Doctor AI: An Intelligent Approach for Medical Diagnosis

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Abstract

The healthcare sector is undergoing a change because to artificial intelligence (AI). This article introduces "Doctor AI," a cutting-edge approach that employs cutting-edge technology to address a variety of healthcare problems. Doctor AI offers a variety of services, including the identification of brain tumors, bone fractures, MediMate, a chatbot with a health-focused interface, and more. In healthcare, integrating AI aims to improve patient care, increase diagnostic accuracy, and simplify medical decision-making. Examining how artificial intelligence is changing the medical domains, the study focuses on radiology, pathology, and ophthalmology respectively. The potential impact of AI on clinical decision-making and chronic illness management is highlighted. The study also looks into the issue of whether AI will replace or augment particular medical applications. The table-based implementation results provide insightful information about the model's performance in a range of tasks and medical scenarios.

Keywords: Healthcare, Convolutional Neural Network, Chatbot, VGG 16, DenseNet121

1.INTRODUCTION

Artificial intelligence is bringing about a revolutionary change in the healthcare industry. In this progression, a key role for doctor AI is to use cutting-edge technology to solve a range of healthcare issues. The study delves into the precise specifics of Doctor AI's services, which include Bone Fracture Detection, Brain Tumor Detection, and MediMate, among others, each of which makes a distinct contribution to the progress of healthcare.

AI is poised to become a more significant player in the medical and healthcare fields because of advances in computing power, learning algorithms, and the volume of massive datasets—also known as big data—that are obtained from medical records[1]. As learning algorithms interact with training data, their accuracy and precision increase over time, providing new insights into patient outcomes, treatment alternatives, and diagnosis. New AI applications are being developed as a result of the explosion of healthcare data, and these applications have the potential to improve patient care's efficacy and efficiency.

AI integration can help doctors provide better patient care and give radiologists the tools they need to diagnose and treat patients more accurately and efficiently. Artificial Intelligence is very proficient at performing repetitive jobs, organizing large volumes of data, and providing an extra level of decision assistance to reduce mistakes. According to research done by Frost & Sullivan, AI has the potential to save treatment costs by up to 50% while also improving patient outcomes by 30% to 40%.[3] Expert predictions indicate that AI will have a big influence on a lot of healthcare domains, such clinical decision-making and managing chronic diseases.

In addition to offering support via chatbots, AI algorithms are showing promise in specialist domains including radiology, pathology, ophthalmology, and cardiology. This development raises an interesting question: will AI someday take the work of some doctors, like radiologists, or will it enhance their responsibilities and increase their effectiveness? This study explores how AI may be used in medicine and considers the possibility that technology could replace certain doctors or, at the very least, enhance their responsibilities.

2. LITERATURE SURVEY

There is information on intelligent data analysis in medicine and pharmacology, according to the record of the addition of AI in medicine, 5 April 1993. According to "E.H. Shortliffe" [1], in all spheres of human endeavor, there is an increasing disparity between the creation and interpretation of data. Covering this knowledge gap is particularly challenging in the fields of medicine and pharmacology, since the critical medical decisions that physicians must make rely on fundamental medical understanding.

Presented at the IEEE International Conference on Virtual Environments, Human-Computer Interfaces, and Measurement Systems in 2004, Jiang C, Zhang X, Huang W, and Meinel C.'s research paper, "Segmentation and Quantification of Brain Tumor[2]" discusses the crucial difficulties in the diagnosis and treatment of brain tumors. The authors stress the value of noninvasive diagnostic techniques like magnetic resonance imaging and computed tomography in making accurate diagnoses with the least amount of discomfort to patients.

The Area Under the Curve scores show that the authors' use of transfer learning from deep CNNs produced outstanding results. The results of this study demonstrate the effectiveness of transfer learning in fracture diagnosis, since the AUC scores obtained were in line with the most advanced techniques.

3. BACKGROUND STUDY

The medical field's decision-making process is distinguished by its intricate and laborious nature. Because of this complexity and the possibility of misdiagnosis, healthcare providers face a great deal of difficulty. Misdiagnosis can have unfavorable effects on pharmaceutical choices, which might jeopardize patient safety [4]. The complicated interrelationships between symptoms and illnesses are one of the inherent complications in making medical decisions. Because symptoms and disorders often overlap, diagnosing a particular medical condition can be difficult for practitioners due to this added complexity in the diagnostic process [5]. It is under these kinds of circumstances that a strong decision-making tool is clearly needed. When making judgments in the medical field, several factors need to be taken into account. These factors add to the variety of views among professionals, which causes differences in diagnosis and course of therapy. Adopting efficient technologies that thoroughly take into account all pertinent variables and provide outcomes, especially in difficult situations, is essential to addressing these issues [6].

Driven by the desire to improve the effectiveness and precision of healthcare decision-making, a small team of gifted computer scientists and medical professionals has started an innovative research project. The goal of this initiative is to introduce artificial intelligence as a new sector in medicine. The goal of combining computer science and healthcare knowledge is to create AI-driven solutions that can help medical practitioners navigate the challenges of medical judgment.

