NLP-Based Clinical Decision Support System using Deep Learning and Transformer

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***Abstract*— The use of Artificial Intelligence (AI) in healthcare has shown great promise in assisting medical professionals with diagnostics and treatment planning. This paper presents CLINT (Clinical Language Intelligence using NLP & Transformers), an NLP-based Clinical Decision Support System that uses deep learning models to analyze multiple medical inputs and natural language processing for summarization. The system integrates three image-based neural networks for ECG, X-ray, and retinal images with a Named Entity Recognition (NER) module and a large language model (LLM). The results include identified diseases, possible causes, and suggested remedies, all shown in a clear summary to support healthcare professionals. This work highlights how AI can improve diagnostic efficiency and accessibility while noting challenges and areas for improvement.**

Index Terms— Clinical decision support, Deep learning, Natural language processing, Medical AI, Named Entity Recognition,Transformers,CLINT,Clinical Language Intelligence using Deep Learning and Transformers

I. Introduction

Advances in deep learning and natural language processing (NLP) have transformed many fields, including healthcare. Clinical diagnostics, however, remain complex. They require interpreting various types of data, such as X-rays, ECG signals, and ophthalmic images. Manual analysis may take considerable time and can result in errors, especially in resource-constrained settings.

This project introduces CLINT, a Clinical Decision Support System that combines multimodal data analysis with NLP-powered summarization. The system processes medical images using specialized deep learning models, extracts meaningful entities using a BERT-based NER pipeline, and generates readable medical suggestions through transformer-based LLMs. The goal is to provide practical insights that can help healthcare professionals during decision-making..

II. System Architecture and Technollogies

The proposed system consists of four main components:

1. **ECG Model** – A TensorFlow-based neural network trained on ECG images to detect cardiac anomalies using EHR report.
2. **X-ray Model** – A CNN pretrained on chest X-ray datasets to identify pulmonary diseases.
3. **Eye Model** – A deep learning model fine-tuned to recognize ophthalmic conditions from retinal images.
4. **NER and Summarization Module** – A BERT-based NER pipeline using PyTorch and BART for extracting entities (diseases, causes, remedies), followed by an LLM for generating coherent medical summaries.

The models interact through a Flask backend that connects with a React-based frontend. The HuggingFace Transformers library powers the LLM inference, while Flask-CORS ensures cross-origin communication.

Technology stack includes: TensorFlow, PyTorch, SpaCy, HuggingFace Transformers, Flask, and React.

III. Implementation Details

Users upload medical images (X-ray, retinal) and clinical questions through a web interface built in React (App.js). The backend (server.py) processes requests and connects with the HuggingFace inference API.

Preprocessing: Each image is adjusted and resized for the best input to the neural networks.

Model Predictions: CNN-based classifiers provide disease probabilities along with confidence scores.

Entity Recognition: Predictions go to the NER pipeline that pulls out disease names, causes, and treatment options.

Summarization: The extracted entities are then sent to a transformer-based LLM, which creates structured medical suggestions in Markdown format.

API Integration: The backend has a /predict endpoint that the frontend uses with user queries. The response is displayed as formatted medical suggestions.

IV. Output

The system provides end-users with actionable medical summaries in a structured format. The frontend interface allows users to:

- Upload clinical reports (PDFs), X-rays, or retinal images.
- Enter medical queries through a text input box.
- Receive structured medical suggestions divided into:
  - **Key Suggestions for Self-Care**
  - **Lifestyle Modifications**
  - **When to Seek Medical Attention**
  - **Warnings & Precautions**

Figure 1. CLINT User Interface (Homepage)

Figure 2. X-ray Prediction Output

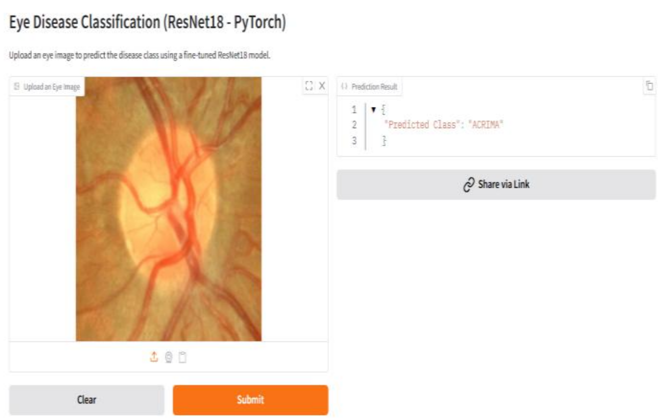

Figure 3. Eye Disease Detection Output using Retinal Model

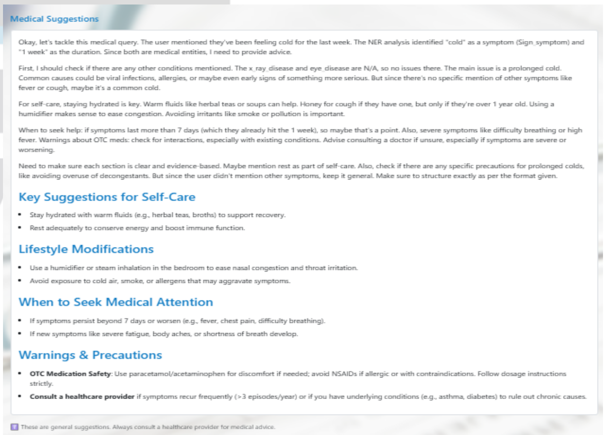

Figure 4. Final Structured Clinical Suggestions Generated by LLM

This structured output improves interpretability and usability compared to raw model predictions.

V. Discussion

This project shows that deep learning and NLP can be combined effectively to support clinical decision-making. Its strengths include:

- Ability to process multimodal data (EHR, X-ray, retinal).

- Structured and easy-to-interpret output summaries.
- Integration of advanced transformer models for NER and text generation.

Limitations include:

- Dependence on dataset quality and size.
- Outputs are generalized and not validated in real medical environments.
- Ethical and legal considerations regarding AI-based medical assistance.

Future enhancements include training with larger clinical datasets, building domain-specific LLMs, and ensuring adherence to medical data privacy standards.

VI. Conclusion

This research introduces an NLP-based Clinical Decision Support System that integrates multimodal deep learning with transformer-based NLP models. The system produces usable medical insights from complex image and text data. It shows the potential of AI in healthcare decision-making. This research presents **CLINT**, a Clinical Decision Support System that integrates multimodal deep learning with transformer-based NLP models. The system converts complex medical images and text into meaningful insights. While not intended to replace professional diagnosis, CLINT can act as a supportive tool for clinicians and patients.

VII. Acknowledgment

The authors acknowledge the support of open-source libraries including TensorFlow, PyTorch, transformers, and HuggingFace, which enabled this project.We also wish to extend our heartfelt thanks to our esteemed professors at Goa University, **Professor Jyoti Pawar** and **Professor Sunayana Gawade**, for their invaluable guidance, support, and encouragement throughout the course of this work.

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