



Automated Image-Based Tuberculosis Diagnosis Using 2D Convolutional Neural Networks

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Abstract: Tuberculosis chest radiography image datasets are used to train convolutional neural networks designed for automated diagnosis of tuberculosis. First, a convolutional neural network of suitable complexity is designed, trained, tested and validated on the tuberculosis chest radiography image sequences. The resulting artificial intelligence models could then be refined and packaged into modules for the automated detection of tuberculosis in chest radiography images and could form part of a comprehensive artificial intelligence-driven framework for the detection, prediction, diagnosis and management of a wide variety of health conditions that could play a crucial clinical decision support role.

Keywords: Artificial Intelligence (AI), Convolutional Neural Network (CNN), TensorFlow, Healthcare System, Automated Disease Diagnosis and Prediction, Tuberculosis.

I. INTRODUCTION

Typically affecting the lungs, tuberculosis is a bacterial infection that can be transmitted aurally when an infected individual coughs, spits or sneezes. It manifests within all age groups in all countries around the world and is responsible for millions of deaths, making it one of the leading causes of mortality globally [1] – [2].

However, tuberculosis is preventable and can be cured using medication although multidrug-resistant tuberculosis (MDR-TB) currently represents a significant public health crisis and threat to health security [1].

Tuberculosis chest radiography image sequences can be processed and analyzed to detect tuberculosis. Other methods of diagnosing tuberculosis include rapid molecular diagnostic tests that could be employed as the initial line of diagnostic activities.

This study presents a system for the automated detection of tuberculosis on the basis of image processing and more specifically, utilizing artificial intelligence through deep learning approaches and convolutional neural networks.

Generally, artificial intelligence and machine learning can be harnessed to detect, diagnosis and predict a plethora of diseases and health conditions. Published studies abound in the literature on the application of these systems to the diagnosis of diseases covering patients in developed countries and leaving open the possibility of biases and restricted global relevance [3] – [21].

Ekpar [22] – [25] created a comprehensive artificial intelligence-driven healthcare system with a modular architecture and features amenable to equitable utilization in diverse environments including both low- and middle-income countries (LMICs) and developed countries and the unique support for advanced novel three-dimensional multilayer electroencephalography (Ekpar EEG) systems and instructions for the adaptation of conventional electroencephalography (EEG) systems to the Ekpar EEG paradigm [26] – [28] for enhanced insights into the functioning of the brain, rehabilitation and the realization of hitherto unattainable applications of the EEG across a wide swath of domains ranging from computing to medicine.

II. MATERIALS AND METHODS

Participant Recruitment

Individuals voluntarily agreed to participate in the research studies that contributed to the development of the AI-powered healthcare system. All participants provided informed consent prior to taking part in the studies.



Ethical Approval

The studies received ethical clearance from the Health Research Ethics Committee of the Rivers State University Teaching Hospital at Rivers State University. They adhered to all applicable ethical and regulatory standards. Publicly available data were used in compliance with the licensing terms established by their creators.

METHODOLOGY

Publicly accessible healthcare datasets can be enhanced by incorporating data from local experiments and data collection efforts. This combined dataset can then be used to train AI models capable of making actionable predictions based on new data. Some examples of publicly available healthcare datasets include sources like the Centers for Disease Control, the University of California Irvine Machine Learning Repository, the American Epilepsy Society, and Kaggle.

Integrating local data strengthens the models, minimizes potential biases, and fosters inclusivity and global relevance. A central approach in this project involves merging diagnostic measurements—such as electrocardiographic data—from local experiments with EEG data, which includes both traditional and advanced three-dimensional multilayer EEG systems.

For data acquisition, the research has obtained ethical approval from the relevant research ethics committees in the regions where the experiments are conducted. Additionally, the project has partnered with licensed medical doctors who have direct access to patients and clinical teams within the community. These medical professionals are contributing anonymized clinical data for AI model validation.

Once the models are trained, they will be incorporated into a comprehensive healthcare system designed to offer clinical decision support to healthcare providers and enable brain-computer interfaces (BCIs). The system will provide actionable insights and predictions based on new clinical data from practitioners, assisting in the early detection, diagnosis, treatment, prediction, and prevention of various conditions, including diabetes, cardiovascular diseases, stroke, autism, and epilepsy.

This project is dedicated to promoting open science, reproducibility, and collaboration. As such, all generated data will be made publicly available via platforms like GitHub.

SYSTEM DESIGN AND IMPLEMENTATION

The healthcare system described in this paper features a modular design, where each health condition (such as chronic kidney disease, heart disease, liver disease, stroke, epilepsy, autism, etc.) is assigned to its own dedicated module. This approach not only allows the system to be flexible in diagnosing and forecasting future conditions but also facilitates the easy updating of modules by integrating new data. Additionally, Brain-Computer Interface (BCI) modules, such as those utilizing the motor imagery paradigm, can analyze EEG data to produce actionable commands and suitable responses.

