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Artificial Intelligence-Driven Liver Disease Diagnosis Using Clinical Measurements

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Abstract: Liver disease is diagnosed automatically using artificial intelligence (AI) models trained, tested and validated on liver disease datasets representing clinical or diagnostic measurements encapsulated in biochemical markers like albumin as well as enzymes implicated in metabolic processes. The responses of the trained AI models to new clinical diagnostic input could drive clinical decision-making support. Ultimately, the trained AI models could be packaged into an automated liver disease diagnosis module and merged with a repertoire of modules for the automated diagnosis of a wide range of health conditions within the context of a comprehensive AI-driven healthcare system.

Keywords: Deep Learning (DL), Artificial Intelligence (AI), Liver Disease, Cirrhosis of the Liver, Albumin, Artificial Neural Network (ANN), TensorFlow, Healthcare System, Disease Diagnosis and Prediction**.**

I. INTRODUCTION

Liver diseases, including cirrhosis of the liver, affect millions of people around the world and lead to significant mortality, economic losses, disability and suffering [1]. The toll of liver diseases is more acute in low- and middle-income countries (LMICs) with some of the most resource-constrained healthcare facilities, amplifying the impact of liver diseases.

It is well known that early and accurate detection of liver cirrhosis can lead to improved health outcomes, helping save lives and improve living conditions.

This work harnesses artificial intelligence (AI) models trained, tested and validated on clinical datasets representing participants with normal liver function as well as those with cirrhosis of the liver where the health condition is predicated on diagnostic measurements including levels of biochemical markers such as albumin and bilirubin as well as other clinical indicators for the automated diagnosis of liver cirrhosis. Upon further refinement, the AI models could be adapted into the fabric of the comprehensive AI-powered healthcare system created by Ekpar [2].

Studies have been published highlighting the application of AI models to the prediction and diagnosis of a wide range of health conditions primarily in developed countries with the possibility of limited applicability and susceptibility to bias with respect to low- and middle-income countries (LMICs) [3] – [21].

Large language models (LLMs) are known to be capable of drawing inferences from AI models trained on input data and learning structured representations of that data [22] – [23] and could be utilized for automated disease diagnosis and prediction.

Contemporary non-invasive brain computer interfaces (BCIs) utilizing electroencephalography (EEG) systems rely on the two-dimensional (2D) single-layer EEG paradigm and are based on a variety of algorithms and systems including convolutional neural networks [24] – [42].

Novel three-dimensional multilayer EEG systems, also known as Ekpar EEG systems [43] - [45] have the potential for the high levels of performance currently only possible with invasive systems involving the implantation of electrodes in the brain while obviating the need for such risky and costly implantation or surgical operations, bring hitherto impossible applications of the EEG within reach.

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II. MATERIALS AND METHODS

Participant Recruitment

Individuals voluntarily agreed to participate in the studies that contributed to the creation of the comprehensive AI-powered healthcare system. Each participant provided informed consent before joining the studies.

Ethical Approval

The Health Research Ethics Committee at Rivers State University Teaching Hospital granted ethical approval for the studies. All research was conducted in accordance with applicable ethical standards and regulatory guidelines. Publicly accessible data was used in line with the licensing terms established by its original creators.

METHODOLOGY

Publicly accessible healthcare datasets can be enhanced by incorporating data from local experiments and collection efforts. This combined dataset can then be used to train AI models that generate actionable predictions from new data.

Examples of public healthcare datasets include sources like the Centers for Disease Control, the University of California Irvine Machine Learning Repository, the American Epilepsy Society, and Kaggle.

Adding local data strengthens the models, minimizes potential biases, and ensures inclusivity and global applicability. A central aspect of this project is merging diagnostic measurements, such as electrocardiogram results, from local studies with EEG data, including both traditional and new three-dimensional multilayer EEG systems.

For data collection, ethical approval has been obtained from the appropriate research ethics boards in the regions where the experiments take place. Additionally, the project collaborates with licensed medical doctors who have direct access to patients and clinical teams. These doctors are providing anonymized clinical data to validate the AI models.

After training, the AI models will be integrated into a holistic healthcare system designed to assist clinicians with decision-making and generate brain-computer interfaces (BCIs). This system will offer actionable insights and predictions based on new clinical data from healthcare providers, aiding in the early detection, diagnosis, treatment, prediction, and prevention of conditions such as diabetes, cardiovascular diseases, stroke, autism, and epilepsy.

