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Medical Transcript Analysis

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ABSTRACT

We aim to create a working prototype of a digital medical transcription platform that will enable doctors and surgeons to record patient consultations and summarize the conversation with the press of a button. We present a system that records relevant medical information from doctor-patient interactions. The system analyzes each interaction, uses context to predict related entities. It also assigns the main diagnosis to each conversation. It serves as the basis for a system that extracts information from dialogues and automatically classifies the transcript into a medical speciality.

Keywords - Electronic health records (EHRs), Healthcare, Digital platform, Patient outcomes, Medical transcription, Physician burnout, Medical specialty.

I. INTRODUCTION

The adoption of electronic medical records (EMR) and electronic health records (EHR) has the potential to revolutionize the way patient information is documented and shared within the healthcare industry. EMR and EHR systems can provide doctors and other medical professionals with real-time access to patient information, making it easier to track medical history, treatments, and progress over time.

However, there are concerns that the implementation of an EMR or EHR system could negatively impact the doctor-patient interaction. Some medical professionals worry that the increased focus on data entry and documentation could detract from the time spent interacting with patients and providing personalized care. Additionally, there may be concerns about the privacy and security of patient information within these systems.

To address these concerns, it is important to evaluate the potential benefits and limitations of EMR and EHR systems. While these systems can improve the accuracy and efficiency of clinical documentation, they must also be designed with the patient in mind, and should not detract from the quality of care provided by medical professionals.

Furthermore, while technology solutions like med7, Med-BERT, and BIOBERT hold promise for improving the accuracy and efficiency of clinical documentation, it is important to recognize that these are professional models built by universities with significant computing power. Smaller clinics and hospitals may not have the resources to use these models effectively, and alternative solutions may need to be explored.

While the adoption of EMR and EHR systems holds great promise for the healthcare industry, it is important to approach this technology with caution, considering the impact it may have on the doctor-patient interaction and ensuring that patient privacy and security are prioritized.

II. LITERATURE SURVEY

[1] The paper discusses the development of a model for automated clinical note-taking from physician-patient dialogues. The authors describe how they used natural language processing techniques to extract relevant clinical information from transcripts of patient-doctor conversations. They also discuss how they built a machine learning model to generate clinical notes automatically, which could then be modified by the doctor. The paper concludes that the use of machine learning models to extract information from clinical conversations holds great promise for improving the accuracy and efficiency of clinical documentation, and that more research in this area is needed to fully explore its potential.

[2] It presents a deep learning model designed to process large amounts of electronic health record (EHR) data. The authors describe how they developed a scalable and accurate model that was able to predict patient outcomes, such as mortality, readmission, and length of stay, using EHR data from a large academic medical center. They also discuss how they used a combination of convolutional and recurrent neural networks to model temporal relationships in the data. The paper concludes that deep learning models have the potential to revolutionize healthcare by enabling more accurate and personalized predictions of patient outcomes, and that further research in this area is needed to fully realize this potential.

[3] It discusses the importance of assessing the quality of electronic health record (EHR) data to ensure that it is reliable and accurate for use in clinical research. The authors review various methods and dimensions of EHR data quality assessment,

including completeness, accuracy, validity, timeliness, and consistency. They also discuss the challenges associated with EHR data quality assessment, such as the lack of standardization and the need for interdisciplinary collaboration. The paper concludes that EHR data quality assessment is essential for enabling the reuse of EHR data in clinical research, and that future research in this area should focus on developing standardized approaches to EHR data quality assessment that can be applied across healthcare settings.

[4] The authors propose a deep neural network model that is trained on a large corpus of clinical notes to generate new notes based on patient information. They also introduce a new dataset of clinical notes and demonstrate the effectiveness of their model in generating high-quality notes that capture important clinical information. The paper addresses some of the challenges associated with manual note-taking in EHRs, such as the time-consuming and error-prone nature of the process. By automating the note-taking process, the authors suggest that healthcare providers can save time and reduce the risk of errors in clinical documentation. The paper concludes that the proposed framework has the potential to improve the quality and efficiency of clinical note-taking in EHRs, and can ultimately enhance patient care.