The system also provides guidelines for upgrading traditional EEG systems to advanced three-dimensional multilayer EEG systems. These systems, developed by Ekpar [26] - [28], are based on a conceptual framework that uses approximations of carefully selected bio-signal features to model or influence the underlying biological systems.

For each module, AI models are developed and trained using appropriately structured data as outlined in this paper. These AI models can take into account various factors, such as genetic, environmental, and lifestyle information, to deliver more accurate depictions of the participants' conditions.

Figure 1 illustrates a conceptual overview of the system's design.

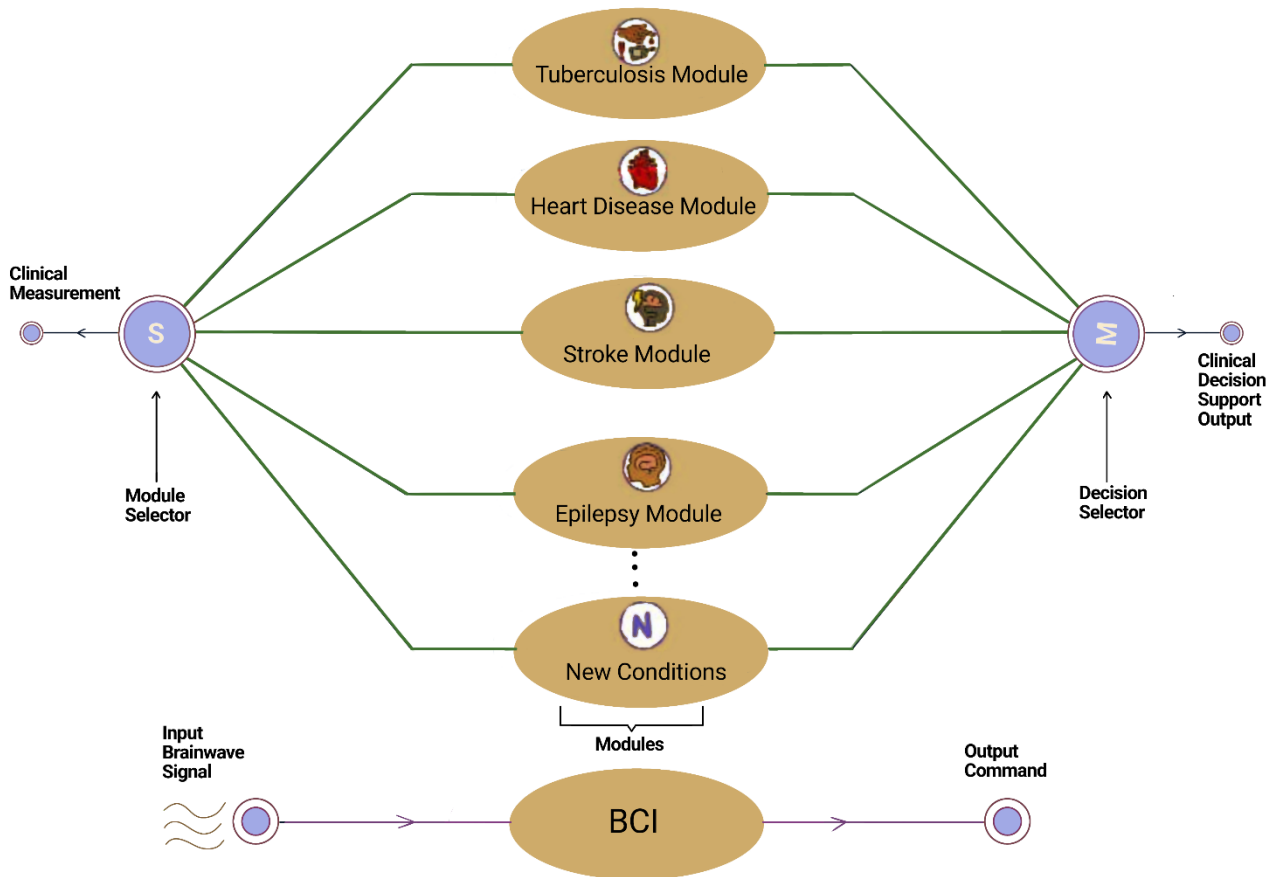


Fig. 1: System Schematic Design Diagram for the Comprehensive AI-Driven Healthcare Solution and Brain Computer Interface System. The New Conditions component represents additional health conditions that can be incorporated into the solution via new modules.

