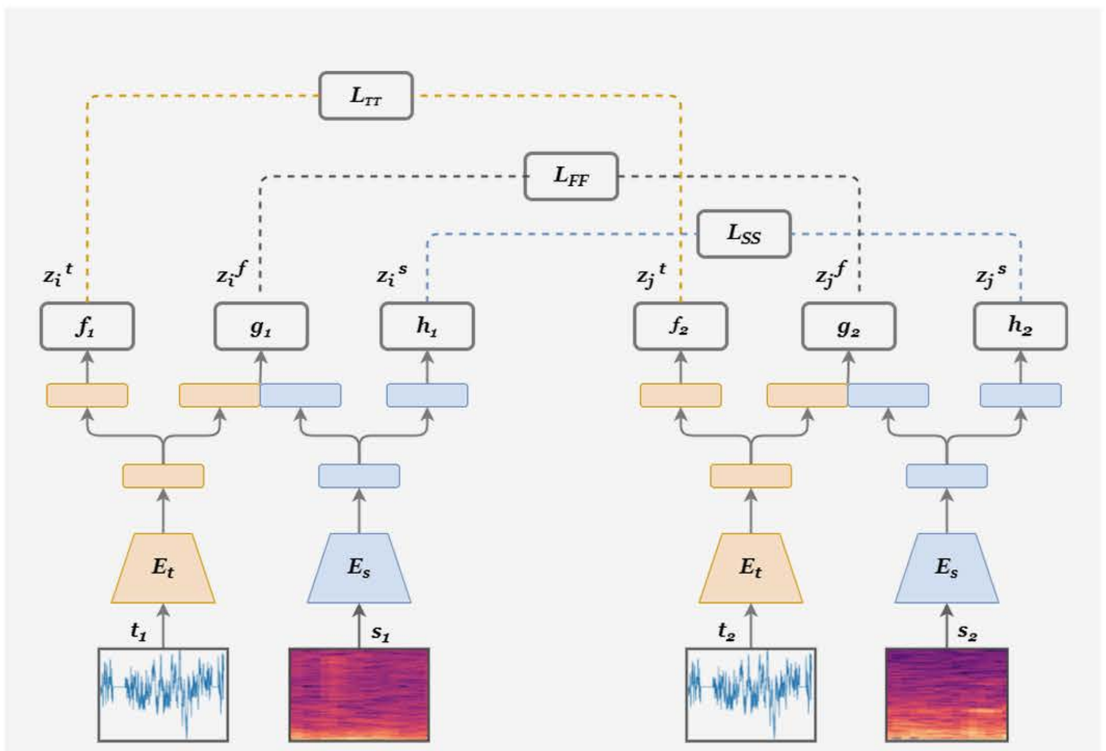

Figure 2: Comparison of Actual and Predicted Hypnograms.
(a) displays the actual hypnogram for one subject, as annotated by a sleep expert.
(b) shows the hypnogram predicted by our model using raw EEG signal input.

Application and Future Scope

Our research demonstrates that EOG signals processed through the model can effectively classify sleep stages, presenting a viable alternative to traditional PSG signals. These promising results suggest that an EOG and electrode-based mask could be a practical solution for non-intrusive, home-based sleep monitoring (See Figure 4 for a possible design). Such a device would offer accurate real-time sleep stage classification essential for diagnosing and managing sleep disorders. This mask could be used in community health-care, clinical settings, and personalised health monitoring systems, providing high-quality, consistent data across diverse populations and environments. Future developments may include integrating additional physiological signals like heart rate and respiratory rate to further enhance diagnostic accuracy, paving the way for improved patient comfort and advancing wearable sleep technology.

