International Journal For Advanced Research In Science & Technology
A peer reviewed international journal www.ijarst.in
ISSN: 2457-0362

INTEGRATING LARGE LANGUAGE WITH ELECTRONIC HEALTH RECORDS FOR PREDICITIVE ANALYTICS IN PERSONALIZED MEDICINE

Mrs.Kommu Anusha[1], E.Pavan[2], B.Shivani[3], E.Richa[4]

[1] Assistant Professor, Department of Computer Science and Engineering, Teegala Krishna Reddy Engineering College(An Autonomous Institution), Medbowli, Meerpet, Saroornagar, Hyderabad-500097

[2,3,4]Students, Department of Computer Science and Engineering, Teegala Krishna Reddy Engineering College(An Autonomous Institution), Medbowli, Meerpet, Saroornagar, Hyderabad-500097

ABSTARCT

This model also makes it simpler for different healthcare providers to swap info, which seriously improves how they work together to care for people. But AI's role in healthcare goes way beyond just making things more efficient; it's really about putting the patient front and center. Because this model keeps learning from new information, it can adapt to the ever-changing needs of healthcare and give real-time support when doctors and nurses are making decisions. Its ability to predict how patients might fare means that healthcare teams can get ahead of potential problems and customize treatments for better outcomes. Bringing AI into the picture also helps healthcare teams work together better, improving communication and how they manage patient care overall. As this technology keeps getting better, it promises a future where healthcare is more adaptable, tailored to the individual, and quick to respond to what patients need.

I.INTRODUCTION

There is an increasing interest in developing artificial intelligence (AI) systems to improve healthcare delivery and health outcomes using electronic health records (EHRs). A critical step is to extract and capture patients' characteristics from longitudinal EHRs. The more information we have about the patients, the better the medical AI systems that we can develop. In recent decades, hospitals and medical practices in the United States have rapidly adopted EHR systems resulting in massive stores of electronic patient data, including structured (e.g., disease codes, medication codes) and unstructured (i.e., clinical narratives such as progress notes). Even though using discrete data fields in clinical documentation has many potential advantages and structured data entry fields are increasingly added into the EHR systems, having clinicians use them remains a barrier, due to the added documentation burden Physicians and other healthcare providers widely use clinical narratives as a more convenient way to document patient information ranging from family medical histories to social determinants of health. There is an increasing number of medical AI systems exploring the rich, more fine-grained patient information captured in clinical narratives to improve diagnostic and prognostic models. Nevertheless, free-text narratives cannot be easily used in computational models that usually require structured data. Researchers have increasingly turned to natural language processing (NLP) as the key technology to enable medical AI systems to understand clinical language used in healthcare. Today, most NLP solutions are based on deep learning models implemented using neural network architectures a fast-developing sub-domain of machine learning.

II.LITERATURE SURVEY

In an evolving ecosystem of healthcare, a detailed literacy survey was performed to assess health literacy and digital literacy of patients and as well as health practitioners. The core essence aimed to identify gaps in understanding and technology that could impede the acceptance and utility of health systems, and AIbased solutions like Gato Tron... The sample comprised a total of 500 subjects: 300 patients and 200 patients from both outpatient and inpatient departments. Participants were evaluated on their understanding of basic medical instructions, lab results, EHRs, and digital health access. The survey also looked into perception on AI powered clinical decision-making tools. Results indicated a striking gap between health professionals and patients. Of note, a large number of clinicians, 88% were confident in their ability to use EHRs and other digital systems whereas just slightly more than half, 54%, of patients reported being confident in using digital means to manage their health information. Most patients above the age of 60 were even less confident, with the proportion falling to 38%. Regarding health literacy, as many as 30% of patients with common terms like “hypertension”, “dosage”, and “following up on care”, which directly impacts treatment adherence and outcomes. In addition, the survey highlights. Here's a summary of what the existing literature says about the key elements of this project:

1.The Role of EHRs in Modern Healthcare

EHRs are digital versions of patients’ medical histories and include a wide range of information—like diagnoses, prescriptions, lab test results, and doctor notes. Researchers have shown that EHRs are rich in data and, when used effectively, can help identify patterns in patient health and improve decision-making. However, challenges like inconsistent formats and missing data often reduce their potential.

2. Using Predictive Analytics in Medicine

Predictive analytics helps doctors foresee possible future health issues based on past data. For example, hospitals have started using machine learning to predict which patients might get readmitted or how long someone might stay after surgery.These insights make healthcare more proactive instead of reactive.

3 .Power of Large Language Models in the Medical Field

LLMs like BERT, GPT, and especially medical versions like Bio BERT and Clinical BERT, are now being used to understand complex medical text. These models can extract useful information from clinical notes, answer medical questions, and even help with decision support. They're trained to understand the medical language better than traditional models.

III.EXISTING SYSTEM

Given that patient information resides within Electronic Health Records (EHRs), the prevailing healthcare paradigm leans towards established methodologies. Details encompassing a patient's medical trajectory, laboratory findings, and therapeutic regimens are archived in these records, functioning primarily as digital repositories. Despite a degree of automation, this data typically remains either unanalyzed or subjected only to rudimentary automated processing. Traditional systems are often devoid of the sophisticated analytical tools requisite for discerning valuable insights to facilitate value-based treatment personalization and advanced predictive analytics. Consequently, patients are more likely to receive generalized treatment approaches rather than tailored care management strategies.