The AI models are created using four distinct methods, described as follows:

1. **Direct Application of LLMs:** Large Language Models (LLMs), like GPT-4, are utilized as inference engines, processing the collected data formatted into multidimensional input vectors. This may involve fine-tuning the LLMs.
2. **Prompt Engineering with LLMs:** LLMs, including Bard and GPT-4 (and their future versions), are employed through prompt engineering to outline the steps for developing the AI system. These steps are then implemented by developers who apply their expertise in AI, neural networks, deep learning, and tools like Python, TensorFlow, Keras, Scikit-learn, and Matplotlib.
3. **Automated Model Generation:** Specific AI models are automatically generated through a pipeline that utilizes the capabilities of LLMs such as Bard and GPT-4 (and their future iterations).
4. **Manual AI Architecture Design:** The AI architecture is designed directly based on the developer's extensive knowledge of AI, neural networks, deep learning, and programming frameworks like Python, TensorFlow, Keras, Scikit-learn, and Matplotlib.

All tools and processes involved in the system's development are carefully documented to ensure seamless transfer and reuse of the solution.



The resulting AI models are assessed and compared using performance metrics, such as specificity and sensitivity, to evaluate their effectiveness in solving the given problems.

AUTOMATED IMAGE-BASED TUBERCULOSIS DIAGNOSIS MODULE

Adopting the fourth approach, namely, the design and construction of custom AI models, two-dimensional (2D) convolutional neural networks for the image-based diagnosis of tuberculosis were designed, constructed, trained, tested, validated and deployed for the automated diagnosis of tuberculosis on the basis of image sequences.

Preprocessing was carried out via augmentation layers implementing a random flip of the images as well as rotations by a factor of 0.05.

The images were resized to 180 pixels by 180 pixels.

Batch normalization was applied.

A Conv2D layer (filters=16, kernel_size=3) was followed by a MaxPooling2D layer, followed by a Conv2D layer (filters=32, kernel_size=3), followed by a MaxPooling2D layer, followed by a Conv2D layer (filters=64, kernel_size=3), followed by a MaxPooling2D layer, followed by a Dropout layer (rate=0.2), followed by a flattening layer, followed by a dense layer with 128 units, followed by the output layer with the number of classes to be identified as the number of units. Rectified linear unit (ReLU) activation was utilized for the Conv2D and dense layers.

Figure 2 is a generalized graphical representation of the two-dimensional (2D) convolutional neural network (CNN) constructed in this study.

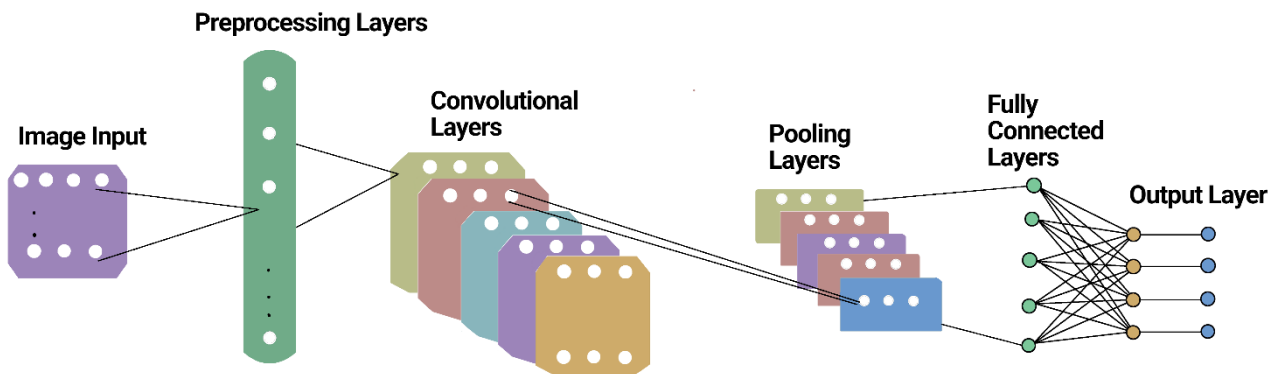


Fig. 2: Generalized Two-dimensional (2D) Convolutional Neural Network (CNN).

DATASET

Tuberculosis chest radiography image datasets donated by Rahman et al [29] were harnessed for the experiments carried out in this study. The dataset comprised 700 images with an indication of the presence of tuberculosis and 720 normal images. Each image had a resolution of 512 pixels by 512 pixels.

Figure 3 displays a group of randomly selected images from the datasets with representative images from each class.