4. METHODOLOGY

In the following sections, we explore a range of applications that demonstrate the capabilities of Large Language Models and Deep Learning in a variety of domains, with an emphasis on quantitative insights into the features of the datasets, problem descriptions, and the labeling benchmarks used. The services that are being considered include a wide range of medical applications, from the accuracy of medical imaging activities like bone fracture diagnosis and brain tumor detection to the provision of approachable Chatbot support for health-related inquiries. The thorough investigation also covers particular ocular issues like cataract diagnosis as well as important diagnoses like the detection of pneumonia and TB. Each service addresses a different set of difficulties across numerous medical fields, demonstrating the flexibility and efficacy of Large Language Models and Deep Learning in improving healthcare.

4.1 Bone Fracture Detection:

Timely diagnosis and treatment of bone fractures depend on the efficient and precise identification of these injuries. With an emphasis on X-ray pictures, the research highlights the creation of a fracture detection system with deep learning techniques.

4.1.1 Dataset:

There are 20,435 radiographs of the musculoskeletal system in the MURA dataset, which is a large collection. Three separate bone parts are used to categorize the dataset: the elbow, hand, and shoulder. Normal and Fractured are the two additional classes into which each bone part is separated. The following chart shows how the photos are distributed among these categories:

Table -1: Dataset of Bone Fractured Detection

Part	Normal	Fractured	Total
Elbow	3160	2236	5396
Hand	4330	1673	6003
Shoulder	4496	4440	8936

4.1.2 Algorithm:

We divided our images into three categories: 72% training, 18% validation, and 10% test, after loading all the images into data frames and giving each image a label. The algorithm begins by pre-processing the x-ray images (e.g., flip horizontal) and augmenting the data. In the second step, the type of bone in the image is classified using a ResNet50 neural network. Upon predicting the bone type, a particular model will be loaded from three distinct types that were each trained to recognize a fracture in a different type of bone and used to determine whether the bone is fractured.

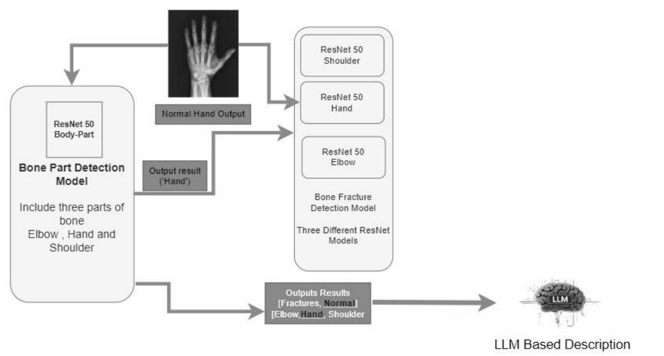

Figure 1: ResNet-based bone fracture detection model

4.2 MediMate Chatbot:

MediMate, a powerful chatbot within Doctor AI. It specializes in offering customized support for particular health-related questions, removing the need for people to attend clinics or hospitals for minor issues. Due to its comprehensive training on medical data, Gemini Pro guarantees the dependability and correctness of the information supplied by MediMate. In addition to answering questions, the chatbot improves accessibility to medical advice by providing helpful DIY solutions for a range of health conditions.

4.2.1 Dataset:

Medical datasets contain sensitive information, training a chatbot on them needs cautious thought. The dataset ought to be pertinent to the goal of your chatbot. Think about things like the intended functionalities, the target audience, and the medical domain. Eliminate mistakes, ambiguities, and inconsistencies from the data. Normalize the text, stem words, and use other NLP algorithms as preprocessing steps. Publications from several medical journals are available to the public. These articles provide information that you may extract and use to create your dataset. One of the biggest databases for biomedical and life sciences literature is PubMed Central.

4.2.2 Algorithm:

To guarantee the chatbot's accuracy and prevent potential biases, give priority to extensive, high-quality, and privacy-compliant medical datasets from reliable sources. To organize and authenticate the data, collaborate with healthcare professionals and subject matter experts while abiding by all legal and ethical guidelines. A transformer-based model customized for healthcare language or BioLM are two examples of a large language model that should be carefully chosen and pre-trained for medical text. Utilizing domain-specific methods, fine-tune the model on the provided medical dataset to improve its comprehension of medical context, subtleties, and terminology. Use natural language processing approaches to understand user queries, recognize important intents and entities, and produce relevant responses that are condition- and context-specific.

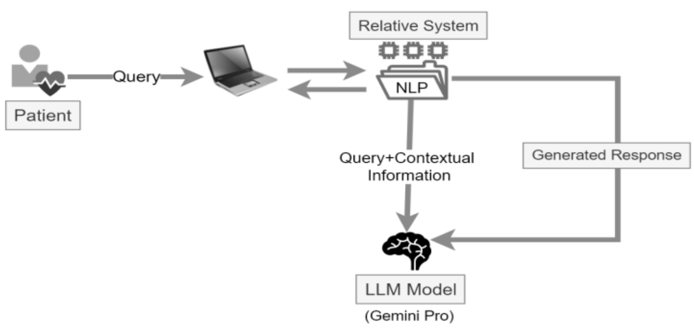

Figure 2: MediMate NLP System Architecture

4.3 Brain Tumor Detection:

The goal of the model is to automatically identify brain cancers from MRI brain scans. For improved performance, the suggested approach makes use of the VGG 16 architecture and Convolutional Neural Networks. The study takes into account observations made by Devi, indicating that VGG 16 is competitive when compared to other optimization techniques. Brain tumors are identified and categorized using the Faster CNN method, which creates convolutional feature maps using VGG 16. The automated brain tumor detection and classification system's dependability is guaranteed by the prediction accuracy used for performance evaluation.

