Designing a Deep Learning Tool for Disease Detection

Muhammed Nashath
Computer Science Engineering
Vimal Jyothi Engineering College
Kannur,India
nashathlalilakath123@gmai.com

Rithin Dev C
Computer Science Engineering
Vimal Jyothi Engineering College
Kannur,India
devisorking17@gmail.com

Sayand Krishna
Computer Science Engineering
Vimal Jyothi Engineering College
Kannur,India
sayandkrishna242003@gmail.com

Sidharth Vattoli
Computer Science Engineering
Vimal Jyothi Engineering College
Kannur,India
sidharth10543@gmail.com

Vanimol Sajan
Computer Science Engineering
Vimal Jyothi Engineering College
Kannur,India
vanimolsajan@vjec.ac.in

***Abstract*—Doc Plus is a medical help platform that utilizes AI for healthcare professionals with deep learning models and chatbot-based knowledge recall. The platform contains two Convolutional Neural Network (CNN)-based models for detecting Alzheimer's disease and lung cancer based on medical images like MRI and CT scans for diagnosis. The platform also consists of two AI chatbots: one that delivers information related to diseases and the other that gives prescription details in the medical field. The site is developed with Streamlit and utilizes transfer learning models such as ResNet and EfficientNet for increased accuracy. Although chatbot capabilities have been implemented effectively, the disease detection models so far suffer from overfitting, restricting real-world application. The project will help medical professionals by enhancing diagnostic effectiveness and remote disease evaluation. Future research will address model generalization to improve dependability in clinical practice.**

Keywords—component, formatting, style, styling, insert *(key words)*

I. INTRODUCTION

Incorporation of artificial intelligence (AI) in healthcare has substantially improved diagnostic precision and medical decision-making. As more emphasis is placed on deep learning for the detection of disease, AI-based tools can potentially increase early diagnosis and patient outcomes. The complexity of medical imaging and the requirement of accurate, interpretable models are however still major challenges.

Doc Plus is a web-based artificial intelligence platform to help medical professionals detect diseases and access knowledge. It integrates AI-based chatbots with deep learning-based diagnosis models to deliver integrated medical insights. The platform has two CNN-based disease detection models with an emphasis on Alzheimer's disease and lung cancer, using MRI scans and CT scans for auto-diagnosis. It also has two AI chatbots that deliver disease information and medical prescription advice.

Built with Python, Streamlit, and transfer learning models like ResNet and EfficientNet, Doc Plus is designed to make medical decision-making easy. Although the chatbot features have been highly accurate, the disease detection models at the moment are showing overfitting, and more optimization is needed for practical use. This article discusses the development, issues, and future upgrades of Doc Plus for ensuring efficient AI-aided healthcare assistance.

II. RELATED WORKS

Recent developments in deep learning (DL) have shown immense potential in medical imaging, particularly for illnesses that involve intricate image analysis like Alzheimer's disease, lung cancer, and others. This section summarizes significant research in DL application to these diseases and presents the methodologies and architectures underpinning the current project.

Alzheimer's disease, a degenerative neurodisease, has been a leading target for DL applications because early diagnosis is potentially feasible via brain imaging.Cui et al. [1] introduced an improved Inception network for MRI-based Alzheimer's diagnosis that improved classification accuracy by fine-tuning the network's feature extraction capabilities for the faint patterns associated with disease progression. Feng et al. [2] built upon this effort by combining a 3D-CNN with an FSBi-LSTM model that used multi-modal fusion to collect spatial and sequential information within MRI scans. This method achieved a significant rise in diagnosing multiple stages of Alzheimer's, alleviating the progressive disease classification issue.
Sarraf and Tofighi [3] worked on using CNNs on fMRI data using deep learning models to identify stages of Alzheimer's. This study pointed toward the possibility of differentiation among various disease stages with precise accuracy, emphasizing the potential of CNNs in diagnostics of neurodegenerative disorders. Such DL applications not only enable early intervention but also allow for treatment targeting through differentiating stages of the disease, further augmenting the role of DL in personalized healthcare.
Lung cancer detection and classification using DL have made tremendous progress, mainly because of the use of CNNs on high-resolution CT scans. Crasta et al. [4] proposed a DL system with a 3D-VNet architecture for lung nodule segmentation and a 3D-ResNet for classification, which had high accuracy and sensitivity on the LUNA16 dataset. The system successfully overcame issues like inter-class similarity and limited annotated data, with a Dice similarity coefficient of 99.34% for segmentation and 99.2%

INTERNATIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT (IJSREM)
VOLUME: 09 ISSUE: 04 | APRIL - 2025 SJIF RATING: 8.586 ISSN: 2582-3930

classification accuracy. By correctly detecting lung nodules, this approach proves the 3D CNNs' reliability in dealing with variations in nodule sizes and shapes. Xie et al. [5] proposed a 2D CNN-based computer-aided framework for pulmonary nodule detection in CT scans, using a region proposal network for candidate detection and a boosting classifier for false-positive reduction. This framework, with a sensitivity of 86.42%, highlighted the capacity of CNN architectures in enabling computer-aided diagnosis (CAD) systems, permitting on-time lung cancer screening and enabling necessary early detection to lower lung cancer mortality. The general area of medical image analysis has heavily relied on deep learning, and real-time, automatic processing of complicated imaging data is possible. Li et al. [6] gave an extensive overview of DL techniques employed in healthcare, highlighting different architectures such as CNNs, RNNs, and GANs. Their work highlighted the importance of DL in examining huge medical datasets, thus improving operational effectiveness and diagnostic accuracy in clinical practice.

This survey classified state-of-the-art methods and identified generic challenges in the domain, including class imbalance, computational costs, and generalizability requirements of models on various datasets. Brain tumor segmentation, aside from Alzheimer's and lung cancer, demonstrates how DL models can generalize across different areas of medicine. Hua et al. [7] suggested a cascaded V-Net model that successfully segmented brain tumors into individual substructures in multimodal MRI images obtaining high accuracy through the use of focal loss to solve classimbalance. This cascaded model highlighted the flexibility of V-Net and other such architectures for multi-stage segmentation tasks. The literature showcases the effectiveness of deep learning in revolutionizing medical diagnosis, particularly for challenging diseases such as Alzheimer's and lung cancer. Deep learning-powered frameworks have taken huge strides with the fusion of segmentation and classification models specialized for medical imaging. Advances in both hardware and model architectures have enabled a reliable and efficient CAD system that gives healthcare professionals tools conducive to early diagnosis and treatment planning. Also, the capacity of deep learning to generalize across various diseases holds great promise for future medical image analysis.

III. PRPOPOSED SYSTEM AND DESIGN

The system mooted here processes early detection and classification of a variety of diseases from medical images and advanced deep learning methods. It overcomes the drawbacks of manual diagnosis with a quick, precise, and consistent solution, thus helping health professionals and making it more accessible in remote areas.

The system utilizes Convolutional Neural Networks (CNNs) and transfer learning (for example, ResNet, EfficientNet) for processing MRI, CT, and X-ray images. A simplified web interface by Streamlit is used to serve healthcare professionals to upload photos and get immediate diagnostic feedback.

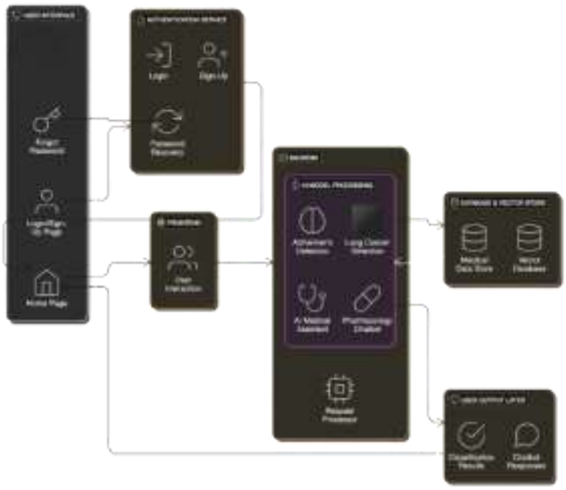

Fig 1 Architecture Diagram

A. Design

(a) Architecture Diagram

The system allows users to sign up or log in to access a dashboard. From the dashboard, users can choose different functionalities: Alzheimer’s detection, chest scan detection, medication guidance, or an AI-powered medical chatbot.

