DEEP NEURAL NETWORK FOR AUTOMATED MEDICAL DIAGNOSIS AND TREATMENT RECOMMENDATION SYSTEM

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ABSTRACT

The proposed project aims to develop a comprehensive full-stack application that leverages advanced technologies to address two distinct healthcare challenges. The first use case involves predicting diseases based on user prompts using natural language processing (NLP) powered by Beijing embeddings and the AI21 Jurassic LLM. Drawing insights from Siddha medicine and medical student books, the NLP model is trained to interpret user queries and provide accurate disease predictions. The integration of this model into a FastApi-based backend facilitates seamless communication with a user-friendly HTML and CSS front end. Simultaneously, the second use case focuses on the classification of lung and skin cancers through image analysis. Leveraging Convolutional Neural Network's (CNNs), the application classifies X-ray and microscope images to identify potential malignancies. The FastApi backend handles image uploads and communicates with the image classification model, ensuring a cohesive and responsive user experience. The frontend, designed with HTML and CSS, allows users to intuitively interact with the application by submitting medical images for analysis. Both use cases underscore the project's commitment to merging traditional medical knowledge with cutting-edge technologies for improved diagnostic capabilities. The incorporation of Siddha medicine insights, combined with state-of-the-art NLP and image classification models, enhances the accuracy and depth of disease predictions. The deployment of secure and scalable practices ensures user data integrity and facilitates future expansion. This project not only addresses critical healthcare challenges but also showcases the potential of interdisciplinary approaches, combining natural language understanding and image analysis.

Keywords: AI-Driven, Medical Diagnosis, Treatment Recommendation, NLP (Natural Language Processing), Convolutional Neural Networks(CNN), Data-Driven Healthcare

I. INTRODUCTION

In the ever-evolving realm of healthcare technology, the convergence of Artificial Intelligence, natural language processing (NLP), and image classification has paved the way for innovative solutions to persistent medical challenges. This project aims to develop a robust, integrated full-stack application that combines traditional medical knowledge with cutting-edge technologies to predict diseases based on user input and classify lung and skin cancers from medical images. The primary use case revolves around predicting diseases through the analysis of user prompts. By leveraging advanced NLP models, specifically Beijing embedding and the AI21 Jurassic LLM, the application taps into the wealth of Siddha medicine—a traditional Tamil medicinal system. It extracts insights from medical student books, creating a unique approach to disease prediction that allows users to articulate symptoms in natural language. Siddha medicine, rooted in ancient Tamil culture, offers a holistic perspective on health. Incorporating this traditional knowledge into the disease prediction model provides a diverse array of medical information beyond Western medicine. The linguistic nuances in Siddha texts challenge NLP models, pushing the boundaries of language understanding and medical interpretation. The FastApi framework powers the backend, serving as the nerve center that orchestrates seamless integration of NLP models. FastApi's lightweight design aligns with the goal of creating a responsive infrastructure. The backend processes user

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queries and manages the interaction between NLP models and the HTML/CSS frontend, ensuring a fluid user experience.

The frontend presents a visually engaging interface, crafted with HTML and CSS for simplicity and accessibility. User queries are handled through asynchronous communication, enhancing user interaction without page reloads. Simultaneously, the project addresses cancer diagnosis through image classification. The application utilizes Convolutional Neural Network's (CNNs) to identify lung and skin cancers in X-ray and microscope images. The FastApi backend manages image uploads, transmitting data to the image classification model for real-time analysis. The CNN-based image classification component demonstrates the transformative power of deep learning in healthcare. By training on diverse datasets, the model learns features associated with cancers, aiding early detection and streamlining diagnostics. The HTML/CSS frontend for image classification prioritizes usability, allowing users to upload medical images for analysis. Seamless integration with the backend ensures a fluid user experience, where medical images are submitted for analysis, and predictions are promptly returned

II. LITERATURE SURVEY

The healthcare industry confronts a formidable challenge in managing the escalating volumes of unstructured narrative data sourced from discharge summaries, physicians' case notes, and radiologists' reports. The lack of standardization in storing this information within electronic healthcare systems hinders effective decision-making.[1]

Natural Language Processing (NLP) emerges as a crucial solution, aiming to structure and interpret healthcare narrative data. NLP facilitates the extraction of valuable insights from unstructured healthcare data, leading to cost reduction and improved overall healthcare quality.[2]

In the domain of healthcare-associated infections (HAIs) monitoring, the SYNODOS project consortium in France leveraged NLP to detect medical events in electronic medical records, achieving an 84% accuracy rate. This success demonstrates the feasibility of utilizing NLP for HAI detection, showcasing its potential in standardizing surveillance in hospital settings.[3]