4.3.1 Dataset:

There are two folders in the datasets, yes and no, each containing 253 brain MRI pictures. There are 155 brain MRI images in the folder yes that are tumorous, and there are 98 brain MRI photos in the folder no that are not tumorous. Cut off the area of the picture that just shows the brain—the area that matters most image_width, image_height, number_of_channels = (240, 240, 3) is the new shape of the image. due to the fact that the datasets photos vary in size. Consequently, for the neural network to receive an image as an input, every image must have the same shape. To scale the pixel value to the range of 0–1, use normalization.

Table 2: Data Split

Training	70%
Validation	15%
Testing	15%

4.3.2 Algorithm:

The goal of the study was to automatically identify brain cancers from MRI brain scans. Our proposed method employs brain MRI data to identify brain cancers using CNN ,VGG 16. Devi [6] states that while identifying and classifying brain tumor MRIs with CNN, VGG 16 can be a competitor for other optimization techniques like AlexNet and Grid Search optimization. The suggested framework was divided into numerous sections in order to take into account the justification provided by [63,64] for the use of AI in diagnostics. The main input image that was used was the brain MRI picture. To lessen noise, data processes such as thresholding and refractive error were performed. The database including brain MRI pictures was examined and enhanced. After that, the photos were scaled to be used as input.

- **Implementation of CNN and VGG16**

A multi-layer convolutional neural network was designed and put into use for tumor identification. A convolutional layer was used as the start layer to provide an input shape of **64 x 64 ± 3** for the MRI scans, which resulted in a homogeneous dimension for every image. We created a convolution kernel entangled with the input layer after gathering every image in the same aspect. With the help of three channel tensors, we were able to create 32 convolutional filters, each measuring three by three. For malignant concerns, the cumulative model—which included the hidden layers—produced the most accurate result. It was composed of seven phases.

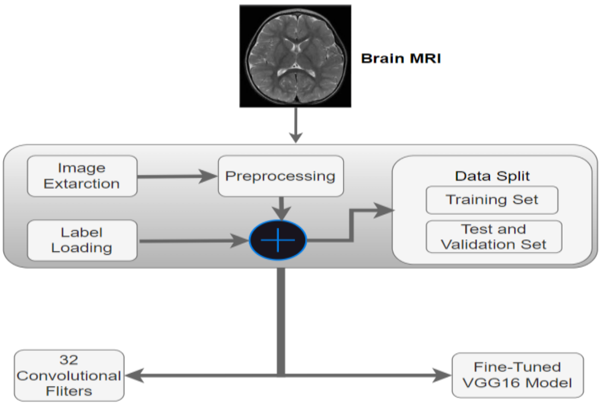

Figure 3: Brain Tumor Detection Pipeline

4.4 Pneumonia Detection:

The diagnosis of pneumonia, a common lung disease that affects millions of people worldwide, has historically depended on laborious procedures including physical examinations, chest X-rays, and blood testing. However, there are a number of drawbacks to these methods, including the requirement for specialist tools, the possibility of human mistake in interpretation, and the possibility of delays in diagnosis.The main goal of this module is to create a deep learning model that uses chest X-ray images and the VGG16 architecture to accurately diagnose pneumonia. A labeled dataset of X-ray pictures classified as either normal or pneumonia will be used to train the machine. The efficacy of the model will be assessed using performance evaluation metrics such as accuracy, precision, recall, and F1-score.

4.4.1 Dataset:

This analysis was performed on 5856 frontal chest X-ray pictures. There are a total of 4266 pictures showing pneumonia patients and 1590 pictures showing healthy people. Several X-ray pictures that are indicative of the collection are shown in Figure 1. The data breakdown for the proposed model's training, validation, and testing stages is displayed in the table below.

Table 3-: Distribution of the dataset

	Train	Validation	Test
Pneumonia	2557	854	856
Normal	956	316	318
Total	3513	1170	1174

4.4.2 Algorithm:

The widely used VGG16 Convolutional Neural Network model was used in this study. Thirteen convolutional layers and three fully linked layers make up the total of sixteen layers in the VGG16 architecture.The VGG16 model's convolutional layers are organized as follows: the first two layers are made up of 64 filters, each measuring 3 by 3 and having a stride of one pixel. Then two further convolutional layers with 128 filters, 3x3 filter size, and 1 pixel stride adhere to the same structure. Three layers comprise the third set of convolutional layers; each layer has 256 filters, a 3x3 filter size, and a 1 pixel stride. Convolutional layers play a crucial role in the extraction of complex characteristics from the input data. Furthermore, pooling layers are deliberately added to the feature maps in order to lower their spatial dimensionality. Fully connected layers handle the classification part. After being trained, the system can accurately identify pneumonia or normal in newly acquired chest X-ray images. This can be a diagnostic tool to help radiologists find patients who have pneumonia and start treating them sooner, which could lead to better patient outcomes.