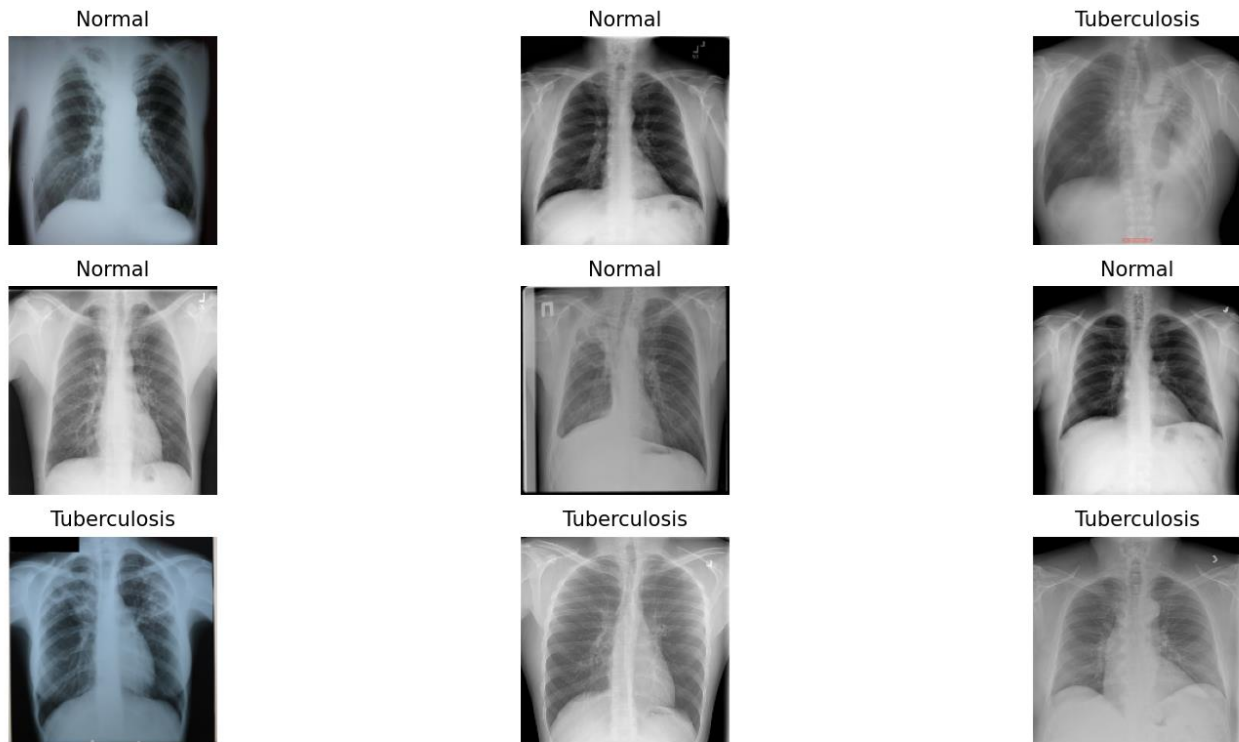


Fig. 3: Randomly Selected Sample Tuberculosis Chest Radiography Images Containing Images Indicating Presence Of Tuberculosis As Well As Normal Images.

DATA AVAILABILITY

The tuberculosis chest x-ray dataset utilized in this study is available from **Kaggle** at <https://www.kaggle.com/datasets/tawsifurrahman/tuberculosis-tb-chest-xray-dataset>.

III. RESULTS

The 2D convolutional neural network (2D CNN) was designed as specified in the foregoing. Implementation was achieved via the TensorFlow platform and Keras Application Programming Interface (API) in Python [30] – [31].

A partitioning of the dataset was performed to generate a training dataset with 80% of the original data and a testing and validation dataset with 20% of the original data.

The 2D CNN was trained over 10 iterations or epochs of the data using the Adam Optimizer [32] – [33].

By the end of the training and validation, an accuracy of approximately 97% was obtained for the training and validation datasets.

Figure 4 tracks the history of the training and validation accuracy and loss and illustrates the performance metrics for the system.



Fig. 4: Trace of Training and Validation Accuracy and Training and Validation Loss Performance Metrics.

The results demonstrate that the accuracy increased over time while the loss decreased over time with the validation performance metrics substantially tracking the training performance metrics.

IV. CONCLUSION

This paper presented a system for the development of artificial intelligence models comprising deep learning convolutional neural networks trained, tested and validated on tuberculosis chest radiography image datasets for the automated diagnosis of tuberculosis. The trained artificial intelligence models could be enhanced through further training utilizing augmented datasets (including datasets acquired through local data collection drives aimed at mitigating bias and improving global relevance) and incorporated into modules for the automated detection of tuberculosis based on chest radiography images within the context of a comprehensive artificial intelligence-driven healthcare system designed to generate timely and actionable insights for clinical decision support in the diagnosis, prediction, detection and management of myriads of health conditions.

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