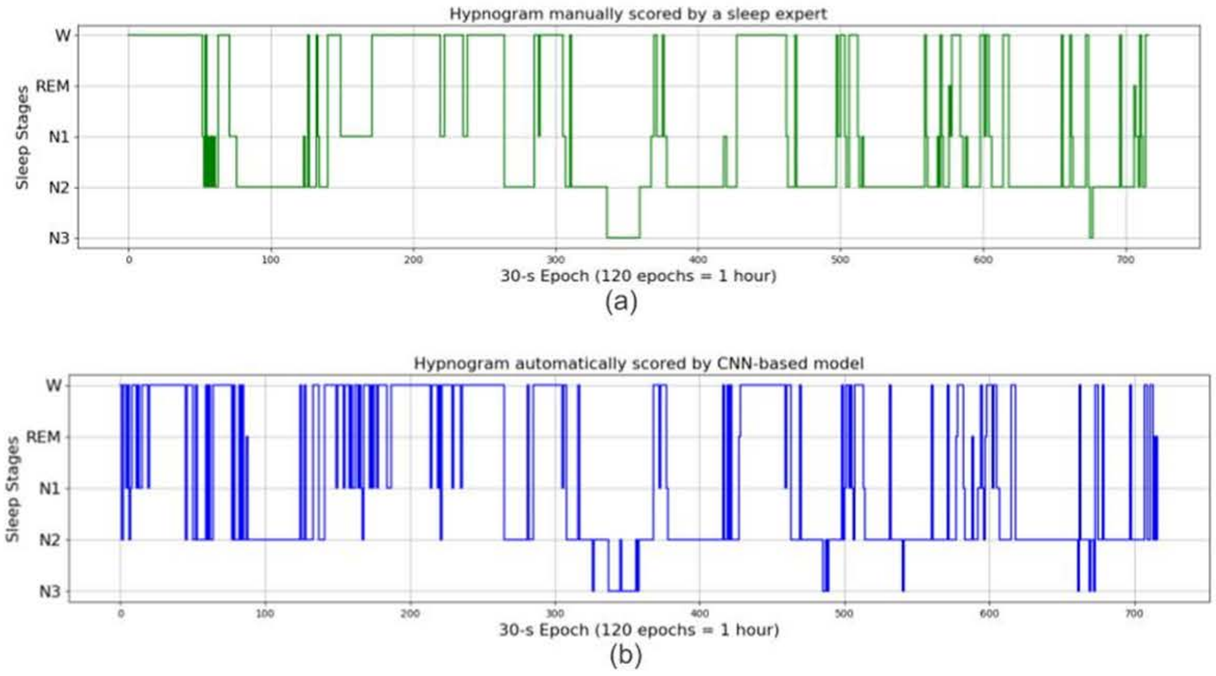

Figure 3: Architecture overview of the multi-view self-supervised learning method (mulEEG). The time, spectrogram, and concatenation of time and spectrogram features (views) are used along with the shared encoders Et, Es. Encoders are jointly trained such that the complementary information of both views is utilized optimally. Thus, the augmented views of time-series and spectrogram ti, si are passed through their respective encoders. mulEEG uses three contrastive losses, each loss working on the time-series feature space LTT, spectrogram feature space LSS and concatenated features space LFF. The proposed setup flexibly optimizes between time, spectrogram, and concatenated features during self-supervised training.

Figure 4: A sleep mask-based wearable device with one or two EOG electrodes (indicated by arrows) to capture eye movement data.

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PROF S. BAPI RAJU

IIIT HYDERABAD

is a professor and head of the Cognitive Science Lab, IIIT Hyderabad. His research interests include neuroimaging methods to study the brain function, developing methods for characterizing structure-function relation and implications for developmental and neurodegenerative disorders. He is currently leading the Healthcare efforts in IHub-Data at IIIT-H. He is a Senior Member of IEEE. Website: https://bccl.iiit.ac.in/people.html