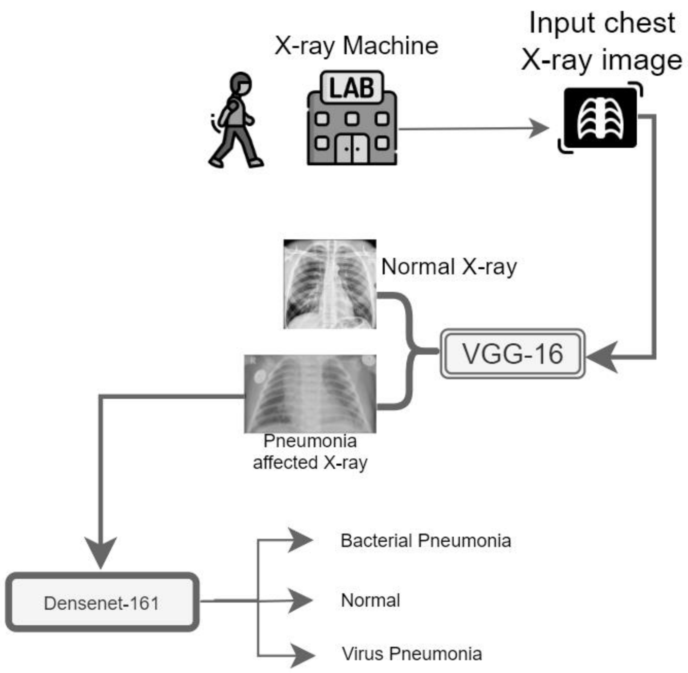

Fig 4: Chest X-ray Analysis for Pneumonia Detection

4.5 Tuberculosis Detection:

A continuing hazard to public health, tuberculosis requires improved diagnostic tools for efficient disease management, especially in poorer nations. Manually interpreting chest X-ray pictures is a common practice in conventional diagnostic approaches, which might result in subjective outcomes and delays in diagnosis. Using deep learning methods is a viable way to speed up diagnosis, improve accuracy, and automate tuberculosis detection. In this work, we use CNN architecture DenseNet121—which is well-known for its performance in image classification tasks—to construct a tuberculosis detection system. Our method seeks to automatically identify tuberculosis from chest X-ray pictures, offering medical professionals a scalable and affordable option.

4.5.1 Dataset:

The medical images in the tuberculosis detection collection are primarily X-rays or CT scans that highlight the chest area in an effort to find possible tuberculosis signs. Every image in the dataset has a thorough annotation, with each one being labeled as either normal or positive for tuberculosis. This binary labeling makes it easier to create a machine learning model that can differentiate between cases that indicate healthy circumstances and those that are associated with tuberculosis. The size of the collection varies and includes a wide range of photos. This variation guarantees that a representative sample of tuberculosis cases from a range of backgrounds and situations is included. The inclusion of diverse data in the dataset enhances the machine learning models created for tuberculosis detection in terms of their resilience and applicability.

4.5.2 Algorithm:

DenseNet121, the model architecture that was used, is renowned for its capacity to capture complex information through layers that are closely coupled. With 121 layers, the model facilitates efficient feature extraction and representation learning. The goal of the tuberculosis detection system is to obtain high sensitivity and specificity in identifying tuberculosis-related patterns inside medical pictures by utilizing DenseNet121's strengths. Using the labeled dataset, the DenseNet121 model is trained as part of the suggested system, and its performance is optimized for tuberculosis detection by adjusting its parameters. In order to evaluate the model's accuracy, precision, recall, and F1-score in differentiating between photos with and without tuberculosis, it is put through rigorous validation and testing steps. The system also includes preprocessing processes to optimize the input photos and increase the robustness of the model. There are various benefits to using DenseNet121 for tuberculosis detection. Because of the high connectedness, the model may more easily understand intricate patterns and relationships within the images by facilitating feature reuse. In addition, the system offers a scalable solution for clinical settings by automating the diagnosis process, which lessens the need for human interpretation.