The project is dedicated to promoting open science, reproducibility, and collaboration, with all generated data being made publicly available through platforms like GitHub.

SYSTEM DESIGN AND IMPLEMENTATION

The healthcare system described in this paper features a modular design, with each health condition (such as diabetes, heart disease, stroke, epilepsy, autism, etc.) assigned to its own separate module. This approach not only enhances the system's ability to diagnose and predict future conditions but also allows for easy updates to existing modules by incorporating new data.

Additionally, Brain-Computer Interface (BCI) modules, like those based on the motor imagery paradigm, are designed to process EEG data, generating actionable commands and appropriate responses.

The system also offers guidelines for adapting traditional EEG systems to more advanced, three-dimensional, multilayer EEG setups. These cutting-edge systems, known as Ekpar EEG systems and developed by Ekpar [43] - [45], are built on a conceptual framework that uses approximations of selected bio-signal features to represent or manipulate the underlying biological processes.

For each module, robust AI models are created and trained using well-structured data, as discussed in this paper. These AI models can incorporate a range of factors, including genetic, environmental, and lifestyle data, to provide more accurate representations of the participants' conditions.

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Figure 1 graphically depicts the concept underlying the design of the system.

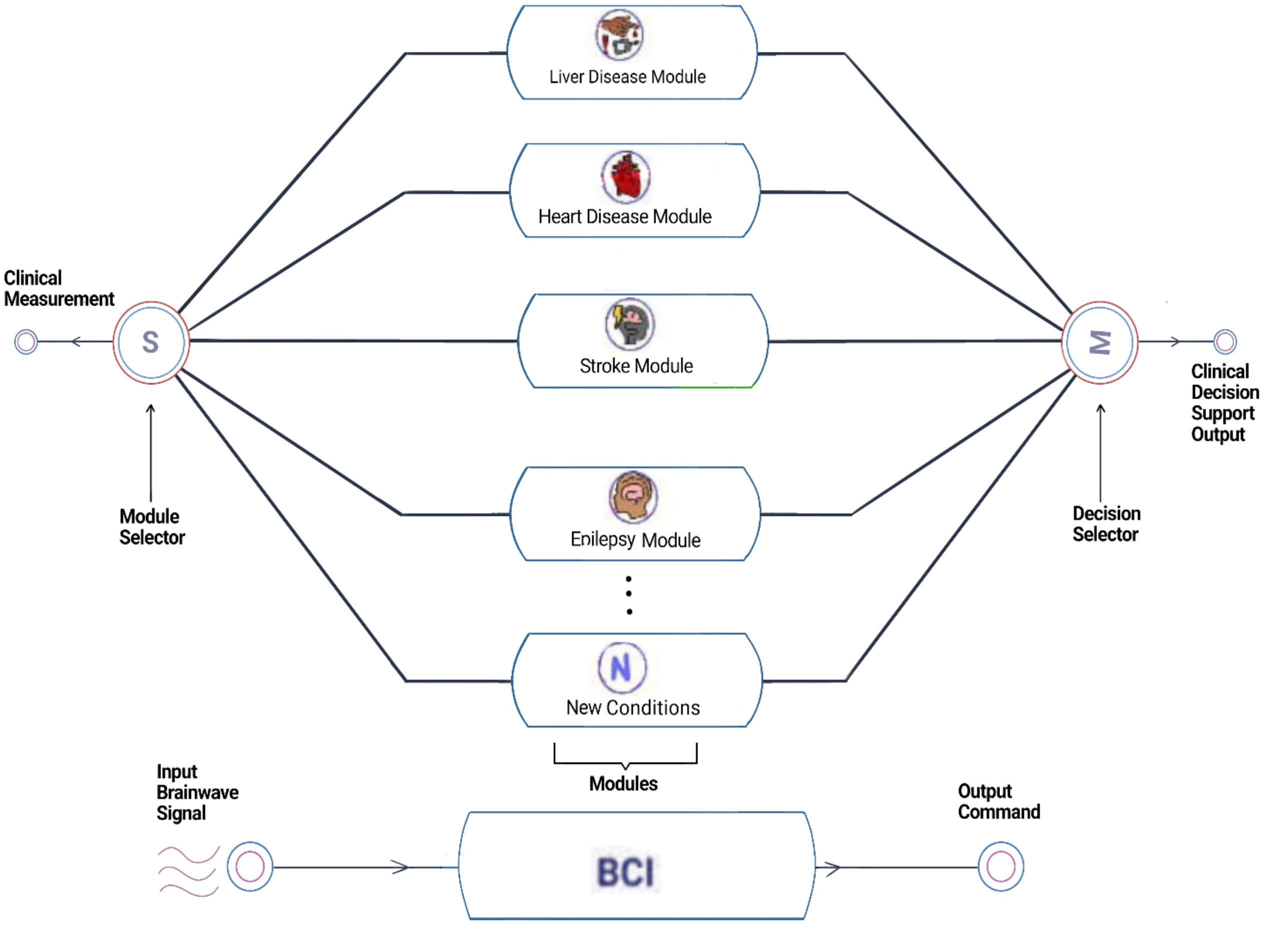

Fig. 1: System Schematic Design Diagram for the Comprehensive AI-Driven Healthcare Solution and Brain Computer Interface System. The New Conditions component represents additional health conditions that can be incorporated into the solution via new modules.

The AI models are developed through four distinct methods, as described below:

1. **Direct Application of LLMs**: Large Language Models (LLMs) like GPT-4 are used as inference engines, processing the collected data formatted into multidimensional vectors. This may involve fine-tuning the LLM as part of the process.

2. **Prompt Engineering with LLMs**: LLMs such as Bard and GPT-4 (along with future iterations) are employed through prompt engineering to define the steps necessary for building the AI system. The developer then carries out these steps, applying their expertise in AI, neural networks, deep learning, and tools like Python, TensorFlow, Keras, and other machine learning and visualization libraries such as Scikit-learn and Matplotlib.