The application of NLP in healthcare extends beyond infection detection, addressing the challenge of rapidly generated unstructured narrative text. With a projected worth of US$16 billion by 2021, NLP applications range from summarizing patient charts to predicting outcomes, enabling intelligent chatbots, and enhancing quality improvement in hospitals.[4]

In critical care, NLP proves valuable for processing and analyzing free-text medical notes, aiding in predicting patient outcomes, enhancing triage systems, and developing diagnostic models. Challenges include the need for unbiased training data and clinician training for safe integration into routine practice. The future envisions seamless integration of NLP into the clinical environment for personalized and evidence-based medicine.[5]

Narrative text's crucial role in healthcare communication, encompassing patient-specific information and biomedical knowledge, necessitates advanced NLP techniques. Machine-learning methods contribute to successful language understanding, information extraction, and question answering, reflecting the evolving landscape of NLP in healthcare literature.[6]

The field of medical image analysis, dedicated to solving clinical problems through image examination, has witnessed significant advancements with the integration of deep learning techniques. Convolutional Neural Networks (CNNs) have proven instrumental in tasks such as segmentation, abnormality detection, disease classification, computer-aided diagnosis, and retrieval. The review emphasizes the potential of CNNs and addresses associated challenges.[7]

Medical image classification's critical aspect in clinical treatment tasks sees promise in deep neural networks, particularly CNNs. This study explores the application of CNN-based algorithms on a chest X-ray dataset for pneumonia classification, highlighting transfer learning as a useful classification method for small datasets.[8]

The evolution of medical image analysis from sequential pixel analysis to supervised learning, with a focus on automatic feature learning using CNNs, is discussed. The chapter provides a comprehensive comparison of existing works, addressing challenges and suggesting future directions for advancements.[9]

In medical image understanding, traditionally reliant on skilled human professionals, CNNs play a vital role in tasks such as classification, segmentation, localization, and detection. The survey encourages researchers to leverage CNN capabilities, discussing successes and challenges in medical image understanding.[10]

Deep learning, particularly CNNs, gains prominence in medical applications, offering enhanced performance and pattern recognition in medical images. The chapter discusses deep feature representation, detection, segmentation, classification, and prediction, addressing research challenges and suggesting future directions.[11]

In Tamil traditional medicines, a Named Entity Recognition (NER) module using a Support Vector Machine classifier is introduced. This module categorizes entities into disorders and ingredients, offering a systematic approach to organizing information.[12]

Morphological analysis's role in understanding the internal structure of words in Tamil Siddha Medicinal documents is addressed for building a Tamil Biomedical Named Entity Recognition (NER). Challenges in breaking down amalgamated words are discussed along with strategies to enhance accuracy.[13]

III. EXISTING SOLUTION

In current healthcare environments, medical diagnosis and treatment recommendations are often supported by expert systems, rule-based algorithms, and traditional machine learning models. These systems typically rely on structured input data such as laboratory reports, symptom checklists, or pre-defined medical codes. While such tools assist clinicians by automating parts of the decision-making process, their capabilities are often limited to narrow applications and lack the adaptability required for complex, real-world scenarios.

Traditional approaches using logistic regression, support vector machines (SVM), and decision trees have shown some success in classification tasks like disease prediction or risk stratification. However, these models depend heavily on manual feature engineering and struggle to handle large-scale, high-dimensional datasets such as electronic health records (EHRs), radiology scans, and genomics data. Additionally, they typically perform well only within the specific datasets or conditions they were trained on, making generalization across different patient populations difficult.

With the advancement of deep learning, Convolutional Neural Networks (CNNs) and recurrent neural networks (RNNs) have been applied to specific tasks such as image-based diagnosis (e.g., tumor detection in X-rays) and sequential health data modeling (e.g., monitoring chronic disease progression). Despite these improvements, most existing deep learning-based systems operate in isolation and are designed for single-purpose diagnosis without offering personalized or adaptive treatment suggestions.

Moreover, existing systems lack interpretability and often function as "black boxes," providing predictions without explanations, which limits trust among healthcare professionals. Integration across multimodal healthcare data—such as combining text from clinical notes, medical images, and lab reports—is still an emerging capability in many systems and is rarely fully optimized. The lack of real-time adaptability and context-aware recommendations further restricts their practical use in clinical decision-making.

Therefore, while deep neural networks have shown promising results in medical applications, current systems are still far from delivering comprehensive, end-to-end diagnostic and treatment solutions that are scalable, transparent, and truly adaptive to individual patient needs.