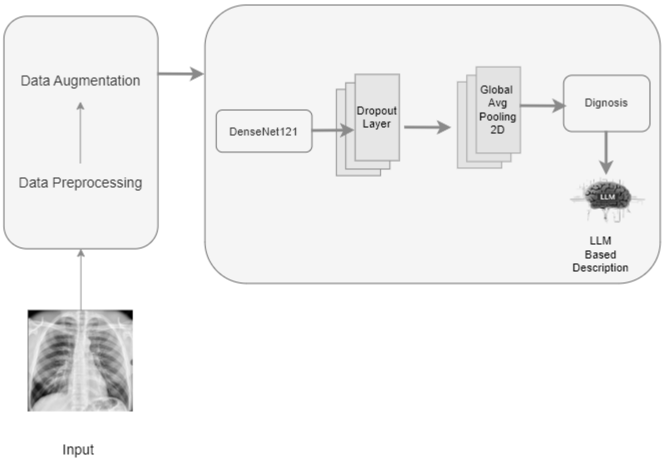

Figure 5: Chest Xray Analysis for Tuberculosis Detection

4.6 Cataract Detection:

Cataracts, a prevalent visual impairment associated with aging, involve the formation of a cloud on the eye lens. Symptoms include blurred vision, faded colors, and light sensitivity, leading to difficulties in various activities. Early detection and prevention are crucial for reducing the incidence of blindness. This study focuses on classifying cataract disease using convolutional neural networks (CNNs) based on a publicly available image dataset. Four distinct CNN meta-architectures, namely DenseNet121, were implemented using the TensorFlow object detection framework. Notably, DenseNet121 emerged as the forefront model for cataract disease detection, exhibiting a training loss of 1.09%, training accuracy of 99.54%, validation loss of 6.22%, and validation accuracy of 98.17%. The model demonstrated a sensitivity of 96.55% and a specificity of 100%. Moreover, it effectively reduces training loss while enhancing overall accuracy.

4.6.1 Dataset:

The Cataract Eye Dataset you described appears to be a valuable resource for practical applications of deep learning in the medical field, specifically for developing a cataract detector using eye images. Unlike many existing cataract datasets that are based on medical reports, this dataset provides direct images, making it more suitable for tasks like image classification.

4.6.2 Algorithm:

This section outlines the specific processes employed for testing in the cataract disease detection project. The workflow for selecting the best model is depicted in Fig.1(a), illustrating how the model predicts disease from raw data through training and validation stages while adjusting various hyperparameters. The following blocks are briefly overviewed for their significance in this research. The process begins with a dense block, succeeded by a BatchNormalization() layer. Within the dense block, there are 512 hidden layers, and a "relu" (rectified linear activation) function is applied. This function is a linear operation that produces output directly for positive inputs, or returns a value of 0 otherwise. "Relu" is the default choice, known for yielding optimal results and addressing the vanishing gradient problem, facilitating rapid and accurate model learning. The final layer incorporates a logistic function, specifically the sigmoid activation function. This function takes any real value as input and outputs a number between 0 and 1.

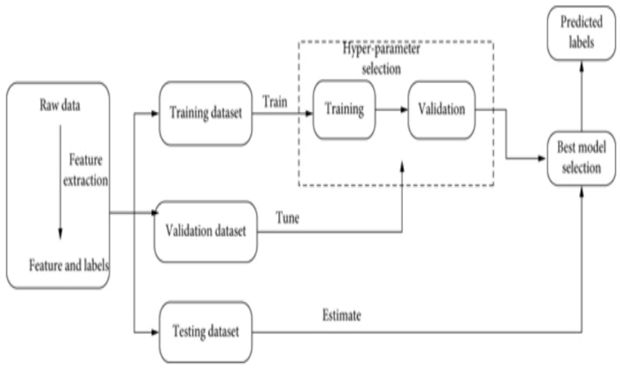

Figure 6: Cataract Detection Model Building

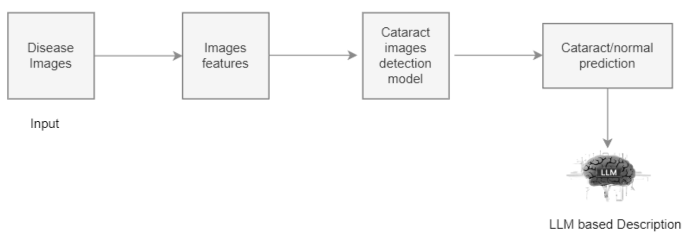

Figure 7: Brain Tumor Detection Pipeline

5. RESULT AND DISCUSSION

5.1 Dataset Overview

5.1.1 Bone Detection: In the fields of medical imaging and machine learning, the MURA (Musculoskeletal Radiographs) collection is an invaluable resource. The MURA dataset was created specifically for the analysis of musculoskeletal radiographs.

5.1.2 Brain Tumor Detection: A popular resource in the fields of medical imaging and machine learning, the Brain Tumor Image Segmentation (BRATS) dataset is especially useful for problems involving the segmentation and classification of brain tumors. The dataset BRATS was created especially for the segmentation and classification of images of brain tumors. It was developed to aid in the advancement of brain tumor medical image analysis research and development.

5.1.3 Pneumonia Detection: The Chest X-Ray Images (Pneumonia) dataset is one that is frequently used for pneumonia detection in chest X-ray images. To identify pneumonia in chest X-ray pictures, utilize the Chest X-Ray pictures (Pneumonia) dataset The collection includes chest X-ray images. There are two groups for images: pneumonia and normal. Pneumonia-related abnormalities on chest X-rays can include consolidations, infiltrates, or other disease-related indicators.