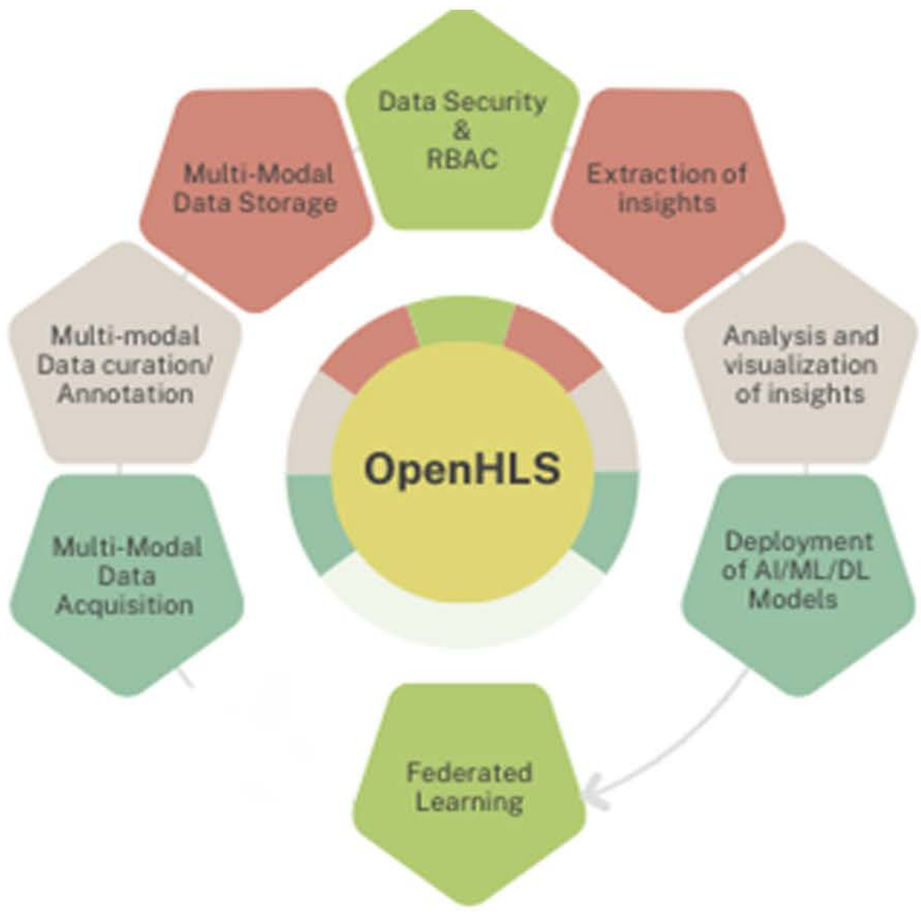
A Multi-Modal Toolset For Healthcare Researchers Integrating Omics Data

INAI/iHub-Data at IIITH has developed a comprehensive healthcare informatics platform. Dr. Ramanathan Sethuraman explains how it overcomes current limitations faced by healthcare researchers.

Healthcare systems the world over have focused more on restoration than on maintenance, thereby leading more to sick care rather than health care. This has led the healthcare system to be more on the catch-up mode as opposed to leading the way. However, with current medical innovation rapidly depending on data and AI algorithms in identifying patterns of disease proliferation, it has led the focus of AI in the recent past to move beyond medical imaging into OMICS (such as genomics, transcriptomics, proteomics, or metabolomics) - a move that will accelerate the transition from sick care to health care.

Data Providing The Big Pic

Health and Life Science (HLS) researchers today want to have a look at comprehensive multi-modal longitudinal data and gain insights that can usher in identification of very early biomarkers – several years early to the full manifestation of the disease. The comprehensive data can also provide us a much deeper understanding of the disease pathways and its causal triggers. Early disease identification can lead to significant reduction in cost of healthcare and improved quality of life post treatment. Understanding the causal triggers will help prevent the onset of diseases and help humanity stay healthy. This should usher in a new era in healthcare through innovation in digital healthcare and life sciences.