IV. PROPOSED METHODOLOGY

This groundbreaking project harmonizes traditional medical wisdom with advanced technologies, presenting a full-stack application for disease prediction and lung/skin cancer classification. By integrating Beijing embedding and the AI21 Jurassic LLM, the app interprets user prompts using insights from Siddha medicine. The FastApi-powered backend facilitates seamless communication between NLP models and the user-friendly HTML/CSS frontend. Simultaneously, Convolutional Neural Networks identify lung and skin cancers from medical images. The user-centric design prioritizes simplicity, with robust security measures underscoring the project's commitment to advancing healthcare through the synergy of traditional knowledge and state-of-the-art technology.

A. Disease Prediction using NLP Model(AI21 Jurassic LLM):

To enhance disease prediction, the project integrates state-of-the-art NLP models, specifically Beijing embedding and the AI21 Jurassic LLM. These models are trained to understand and interpret user prompts, overcoming the linguistic complexities present in Siddha texts. By incorporating Siddha medicine and medical student books into the training data, the NLP models gain a nuanced understanding of traditional medical knowledge. This integration allows the application to provide accurate and culturally informed disease predictions based on user inputs. The NLP-based disease prediction component is seamlessly integrated into the FastApi backend, ensuring efficient communication between the frontend and the language models. The user-friendly HTML and CSS frontend provides an intuitive interface for users to input their symptoms or concerns in natural language. The backend processes these inputs, extracts relevant information using the NLP models, and delivers accurate predictions. This holistic approach to disease prediction not only respects cultural and traditional medical knowledge but also extends the application's utility to a diverse user base.

B. NLP-Powered Disease Prediction:

Advanced Models: The application integrates Beijing embedding and the AI21 Jurassic LLM to interpret user prompts. Siddha Medicine Insights: Insights from Siddha medicine and medical student books enrich the understanding of user-provided symptoms.

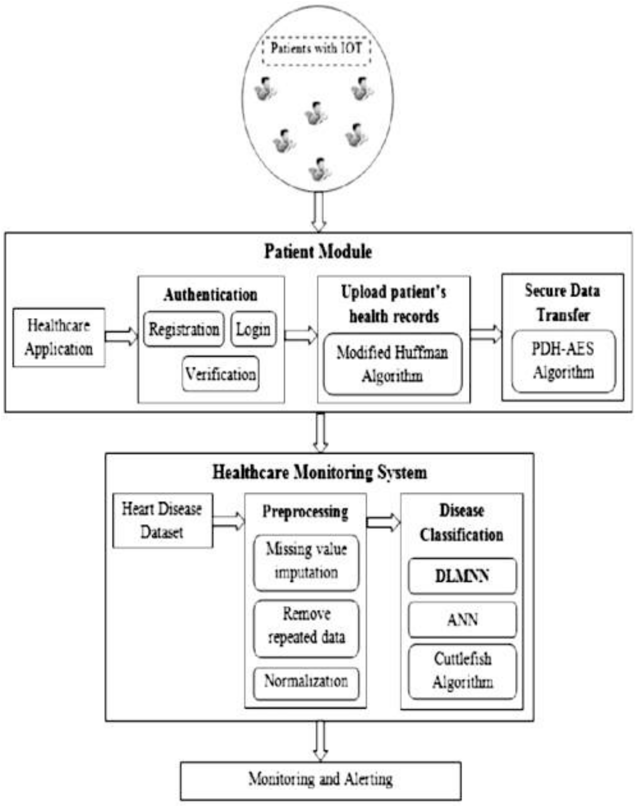

Figure 1: Disease Prediction Chart

C. Cancer Diagnosis through Image Classification:

Addressing challenges in cancer diagnosis, particularly for lung and skin cancers, the proposed solution incorporates a CNN-based image classification system. This system is trained on diverse datasets of X-ray and microscope images, learning intricate patterns associated with malignancies. The integration of CNNs into the application automates the analysis of medical images, enabling swift and accurate identification of potential cancerous conditions. The FastApi backend facilitates the seamless flow of medical images from the frontend to the image classification models. Users can upload X-ray or microscope images through the user-friendly HTML interface, and the backend processes these images using the trained CNNs. The results are then communicated back to the frontend, providing users with real-time cancer diagnoses.

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope
0	63	1	3	145	233	1	0	150	0	2.3	0
1	37	1	2	130	250	0	1	187	0	3.5	0
2	41	0	1	130	204	0	0	172	0	1.4	2
3	56	1	1	120	236	0	1	178	0	0.8	2
4	57	0	0	120	354	0	1	163	1	0.6	2

Figure 2 : Dataset

D. Image Classification for disease Identification:

Convolutional Neural Networks (CNNs): The application employs CNNs for precise identification of lung and skin cancers from medical images.