For Alzheimer’s and chest scan detection, users upload MRI or CT scans, which go through preprocessing before AI analyzes them and generates detection results. The medication guidance feature lets users enter symptoms or medications, which are processed using a language model to provide relevant medical advice. Similarly, the AI chatbot processes medical queries using natural language processing (NLP) to offer useful guidance.

To break this down further, the underlying architectures provide more clarity. The AI model training and deployment process ensures the system can efficiently analyze medical scans, while the information retrieval mechanism enables accurate responses for medication and chatbot queries. Together, these components form an intelligent healthcare assistant that enhances medical decision-making.

IV. METHODOLOGY

A. Medical Image Processing & AI Analysis

The system allows users to upload MRI or CT scans for Alzheimer’s or chest disease detection. Once an image is uploaded, it undergoes a preprocessing stage to enhance its quality by removing noise and improving feature clarity. The AI model, based on CNN architectures, then analyzes the processed image to detect disease patterns. Once the analysis is complete, the system generates a detection report for Alzheimer’s cases or a diagnostic result for chest scans. To ensure accurate detection, the system collects data from public medical sources such as Kaggle and NIH, where MRI, CT, and X-ray images are labeled with disease categories for supervised learning. The detection models incorporate both transfer learning with pre-trained architectures like ResNet and EfficientNet, as well as baseline CNN models, providing diverse approaches for disease identification.

B. AI-Powered Medical Chatbot

The chatbot module enables users to ask medical-related queries in natural language. Once a query is entered, an NLP model processes the input to extract key medical terms and understand the intent. The AI then retrieves relevant information from a structured knowledge base and provides users with appropriate medical advice. The chatbot is powered by advanced language models from Hugging Face, ensuring accurate and context-aware responses. To enhance retrieval efficiency, FAISS is used for vector-based search, allowing quick access to relevant medical data. Additionally, LangChain is integrated to support structured question-answering, ensuring users receive well-organized and precise responses.

C. Medication Guidance System

This module allows users to enter medication names or symptoms to receive relevant guidance. The input is processed using an LLM-based analysis that verifies the details against a medical knowledge base. AI then provides recommendations regarding dosage, potential side effects, and alternative medications based on the entered information. The system uses Hugging Face's LLMs to ensure accurate language-based analysis, while FAISS enables efficient retrieval of stored medical data. LangChain is also incorporated to structure the extracted information, providing users with clear and medically reliable insights.

D. User Authentication & Dashboard Management

The user management module ensures secure access to the system through a structured authentication process. Users can sign up or log in to access the dashboard, which serves as the central hub for navigating between different modules. If a user forgets their password, an OTP-based recovery system helps them regain access. The frontend is built using Streamlit, providing an interactive and user-friendly interface. The backend manages authentication and session handling, ensuring that user data remains secure. Additionally, a database is used to store medical records and session data for seamless access and continuity.

V. RESULTS AND DISCUSSIONS

The system provided a smooth and user-friendly experience, guiding users through each step, from signing up or logging in to selecting a disease and getting a prediction .The login/signup page, built with HTML, JavaScript, and Node.js, ensured secure and easy user authentication. After logging in, users could access the index page, where they could choose from available disease detection options, specifically lung cancer and Alzheimer's. Clear navigation made it easy to move to the next step without confusion. The prediction interface, created using streamlit, allowed users to upload medical images and get real-time disease predictions along with confidence scores. This interactive design made it simple for users to engage with the system and receive timely and accurate health analysis.

Model	**Precision**	**Recall**	**F1-Score**	**Accuracy**
Alzheimer's Detection	0.97	0.97	0.97	0.97
Lung Cancer Detection	0.85	0.84	0.84	0.84

Table 1 *Performance Comparison for disease detection models.*

Benchmark	***Performance***
MMLU (Multitask Language Understanding)	*70.6%*
GSM8K (Mathematical Problem Solving)	*82.4%*
Medical Query Accuracy	*Context-Dependent*

Table 2 Mistral 7B Language Model Performance

.