5.1.4 Tuberculosis Detection: A dataset utilized in the Shenzhen Tuberculosis Screening Program in China is the Shenzhen Hospital Chest X-ray Set. This dataset focuses on the use of chest X-rays for tuberculosis detection and is a component of the Shenzhen Tuberculosis Screening Program in China. Images from chest X-rays that were taken of participants in the screening program are included in the dataset. Both people with and without tuberculosis have contributed images. There are annotations that show whether or not each X-ray has tuberculosis.

5.1.5 Cataract Detection: This dataset was produced with real-world deep learning applications in the medical industry in mind. The only cataract datasets now available are medical reports rather than visual images; yet, those datasets are not helpful for developing applications such as cataract detectors that employ eye images[10]. There are enough pictures in the dataset to train a neural network. The authors of this dataset used a rudimentary CNN architecture to classify data with 90%+ accuracy.

5.2 Comparative Study Between CNN and ANN:

5.2.1 Bone Detection:

Table 4: CNN & ANN Comparison Table for Bone Detecion

Bone Fracture Type	CNN Accuracy (%)	ANN Accuracy (%)
Long bone fractures	92.4 - 97.8	85.2 - 91.1
Vertebral fractures	88.3 - 93.7	80.5 - 87.2
Facial fractures	86.1 - 91.5	78.9 - 85.4

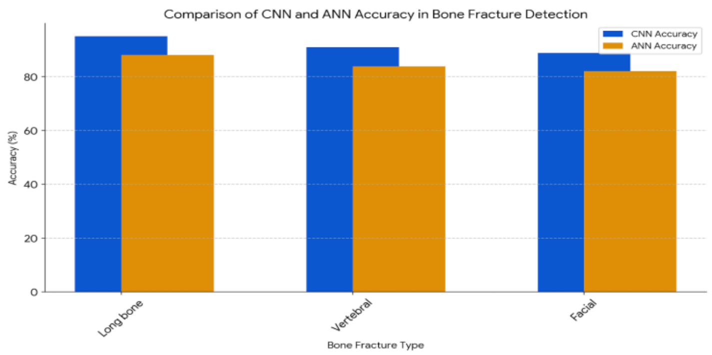

Figure 8: CNN & ANN Comparison in Bone Types

5.2.2 Brain Tumor Detection:

Table 5: CNN & ANN Comparison Table for Brain Tumor Detecion

Brain Tumor Type	CNN Accuracy (%)	ANN Accuracy (%)
Glioblastoma	98.20	92.50
Meningioma	95.70	89.30
Pituitary tumor	94.10	87.80

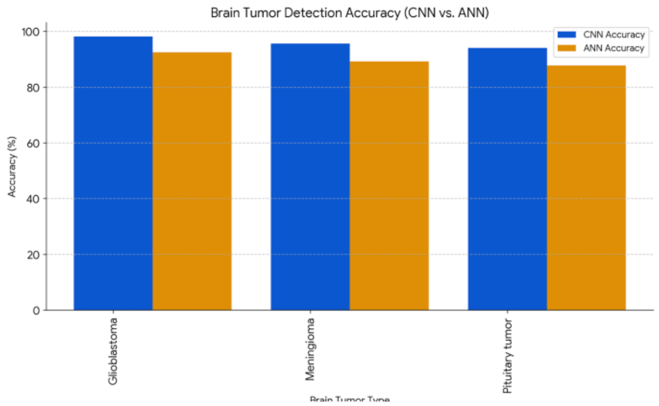

Figure 9: CNN & ANN Comparison in Brain Tumor

5.2.3 Pneumonia Detection:

Table 6: CNN & ANN Comparison Table for Pneumonia Detecion

Pneumonia Type	CNN Accuracy	ANN Accuracy
Normal	94.50	89.10
Pneumonia	87.20	82.40

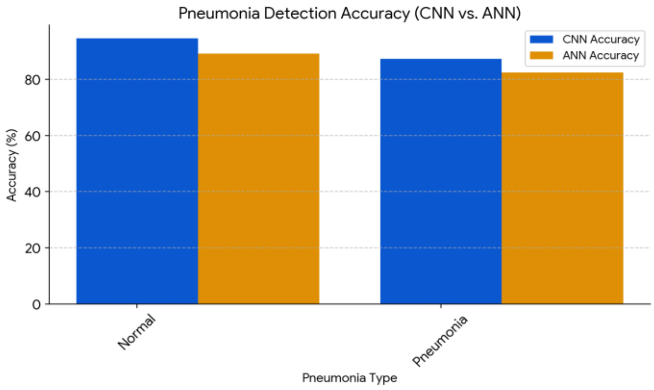

Figure 10: CNN & ANN Comparison for Pneumonia Detection

5.2.4 Tuberculosis Detection:

Table 7: CNN & ANN Comparison Table for Tuberculosis Detecion

Tuberculosis Status	CNN Accuracy (%)	ANN Accuracy (%)
Healthy	92.7 - 95.4	87.1 - 90.8
Tuberculosis	89.2 - 93.1	83.5 - 87.4