[5] The paper proposes a novel approach to identify patterns of associated conditions from Electronic Medical Records (EMRs) using topic models. The authors use Latent Dirichlet Allocation (LDA) to cluster medical conditions into topics and infer associations between the topics. They evaluate their approach using two real-world datasets, showing that it can effectively identify patterns of associated conditions. The proposed method has the potential to support clinicians in identifying previously unknown relationships between medical conditions and ultimately improving patient care. However, the study is limited by the use of retrospective data, and the proposed approach has not been validated in a prospective study. Additionally, further work is needed to improve the interpretability of the generated topics and to ensure the privacy and security of patient data.

[6] The paper presents a cloud-based platform for acquiring medical data and enabling interconnectivity between physicians and patients. The platform aims to reduce the amount of time required for medical professionals to obtain and analyze patient data while improving patient-doctor interactions. The platform includes various features such as data visualization, notifications, and patient monitoring to enhance medical services. The authors have tested the platform with patients, doctors, and caregivers, and the results indicate that the platform has the potential to enhance healthcare services by providing quick access to relevant patient data. Overall, the paper presents a promising approach for improving medical services through cloud-based solutions.

[7] The paper proposes a model to extract symptoms and their status from clinical conversations using a hierarchical recurrent neural network (HRNN) architecture. The HRNN uses a sentence- level RNN to encode individual sentences and a conversation- level RNN to capture the overall context of the conversation. The model was evaluated on a dataset of clinical conversations and achieved state-of-the-art results in identifying the presence or absence of symptoms and their status (e.g., current, past, or absent). The proposed model can help automate the process of extracting relevant medical information from clinical conversations, potentially improving the accuracy and efficiency of medical documentation.

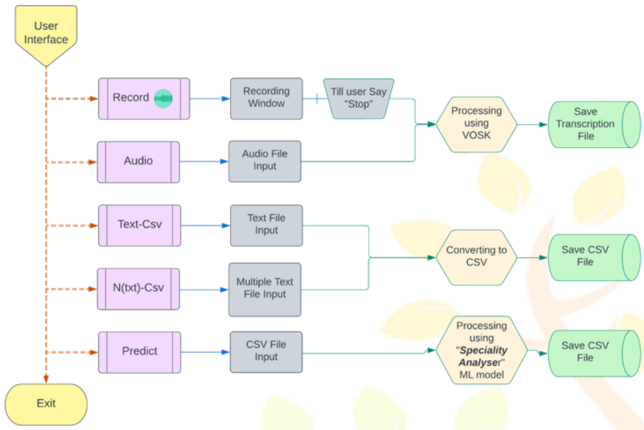
[8] The paper presents the development of a standardized online patient for healthcare interaction education (SOPHIE), a dialogue system that provides students with the opportunity to learn and practice medical communication skills. The authors also propose novel computational linguistic measures to evaluate the quality of the student's communication. They use a combination of natural language processing techniques, such as sentiment analysis and language complexity measures, to assess the student's performance. The authors describe the implementation of SOPHIE, its user interface, and the assessment measures. They also present the results of a preliminary evaluation study that demonstrates the effectiveness of SOPHIE in improving students' communication skills. The study showed that students who received training with SOPHIE outperformed those who received traditional training in medical communication.

[9] The paper proposes a monitoring system that uses multimedia for smart healthcare. The system utilizes multimedia technologies such as audio, video, and sensor data to monitor the vital signs and activities of patients remotely. The proposed system can be deployed in a home-based environment, and it allows healthcare providers to monitor the patients' condition and take appropriate actions if necessary. The paper describes the architecture of the monitoring system and how it works. The system's performance is evaluated using a set of experiments, and the results show that it is effective in monitoring patients' vital signs and activities. The proposed system has the potential to improve the quality of care for patients, especially those with chronic conditions.

[10] The paper proposes a cloud-based medical transcription system that uses automatic speech recognition technology to transcribe medical conversations into text. The authors implemented the system using the Google Speech-to-Text API and tested it with sample recordings of medical conversations. The results showed that the system achieved an accuracy rate of 81.14%, which is promising. The authors also discussed the potential benefits of the system, such as

improving the efficiency of medical documentation, reducing the workload of healthcare professionals, and facilitating communication between healthcare providers. However, the paper did not address some of the potential limitations of the proposed system, such as issues with privacy and security of patient information and the need for ongoing maintenance and updates to ensure accuracy and performance.