Fig 2 Home page

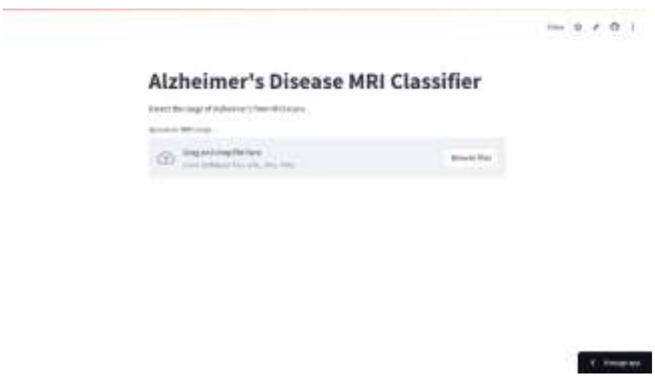

Fig 3 Alzheimers Detection

Fig 4 Lung cancer

Fig 5 Docplus Assist

Fig 6 Mediplus Assistant

VI. CONCLUSION

This system shows how deep learning can be very useful in medical diagnosis, especially for diseases like Alzheimer's and brain tumors. Traditional methods rely on doctors manually analyzing images, which can be slow subjective, and prone to human errors. By using deep learning, this system automates disease detection, providing faster and more consistent diagnoses.

To achieve high accuracy, the system goes through careful data preparation, model improvements, and choosing the right architecture. This helps solve common problems in medical imaging, such as imbalanced data, where some diseases may have fewer examples than others.Overall, this system is an important step in AI-driven healthcare. It helps with early disease detection, improves patient care, and proves how deep learning can be applied effectively in real-world healthcare.

In the future, this system could be expanded to detect more diseases and become even more reliable. Further improvements could include connecting it to real-time hospital data, making its predictions even more accurate and adaptable to medical needs. Adding user feedback features will also be important to make sure the system remains easy to use and trustworthy.

As the system improves, it could also help with monitoring disease progression or assisting doctors in planning treatments. This would make it an even more valuable tool for healthcare professionals.

VII REFERENCES

[1] Cui, Zhenyu and Gao, Zhiao and Leng, Jiaxu and Zhang, Tian lin and Quan, Pei and Zhao, Wei, "Alzheimer's disease diagnosis using enhanced inception network based on brain magnetic resonance image," in 2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), pp. 2324–2330, 2019.

[2] Feng, Chiyu and Elazab, Ahmed and Yang, Peng and Wang, Tianfu and Zhou, Feng and Hu, Huoyou and Xiao, Xiaohua and Lei, Baiying, "Deep learning framework for alzheimer's disease diagnosis via 3d-cnn and fsbi-lstm," IEEE Access, vol. 7, pp. 63605–63618, 2019.

[3] Sarraf, S. and Tofighi, G., "Classification of alzheimer's disease using fmri data and deep learning convolutional neural networks," arXiv preprint arXiv:1603.08631, 2016.

[4] Lavina Jean Crasta and Rupal Neema and Alwyn Roshan Pais, "A novel deep learning architecture for lung cancer detection and diagnosis from computed tomography image analysis," Healthcare Analytics, vol. 5, p. 100316, 2024.

[5] Hongtao Xie and Dongbao Yang and Nannan Sun andZhineng Chen and Yongdong Zhang, "Automated pulmonary nodule detection in ct images using deep convolutional neural networks," Pattern Recognition, vol. 85, pp. 109–119, 2019.

[6] Li, Mengfang and Jiang, Yuanyuan and Zhang, Yanzhou and Zhu, Haisheng, "Medical image analysis using deep learning algorithms," Frontiers in Public Health, vol. 11, 2023.

[7] Hua, Rui and Huo, Quan and Gao, Yaozong and Sui, He and Zhang, Bing and Sun, Yu and Mo, Zhanhao and Shi, Feng , "Segmenting brain tumor using cascaded v-nets in multimodal mr images," Frontiers in Computational Neuroscience, vol. 14, 2020.