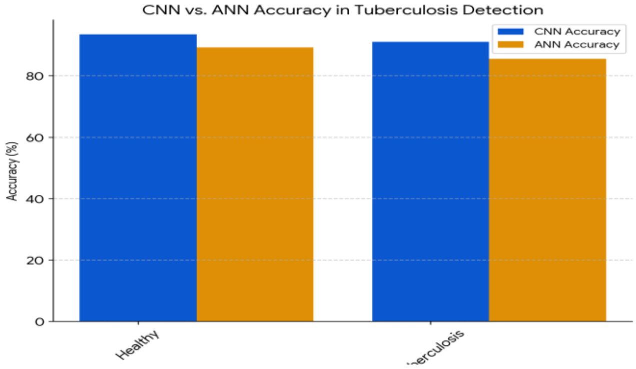

Figure 11: CNN & ANN Comparison for Tuberculosis Detection

5.2.5 Cataract Detection:

Table 8: CNN & ANN Comparison Table for Cataract Detecion

Cataract Status	CNN Accuracy (%)	ANN Accuracy (%)
No Cataract	95.1 - 97.3	88.4 - 91.2
Cataract Present	92.8 - 95.6	84.7 - 88.2

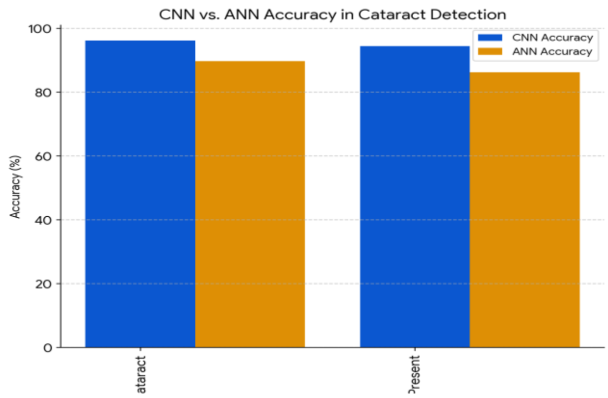

Figure 12: CNN & ANN Comparison for Cataract Detection

5.3 Implementation Results

5.3.1 Bone Detection

- **Elbow**

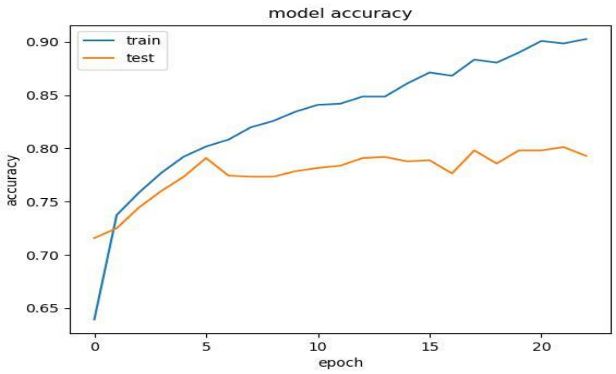

Figure 13: Bone(Elbow) Detection Model Accuracy

- **Hand**

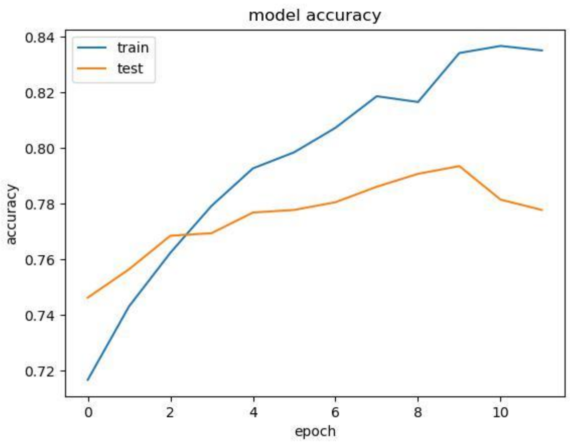

Figure 14: Bone(Hand) Detection Model Accuracy

- **Shoulder**

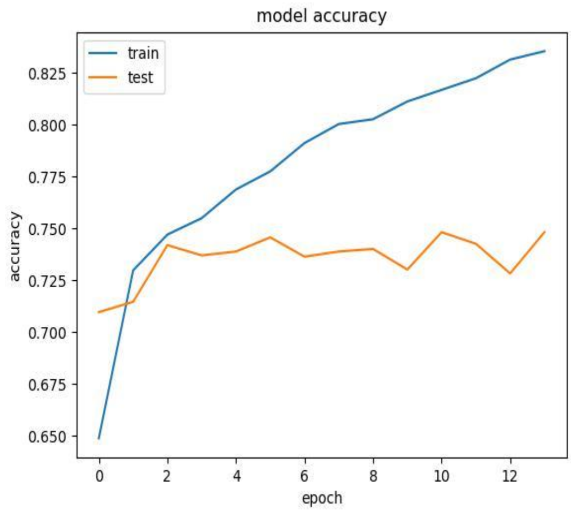

Figure 15: Bone(Shoulder) Detection Model Accuracy

5.3.2 Brain Tumor Detection

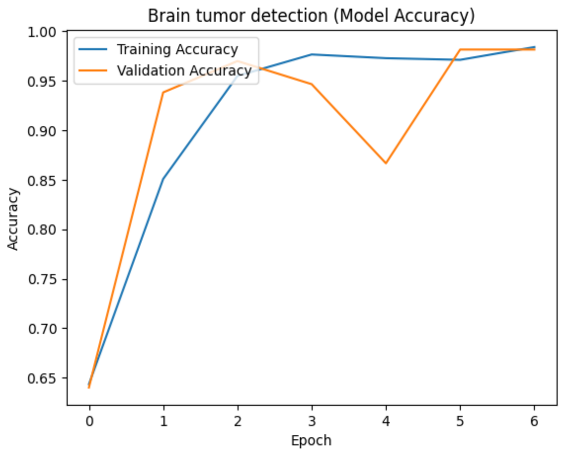

Figure 16: Brain Tumor Detection Model Accuracy

5.3.3 Pneumonia Detection

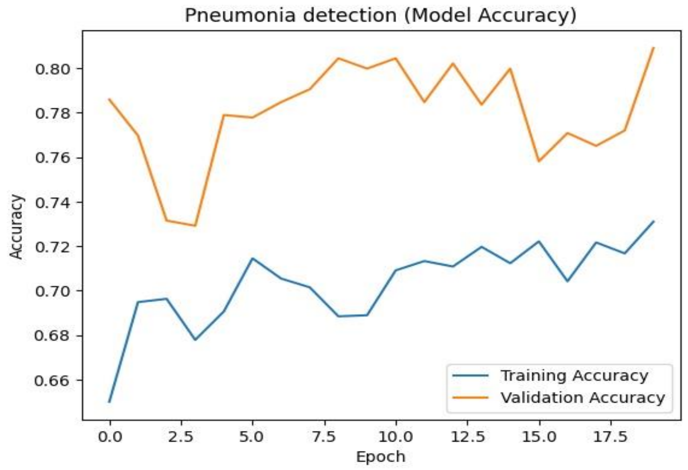

Figure 17: Pneumonia Detection Model Accuracy