3. **Automated Model Creation**: Certain AI models are generated automatically through a pipeline that utilizes the capabilities of LLMs like Bard and GPT-4 (and their future versions).

4. **Manual AI Architecture Design**: The AI architecture is manually crafted based on the developer's in-depth knowledge of AI, neural networks, deep learning, and the use of programming languages and frameworks like Python, TensorFlow, Keras, Scikit-learn, and Matplotlib.

All development processes and tools are carefully documented to ensure the system can be smoothly transferred and reused. The performance of the resulting AI models is evaluated and compared using metrics like specificity and sensitivity to determine their effectiveness in addressing the problem at hand.

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AUTOMATED LIVER DISEASE DIAGNOSIS MODULE

The fourth method (manual or custom AI architecture design) is followed to create suitably complex artificial neural networks for the automated diagnosis of liver cirrhosis based on clinical measurements.

DATASET

A publicly accessible liver disease dataset originally proposed by Ramana et al [46] was harnessed for the training, testing and validation of the AI models.

The dataset contains a total of 583 rows of data – one for each of the 583 patients or participants – 416 of whom were diagnosed with liver disease while 167 presented with normal liver condition or without liver disease.

Each data row contains 11 columns, the first 10 columns of which are clinical measurements for the following diagnostic criteria: age, gender, total Bilirubin, direct Bilirubin, total proteins, albumin, Albumin and Globulin Ratio, Alanine Aminotransferase, Aspartate Aminotransferase and Alkaline Phosphatase. The eleventh column indicates the presence or absence of liver disease.

DATA AVAILABILITY

The data utilized in this study are available from the University of California Irvine Machine Learning Repository at https://archive.ics.uci.edu/dataset/225/ilpd+indian+liver+patient+dataset.

ARTIFICIAL NEURAL NETWORK (ANN)

An artificial neural network was constructed for automated diagnosis of liver disease based on the available data with 10 input units (one for each clinical measurement or feature), one output unit for the diagnostic output or binary decision (presence or absence or liver disease) and two hidden layers with 128 and 64 units respectively. Rectified linear units (ReLU) were used in the rest of the network with sigmoid activation specified for the output unit.

Figure 2 illustrates schematically the artificial neural network. CM_1, CM_2, ..., CM_N are the relevant clinical indicators with N=10 in this case. CD is the output decision or clinical diagnosis.

