BERT-driven Automation in Electronic Health Record Management System

Furqan Ali Khan
Department of Computer Science
Purdue University Fort Wayne
Fort Wayne, Indiana, USA
khanfa01@pfw.edu

Mohammadreza Hajiarbabi
Department of Computer Science
Purdue University Fort Wayne
Fort Wayne, Indiana, USA
hajiarbm@pfw.edu

***Abstract*—Within the Electronic Health Record (EHR) Systems, physicians spend extensive time on patient documentation, leading to an alarming increase in mental burnout. The disproportionate focus on data entry, eclipsing time spent on direct patient care, highlights a critical concern. To address this pervasive burnout, a unified effort is imperative. The urgency of the matter is accentuated by the integration of Natural Language Processing (NLP) powered EHR systems, poised to alleviate the substantial time and effort required for health record maintenance.**

Our research unveils a cutting-edge solution—the Automated Electronic Health Record System, a transformative innovation that not only transcribes dialogues but also employs advanced clinical text classification. This System empowers physicians by pre-filling EHR sections, enhancing accuracy and facilitating comprehensive review before integration. With an outstanding accuracy exceeding 98.97%, our System represents a breakthrough, saving over 90% of time compared to manual data entry. Rigorous testing on MIMIC III and MIMIC IV datasets underscores the reliability and effectiveness of our classification model, marking a pivotal stride in the evolution of healthcare documentation.

***Index Terms*—Whisper AI, Transcriber, Text Classification, Electronic Health Records, Bidirectional Encoder Representations from Transformers(BERT)**

I. Introduction

In our contemporary digital era, the convergence of computer technology and the Internet has triggered transformative changes across various industries, healthcare being a notable participant. At the forefront of this technological evolution is the advent of Electronic Health Records (EHR), a groundbreaking innovation designed to elevate patient care, fortify medical decision-making, and facilitate seamless information exchange within the healthcare ecosystem. However, despite the benevolent intentions underlying EHR systems, clinicians find themselves grappling with an increasingly prevalent challenge known as burnout, a phenomenon that bears profound implications for both healthcare professionals and the quality of patient care.

The concept of Electronic Health Records (EHR) traces its roots back to the mid-20th century, with early attempts to digitize patient information. However, it was not until the late 20th and early 21st centuries that technological advancements and a growing recognition of the potential benefits fueled a more widespread adoption of EHR systems.

The primary motivation behind the introduction of EHR was to overcome the limitations of traditional paper-based medical records. Paper records posed challenges in terms of accessibility, portability, and the ability to efficiently share information among healthcare providers. EHR aimed to address these issues by digitizing patient data, enabling real-time access to comprehensive health information, and facilitating seamless communication between different healthcare entities.

As the healthcare landscape evolved, the need for a more integrated and efficient system became apparent. EHR systems aimed to enhance patient care through a centralized repository of health information, reducing medical errors, improving coordination among healthcare providers, and supporting evidence-based decision-making. However, EHR systems also introduced various challenges. Primarily, the implementation of EHR systems introduces an onerous administrative burden for clinicians. The meticulous documentation of patient interactions, updating of medical records, and navigation of intricate digital interfaces divert valuable time away from direct patient care, contributing significantly to escalating burnout levels.

Furthermore, the need for extensive data entry becomes a substantial contributor to burnout. Clinicians dedicate considerable time on recording information into EHR systems, diverting their focus from meaningful patient interactions. The clerical nature of this task contributes to dissatisfaction and emotional exhaustion. The demand to fulfill documentation requirements within limited time frames not only contributes to burnout but also compromises the overall well-being of healthcare providers.

In conclusion, while EHR systems have indisputably revolutionized healthcare by digitizing patient records, the unintended consequences of increased administrative burden and clinician burnout cannot be understated. Navigating these challenges is imperative to ensure that technological advancements in healthcare serve to enhance quality patient care.

Automating healthcare records through Natural Language Processing (NLP) faces various challenges, including deciphering complex medical terminology and upholding patient confidentiality. NLP systems must navigate intricate medical language while prioritizing data security. Ensuring data accuracy and addressing ethical and legal concerns, such as eliminating biases and promoting transparency, are paramount. Before widespread implementation in healthcare settings, NLP solutions must undergo rigorous clinical validation and comply with regulatory standards. Collaborative efforts among healthcare professionals, data scientists, and technology experts are crucial for surmounting these obstacles and harnessing NLP's potential to streamline healthcare operations and improve patient outcomes.

In response to the prevalent challenges faced by healthcare professionals in managing Electronic Health Records (EHR), this research proposes the development of an innovative automated transcription System. Tailored for doctor-patient conversations, this System employs advanced natural language processing to efficiently transcribe and classify text into pertinent EHR fields, such as medical history, symptoms, allergies and treatment plans. The primary objectives include enhancing doctor-patient relationships through real-time transcription, providing an intuitive interface for simplified navigation, and significantly reducing doctors' manual efforts in EHR maintenance.