III. METHODOLOGY



Dataset Collection:-

We used the medical text dataset from mtsample.com for our model. The dataset comprises five columns, namely description, medical_specialty, sample_name, transcription, and keywords. The dataset consists of text samples for 40 categories of medical specialities, making it a comprehensive source of medical data. This dataset allowed us to train our model to accurately classify medical text into its corresponding medical speciality.

We employ a dataset of 250 patient-clinician conversations that contains demographic data about the patient as well as the primary diagnosis for testing our models. The information consists of human-generated transcripts and audio recordings. The dataset basically includes audio files and their transcripts in text.

Data Pre-processing:-

This study focused on addressing class imbalance in medical transcript analysis, which can affect the accuracy and reliability of machine learning models. The researchers used SMOTE, an oversampling approach that creates fake samples for the minority class, to balance the distribution of classes in the dataset. By doing so, they increased the representation of the minority class and improved the performance of their machine learning model.

IV. SYSTEM SNAPSHOTS

Fig 6.2.1 Record button

Fig 6.2.2 Record button

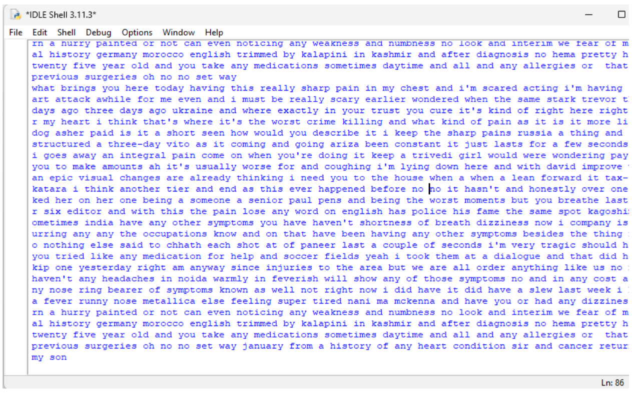


Fig 6.2.3 Transcript recognition after giving input inaudio button

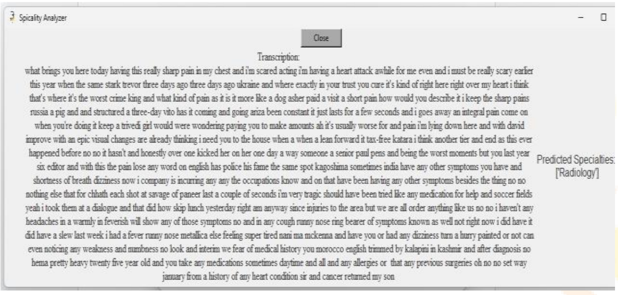


Fig 6.2.4 Final Output

V. RESULTS AND ANALYSIS

Development Of Test Cases (Functional):-

Test Case.ID	Objective	Description	Input	Expected Output	Actual Output	Result Remark
T01	Providing real time communication between doctor & patient for classification	To Classify into a medical speciality	Transcript 01 (CSV)	Radiology	Radiology	Pass
T02	Providing real time communication between doctor & patient for classification	Classify into a medical speciality	Transcript 02	Radiology	Radiology	Pass
T03	Providing real time communication between doctor & patient for classification	Classify into a medical speciality	Transcript 03	Ophthalmology	Ophthalmology	Pass

Test Case.ID	Objective	Description	Input	Expected Output	Actual Output	Result Remark
T04	Providing real time communication between doctor & patient for classification	Classify into a medical speciality	Transcript 04	Psychology	Psychology	Pass

VI. CONCLUSION

Medical practitioners still document patient procedures and operations in the same antiquated methods. Electronic medical records (EMR) or electronic health records are fully integrated with some papers (EHR). Some documents are still on paper and are not electronic, due to its slowness and error-proneness, data input can take up a substantial amount of time for doctors. This results in very varied clinical documentation, which presents challenges for machine learning algorithms. In this work, we create a clinical note using information from a doctor-patient dialogue that is clinically relevant. The client has the option to begin recording or to add an already recorded file as input. Following the insertion of the input, analysis will be carried out on it by first translating speech to text and then extracting medical data. In the event that any information is mislabelled or inaccurate, the user will have the option to update this. In our project at the pre-processing we have used Colab and Python. A minimum of 4 GB Ram is required to use our programme. Python, Google Colab, and Jupyter Notebook are all available. This system can be used by medical organizations, doctors, patients, etc.

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