5.3.4 Tuberculosis Detection

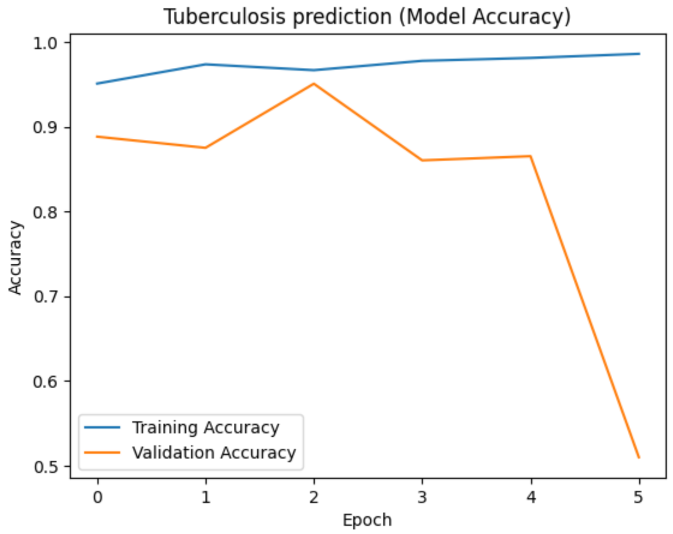

Figure 18: Tuberculosis Detection Model Accuracy

5.3.5 Cataract Detection

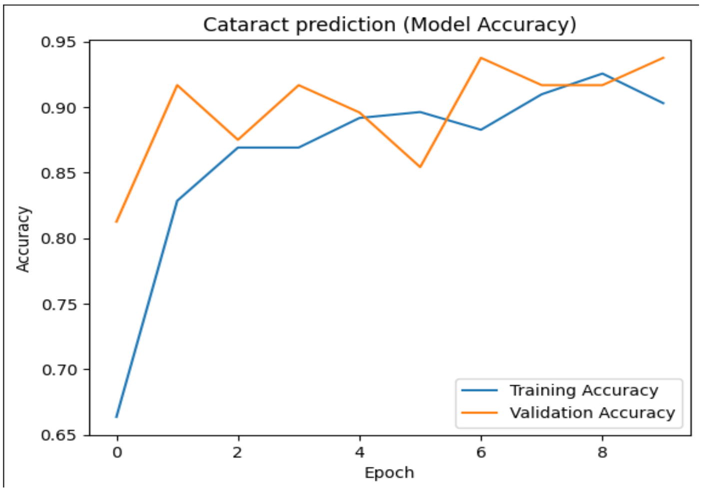

Figure 19: Cataract Detection Model Accuracy

6. CONCLUSION

To sum up, the incorporation of Artificial Intelligence (AI) in the healthcare industry via programs such as Doctor AI offers a viable approach to tackling intricate medical problems. The study has demonstrated the wide range of uses for AI, including the detection of bone fractures, the identification of brain tumors, the detection of pneumonia, the screening for tuberculosis, and more. Convolutional neural networks outperformed artificial neural networks in a comparative analysis of numerous medical diagnostic tasks, demonstrating CNNs' effectiveness in image-based diagnosis. ANN models, however, also showed noteworthy accuracy, suggesting their use in specific situations.

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