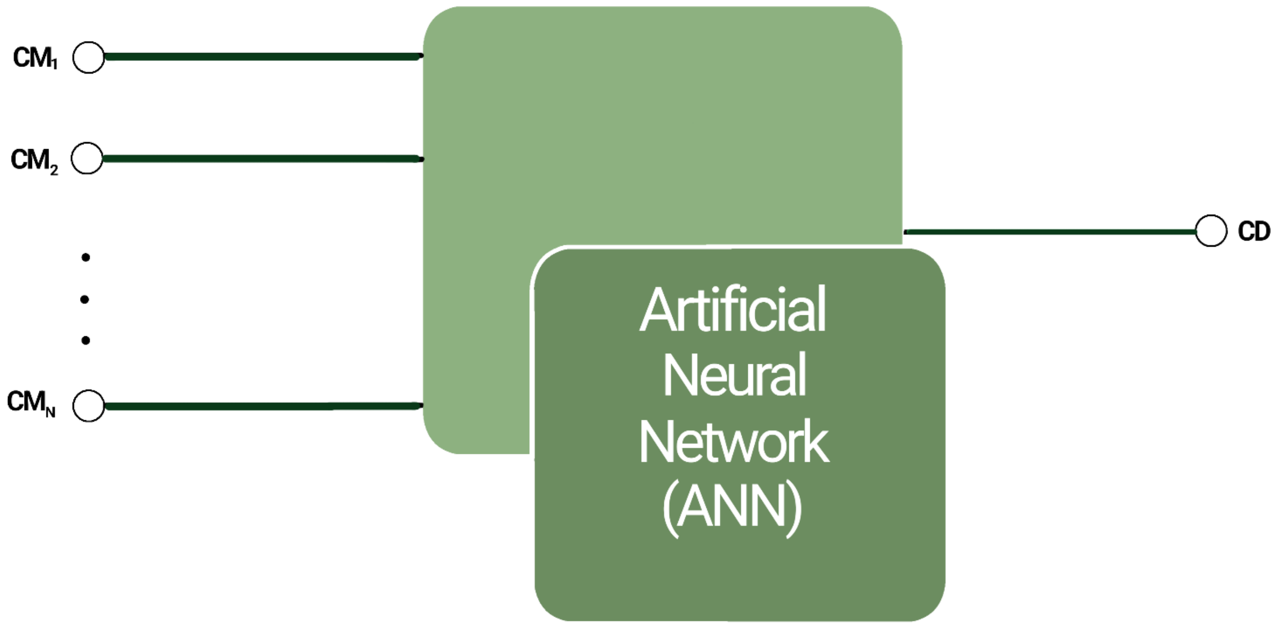

Fig. 2: Schematic Graphical Representation of Artificial Neural Network (ANN) Architecture. CM_1, CM_2, ..., CM_N represent the inputs while CD represents the output indicating the suggested clinical diagnosis.

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III. RESULTS

The artificial neural network was implemented with the TensorFlow platform and Keras Application Programming Interface (API) [47] – [48].

First, the data was shuffled to minimize bias followed by a split of 80% for training and 20% for testing and validation. Training was carried out over 150 iterations or epochs using the default batch size and learning rate and the binary cross entropy loss function. Adam Optimizer was employed for model optimization [49] – [50].

The results indicated a specificity of 90%, precision of 87% and sensitivity of 83%.

The implementation of the AI system described here will offer valuable insights for clinical decision support, ultimately saving lives and enhancing quality of life by reducing the economic, social, psychological, and physical challenges associated with conditions that can be predicted, prevented, detected early, diagnosed, treated, and managed more efficiently.

Electronic Health Records (EHR), including clinical diagnostic measurements and EEG data, will be collected by healthcare professionals and their teams. EEG data may also be gathered during Brain-Computer Interface (BCI) experiments. All data will be collected in accordance with ethical standards, anonymized before publication, and made available in public repositories alongside related research articles.

IV. CONCLUSION

This paper presented a system for the automated diagnosis of liver disease using artificial intelligence (AI) models trained on clinical measurements contained in liver disease datasets. The system could be harnessed to support clinical decision-making in the diagnosis and management of liver disease. Furthermore, the trained AI models could be packaged in modules and deployed in a comprehensive AI-based healthcare system amenable to the automated diagnosis, prediction and management of a wide variety of health conditions. Such a system could improve health outcomes in both resource-constrained and resource-rich environments.

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