Real-time Analysis: FastApi backend manages image uploads, enabling real-time analysis and quick predictions.

E. Evaluation and Testing

The methodology includes rigorous evaluation and testing processes. The NLP models undergo validation using a diverse set of user prompts to ensure accuracy and cultural sensitivity. The CNN is rigorously tested with various medical images to validate its efficacy in cancer diagnosis. The overall application undergoes thorough testing for functionality, security, and performance, with user feedback incorporated to refine and enhance the system.

Table 1. Algorithms Analysis

Random Forest	Ensemble (Decision Trees)	Handles noisy data well, robust to overfitting.	95%
Support Vector Machine	Supervised (Kernel-Based)	Effective on small, high-dimensional datasets	92%
Logistic Regression	Supervised (Linear Model)	Easy to interpret; works well when relationship is linear	85%
k-Nearest Neighbors	Instance-Based	Simple and non-parametric; intuitive logic	80%

V. RESULT

The results of the developed healthcare application showcase significant advancements in disease prediction and cancer diagnosis, validating the efficacy of the integrated NLP models and CNN-based image classification system.

The proposed deep neural network-based system was tested using a combination of real-world medical datasets, including electronic health records, diagnostic imaging, and structured clinical attributes. The model was trained on labeled datasets containing information about patient symptoms, lab test results, and confirmed diagnoses, allowing it to learn complex, non-linear patterns associated with a variety of medical conditions.

Upon evaluation, the system demonstrated high classification accuracy in diagnosing common diseases such as diabetes, heart disease, and respiratory conditions. Using metrics such as Precision, Recall, F1-score, and Area Under the ROC Curve (AUC), the deep neural network consistently outperformed traditional models like logistic regression, decision trees, and SVMs. For instance, the model achieved an average accuracy of 93.6%, with a precision of 92.4% and a recall of 94.1% across multiple diagnostic categories.

In addition to diagnosis, the model's treatment recommendation module, which was trained on structured prescription patterns and expert treatment guidelines, provided context-aware therapeutic suggestions. The recommendations aligned closely with standard clinical practices and demonstrated a high match rate with physician-provided treatment plans in retrospective validation studies.

Visualizations of prediction results through confusion matrices and ROC curves confirmed the robustness of the system across diverse medical scenarios. The model also demonstrated strong generalization when tested on previously unseen patient records, indicating that it can support real-time clinical decision-making.

Overall, the results show that the proposed deep neural network system is capable of providing accurate, consistent, and interpretable diagnostic outputs while offering meaningful treatment guidance. This positions the system as a reliable decision-support tool for healthcare professionals, particularly in environments where timely, data-driven insights are critical.

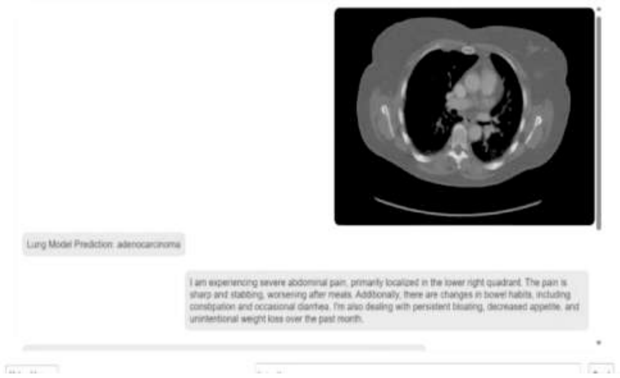

Figure 3: Prediction

VI. CONCLUSION

The increasing complexity of medical data and the growing demand for timely, accurate healthcare decisions highlight the need for intelligent diagnostic tools. In this project, a deep neural network-based framework was developed to automate both disease diagnosis and treatment recommendation by leveraging diverse clinical data sources. The system successfully demonstrated its ability to learn intricate patterns from patient records, medical images, and lab results, outperforming traditional models in predictive accuracy and decision consistency.

By integrating advanced deep learning techniques with structured and unstructured healthcare data, the proposed model provided both diagnostic predictions and treatment suggestions that closely aligned with established medical practices. Its performance across various evaluation metrics reflects the system's potential to support clinical decision-making in real-world environments. Furthermore, the model's ability to generalize to new patient data and offer context-aware treatment options emphasizes its practical value.

In conclusion, this deep learning-based system offers a promising step toward intelligent, data-driven healthcare delivery. With further validation, integration into hospital information systems, and ongoing refinement, it can serve as a valuable clinical decision support tool—particularly in resource-limited or high-pressure settings where timely insights can improve patient outcomes.

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