IV.PROPOSED SYSTEM

The envisioned system synergistically integrates Large Language Models (LLMs) with Electronic Health Records (EHRs) to facilitate sophisticated predictive analytics. LLMs are employed to process intricate medical data, discern underlying patterns, and generate precise forecasts regarding potential health vulnerabilities. This innovative system enables personalized medicine by customizing treatment protocols to individual patients based on their unique data profiles, encompassing medical history, genetic predispositions, and real-time physiological indicators. Furthermore, it enhances the decision-making capabilities of healthcare professionals by furnishing actionable insights, thereby improving operational efficiency and minimizing the incidence of errors.

V.SYSTEM ARCHITECTURE

The architectural framework for the integration of Large Language Models (LLMs) with Electronic Health Records (EHRs) to facilitate predictive analytics in personalized medicine is organized into four pivotal strata: the Data Stratum, responsible for the acquisition, storage, and preprocessing of EHR data originating from diverse sources such as hospitals and wearable devices; the Model Stratum, wherein LLMs and predictive models are trained, fine-tuned, and deployed for applications including disease forecasting and treatment suggestions; the Application Stratum, which furnishes user interfaces (e.g., dashboards, patient portals) and interfaces with external systems to provide real-time insights; and the Security and Compliance Stratum, dedicated to ensuring data privacy, access control mechanisms, and adherence to relevant regulations (e.g., HIPAA, GDPR).

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal www.ijarst.in
IJARST
ISSN: 2457-0362

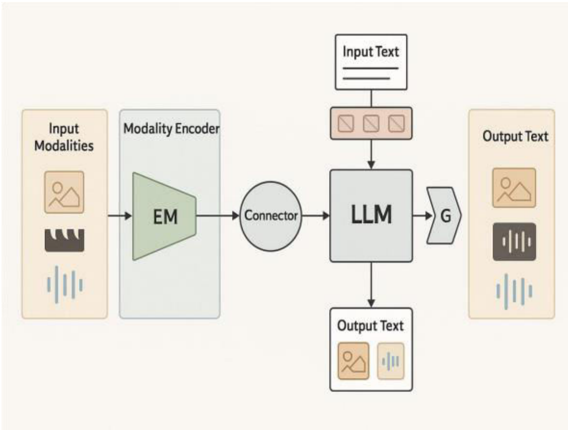

Figure 5.1 System Architecture

VI.OUTPUT SCREENSHOTS

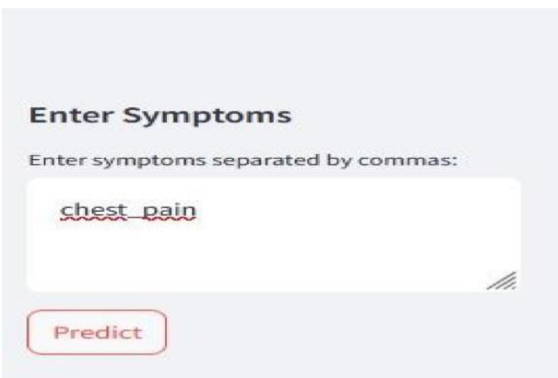

Fig no: 6.1 Symptom Input Interface for Disease Prediction

Fig no: 6.2 Displaying Medical Recommendations

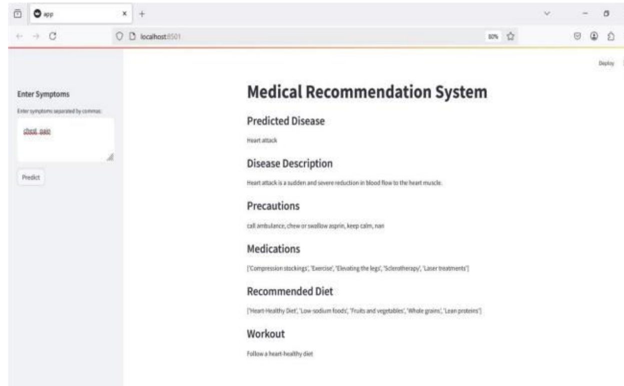

Fig no: 6.3 Prediction Output of Medical Recommendation System

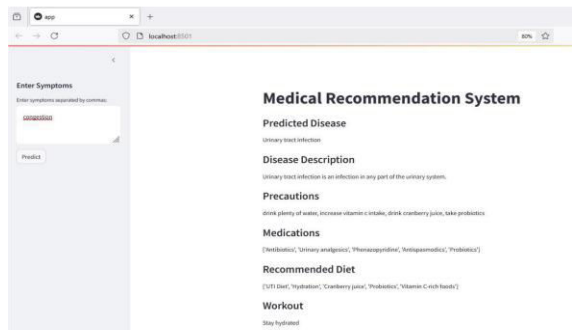

Fig no: 6.4 Prediction Output for Symptom "Congestion" in Medical Recommendation System