Bottlenecks In Healthcare Data

The future of precision medicine, which allows tailoring diagnosis and treatment to each patient to optimize the outcome, is dependent on the ability to jointly analyse large datasets of heterogeneous biological (e.g., metabolic, genomic, imaging) and clinical measures while incorporating critical clinical domain knowledge. The current toolsets available to HLS researchers still do not allow them to work seamlessly. The following are key pain points raised by HLS research, validation and deployment community:

Inefficient Multi-Modal Data Management: Researchers struggle to efficiently capture and manage diverse multi-modal healthcare data like clinical reports, diagnostic data, demographics, genomics data hindering data organization and accessibility.

Challenges in Data Annotation: Researchers encounter difficulties in accurately and efficiently annotating multi-modal healthcare data, impacting the quality and reliability of insights.

Limited Analysis and Insight Extraction Across Modalities: Researchers find it challenging to conduct comprehensive analysis and extract insights when dealing with diverse multi-modal healthcare data.

Limited Collaboration Opportunities: Healthcare professionals face challenges in collaborative research due to the absence of a centralized platform, impacting transparency and efficiency.

Complex Workflow Orchestration: Orchestrating tasks like data curation, annotation, and ML model training poses challenges, causing inefficiencies in the research workflow.

i-Hub-Data's Solution That Integrates Omics Data

OpenHLS (Open Healthcare and Life Sciences) is a comprehensive healthcare informatics system being developed at IIIT Hyderabad by the Applied AI Research Centre (INAI)/I-Hub Data (a tech innovation hub for data banks, data services, and data analytics) to address the above mentioned pain points and facilitate the collection, management, distribution, and analysis of multi-modal healthcare data. By integrating comprehensive omics data, including genomics, proteomics, and metabolomics with AI, OpenHLS provides a robust platform for development of solutions for a wide set of use cases (Ex. pathogen surveillance, cardio-metabolic risk prediction, cancer screening protocols etc.). This integration allows for early detection of diseases, precise risk stratification, and effective pandemic readiness by identifying new pathogens and the development of effective public health strategies.

How OpenHLS Overcomes Key Roadblocks

Inefficient Multi-Modal Data Management: OpenHLS streamlines data acquisition, storage, and retrieval for easy management and access.

Challenges in Data Annotation: OpenHLS provides systematic annotation processes.

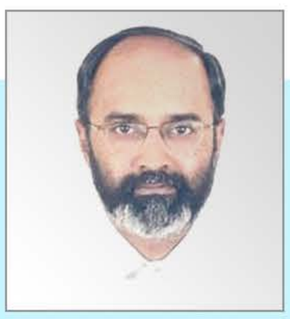
Limited Analysis Across Modalities: OpenHLS enables integrated analysis across clinical, diagnostic, sequencing, and imaging data.

Limited Collaboration Opportunities: OpenHLS promotes collaboration through open data hosting, role-based access control, and federated learning.

Complex Workflow Orchestration: OpenHLS integrates tools to streamline workflows and enable predictive analysis.

Current Scenario

As of date, we have successfully onboarded a pathogen surveillance project that can help track pathogen evolution. This can not only be of help during epidemics and pandemics by providing a framework for surveillance of pathogens, but also provide researchers risk stratification models for patients that can help in managing limited healthcare resources like ICUs and medical supplies. We are currently in the process of onboarding a gut microbiome project that will enable researchers to find connects between lifestyle (including food, physical activities) and metabolic diseases, wherein there is a role play for gut microbes. As we on-board more projects onto OpenHLS that have multimodal data streaming from multisite collaborators, the versatility and ease of use of the platform for performing research will be exemplified.



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Microfluidics: The Future Of Healthcare?

***Dr. Debjani Paul** explores trends in healthcare and pharma that rely on the multidisciplinary field of microfluidics.*

What is microfluidics?

Microfluidics deals with fluid flow through tiny microchannels that have the dimensions of a human hair. It is the same technology that allows an inkjet printer to dispense inks drop by drop on paper during printing. It is an interdisciplinary field of study that integrates insights from multiple traditional domains of knowledge such as fluid physics, engineering, chemistry, materials science, biology and medicine. The main advantages of microfluidic systems are the ability to control fluid flow through complex networks of microchannels in a precise manner, parallelization of hundreds of biochemical reactions and an automated process flow. Today, the biggest applications of microfluidics lie in biotechnology, pharmaceuticals and healthcare sectors.