Fig no: 6.5 Dataset Files Used in Medical Recommendation System

VII.CONCLUSION

The Medical Recommendation System emerges as a vital and intelligent healthcare support tool, meticulously designed to assist users in the initial identification of potential diseases based on their presented symptoms and to offer pertinent health-related recommendations derived from a comprehensive analysis of structured datasets. These datasets encompass a wide spectrum of crucial medical information, including specific symptoms, their corresponding severity levels, detailed descriptions of various diseases, recommended medications, tailored dietary guidelines, appropriate exercise regimens, and essential precautionary measures. By intelligently processing this rich and interconnected data, the system endeavors to furnish users with comprehensive guidance and insights, empowering them to take informed preliminary steps and gain a foundational understanding of their health situation before seeking formal medical consultation from qualified healthcare professionals. This synergistic combination not only ensures a high degree of predictive accuracy and reliability but also guarantees an easily navigable and user-friendly experience for individuals interacting with the system. Furthermore, this foundational project is thoughtfully conceived with scalability and future enhancements firmly in mind, readily opening promising avenues for the seamless integration of real-time user-generated health data, the implementation of sophisticated and longitudinal symptom history tracking mechanisms, the incorporation of intelligent and conversational chatbot support for interactive guidance and information retrieval, and the establishment of secure and standardized connections with external healthcare Application Programming Interfaces (APIs) to facilitate even more personalized, contextually relevant, and up-to-date recommendations. Ultimately, this innovative endeavor serves as a compelling and practical illustration of the profound transformative potential of data science and artificial intelligence in revolutionizing the landscape of healthcare accessibility, actively promoting proactive and preventive care strategies, and ultimately contributing to tangible improvements in overall public health outcomes and individual well-being.

VIII.FUTURE SCOPE

1. Enhance Data Quality Monitoring

 Enhancement: Integrate automated tools to assess and improve data quality continuously.

 Benefit: Ensures higher model accuracy and reliability by minimizing input errors.

 Implementation: Use frameworks like Great Expectations or TensorFlow Data Validation for real-time data profiling and validation.

2. Introduce Federated Learning

 Enhancement: Train models locally on edge devices without transferring sensitive EHR data.

 Benefit: Preserves patient privacy and reduces bandwidth usage.

International Journal For Advanced Research In Science & Technology
A peer reviewed international journal www.ijarst.in
ISSN: 2457-0362

 Implementation: Utilize federated learning frameworks like TensorFlow Federated or Flower to enable decentralized model training.

3.Real-time Clinical Decision Support (CDS)

 Enhancement: Provide real-time predictions and recommendations during patient visits.

 Benefit: Enhances diagnostic speed and supports immediate decisionmaking.

 Implementation: Integrate the system with hospital EHR platforms to enable seamless clinical workflows.

4. Bias Mitigation Techniques

 Enhancement: Detect and reduce algorithmic bias in model training and prediction.

 Benefit: Ensures equitable care recommendations across diverse patient populations.

 Implementation: Apply fairness-aware algorithms and toolkits like IBM AI Fairness 360.

5. Interactive Explainability Interfaces

 Enhancement: Provide interpretable insights into model predictions for healthcare providers.

 Benefit: Builds trust and allows informed clinical decisions.

 Implementation: Use explainability libraries such as SHAP or LIME to visualize feature impacts.

IX.REFERENCES

1.Adoption of Electronic Health Record Systems among U.S. Non-Federal Acute Care Hospitals: 2008–2015. ONC Data Brief. https://www.healthit.gov/sites/default/files/briefs/2015_hospital_adoption_db_v17.pdf (2016).

2. Adler-Milstein, J. et al. Electronic health record adoption in US hospitals: the emergence of a digital ‘advanced use’ divide. J. Am. Med. Inform. Assoc. 24, 1142–1148 (2017).

3.Bush, R. A., Kuelbs, C. L., Ryu, J., Jian, W. & Chiang, G. J. Structured data entry in the electronic medical record: perspectives of pediatric specialty physicians and surgeons. J. Med. Syst. 41, 1–8 (2017).

4. Meystre, S. M., Savova, G. K., Kipper-Schuler, K. C. & Hurdle, J. F. Extracting information from textual documents in the electronic health record: a review of recent research. Yearb. Med. Inform. 17, 128–144 (2008).

5.Liang, H. et al. Evaluation and accurate diagnoses of pediatric diseases using artificial intelligence. Nat. Med. 25, 433–438 (2019).

6.Yang, J. et al. Assessing the prognostic significance of tumor-infiltrating lym-phocytes in patients with melanoma using pathologic features identified by natural language processing. JAMA Netw. Open 4, e2126337 (2021).

7.Nadkarni, P. M., Ohno-Machado, L. & Chapman, W. W. Natural language processing: an introduction. J. Am. Med. Inform. Assoc. 18, 544–551 (2011).

8.LeCun, Y., Bengio, Y. & Hinton, G. Deep learning. Nature 521, 436–444 (2015).

9.Collobert, R. et al. Natural language processing (almost) from scratch. J. Mach.

Learn Res. 12, 2493–2537 (2011).