Microfluidics in diagnostics

Microfluidics has made a huge impact in diagnostics by allowing integration of sample preparation, multiplexed testing and detection steps into a single automated process flow without needing any user intervention. Use of microlitres and nanolitres of sample volumes leads to fast reactions and cuts down reagent costs. The GeneXpert system, a molecular diagnosis technology used worldwide to detect tuberculosis, is built using microfluidic concepts. It can detect the presence of Mycobacterium tuberculosis, the bacterium causing tuberculosis, within a few hours as opposed to traditional methods that take several weeks. Another major contribution of microfluidics in diagnosis lies in developing various simple point-of-care tests, ranging from glucose testing to HIV detection. Even the emerging area of wearable sensors for continuous monitoring of various biomarkers rely on microfluidic technology for fluid handling.

Microfluidics in drug discovery and drug delivery

In the pharmaceutical industry, microfluidics can play an important role in both drug discovery and drug delivery. Droplet microfluidics, which involves performing a very large number of chemical reactions inside thousands of picolitre-volume droplets in parallel, allows high-throughput screening of drug candidates. This kind of parallelization can significantly speed up the initial screening process during drug development. Microfluidics has also been successfully used to develop particle-based drug delivery systems, such as liposomes. Access to these kinds of delivery systems played a major role in the rapid development of mRNA vaccines during the Covid-19 pandemic. Three-dimensional cell culture systems are now being widely used to mimic the physiological conditions inside the body. This is another area where microfluidics plays a key role by generating the necessary microenvironment (i.e. presence of different kinds of cells, chemicals, mechanical properties, fluid flow, etc.) for 3D culture. Microfluidics can play a huge role in development of personalized therapies.

Organ-on-chip systems

The long waiting times for organ transplants and increasing bans on the use of animals for research has led to research on artificial organ-like systems, known as 'organs-on-chip (OOC)'. Two emerging technologies, bioprinting and microfluidics, play complementary roles in the development of OOC systems. By controlling the fluid flow, microfluidics ensures delivery of nutrients and other chemicals into OOC systems. Response of these systems to different drugs can also be tested using microfluidics. On the other hand, bioprinting brings together different kinds of cells and the surrounding materials to generate cell spheroids for the OOC systems. Liver-on-chip, lung-on-chip, heart-on-chip, placenta-on-chip, etc. are some of the OOC systems that are being developed with the help of microfluidics.

Challenges

While microfluidics has an immense potential in the area of healthcare and pharmaceuticals development, only a few technologies have come out of research labs into the market. One of the key challenges in translating microfluidic technologies is the lack of integration with existing manufacturing processes. 3D printing is being explored as an alternative technology to cleanroom-based fabrication of microfluidic devices to help scalability. Another challenge lies in standardization of the 'world-to-chip' interface, i.e. having standardized integration of these micron-sized channels with macroscopic fluidic components. Moreover, there is a lack of necessary infrastructure for large-scale manufacturing and deployment of microfluidic devices in India. Solving some of these issues requires close collaborations between engineers who develop the devices and the users in the healthcare sector. Investment in infrastructure and collaborative development of microfluidic devices are necessary to harness the true potential of this technology.

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is a Professor in the Department of Biosciences and Bioengineering, and the Professor in-Charge of the Wadhwani Research Centre for Bioengineering, IIT Bombay. Following her Ph.D. in Physics from Indian Institute of Science, she did postdoctoral research in Curie Institute and the University of Cambridge. Her research group uses microfluidic technology to develop solutions for healthcare and answers questions at physics-biology interface. She is an associate editor of Bioengineering and Translational Medicine and a member of the editorial boards of PLoS Global Public Health and NPJ Biomedical Innovations.

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