The automated transcription System is expected to improve overall efficiency by streamlining documentation, ensuring high data accuracy, and offering substantial time savings for healthcare professionals. By fostering a patient-centric approach, this System aims to reinvigorate the doctor-patient relationship, mitigate the risk of burnout, and contribute to a more effective and compassionate healthcare delivery system. This research explores the transformative potential of such a System in alleviating the administrative burdens associated with EHR, ultimately enhancing the quality of patient care.

This paper is divided into following sections (II) Literature Review, (III) Proposed Methodology (IV) Results (V) Conclusion and Future Work.

II. Literature Review

There has been active research going on in the field of Medicine and AI to make Electronic Health Records Systems more accessible and simpler to reduce the workload. In the Paper, "An Automated Medical Scribe for Documenting Clinical Encounters," the authors introduce a novel automated medical scribe designed to enhance clinical documentation efficiency. This system, integrating speech and language technologies like speaker diarization, medical speech recognition, and natural language generation, aims to reduce the administrative burden on physicians. It serves as an alternative to human medical scribes, promising scalability, standardization, and economic benefits. [1]

Consultation summarization has been discussed in [2]. This aims to inform the development of automated summarization of clinical conversations by estimating the proportion of doctor-patient communication in general practice (GP) consultations used for generating a consultation summary. The study suggests that automated summarization solutions, such as digital scribes, must focus on identifying the 20% relevant information for automatically generating consultation summaries. Another Paper discusses about multi-head attention-based mechanism for extractive summarization of clinical notes, aiming to identify and extract meaningful phrases relevant to reported diseases.[3]

The challenges of developing a digital scribe to reduce clinical documentation burden involve the complexity of processing spoken conversations. Spontaneous speech presents phenomena such as zero anaphora, thinking aloud, and topic drift, which differ from written passages and make it difficult to apply natural language processing (NLP) techniques directly. Moreover, the lack of a command-like structure in conversations hinders intent recognition and the application of NLP techniques. Generating a medical summary from clinician-patient conversations is a supervised learning task, but obtaining gold standard summaries for training is costly due to the variability in clinician notes. Even unsupervised learning requires gold standard summaries for evaluation. Additionally, the large and complex medical vocabulary and the nature of conversations complicate contextual inference, which is crucial for understanding the conversation. The challenges also involve the need to draw on medical knowledge and capture nonverbal information from the transcripts.[4]

Whisper AI stands as a cutting-edge breakthrough in speech-to-text conversion, leveraging a sophisticated neural architecture with adaptive learning for continual enhancement. Proficient in multiple languages, it excels in real-time processing and context-aware transcription, providing not only accuracy but also contextual coherence. Its resilience against ambient noise, commitment to continuous improvement, customizable language models, and seamless cloud integration position it as a transformative force in speech recognition technology, ensuring an unparalleled and immersive user experience.[5]

BERT, the groundbreaking Bidirectional Encoder Representations from Transformers, emerges from Google's innovation in Natural Language Processing (NLP). By adopting a transformer architecture, BERT uniquely captures contextual nuances, considering both preceding and subsequent words bidirectionally. Trained comprehensively, BERT excels in understanding context, making it a pivotal player in various NLP tasks, including healthcare applications such as accurate classification and information extraction from medical texts for Electronic Health Record (EHR) systems.

In a recent scholarly exploration within this domain, Jiang et al. introduced a groundbreaking study titled "Integrating Contextualized Embeddings and Prior Knowledge for Clinical Named Entity Recognition: An Evaluation." Their innovative approach combines contextualized embeddings such as ELMo and Flair, presenting a hybrid methodology for improved named entity recognition in medical text. Through meticulous evaluation, the authors demonstrated the superior efficacy of this combined approach over individual methods, showcasing promising outcomes across diverse medical named entity recognition tasks and achieving an impressive F1-score of 87.44%.[5]

The suggested semantic topics by NAMI Montana's domain experts pertain to vital sections within Electronic Health

Record (EHR) forms. These categories encompass Client Details, focusing on patient demographics; Chief Complaint, highlighting the primary reason for the visit; Medical History, capturing past conditions and treatments; Family History, indicating the health background of relatives; and Social History, gathering insights into the patient's lifestyle. These designated "EHR categories" provide a structured framework for comprehensive patient information documentation. The formal text within the EHR, generated by clinicians based on patient interactions, serves as a succinct summary, ensuring standardized and thorough healthcare documentation.[6]

Another research paper [7] alleviated the time burden of medical documentation contributing to physician burnout by introducing a patient-centered digital scribe. Incorporating principles of patient-centered communication, including summarization and signposting, we sought to improve patient satisfaction and reduce healthcare costs. In a proof-of-concept study with medical students, the digital scribe demonstrated notable efficiency, surpassing traditional typing and dictation methods. With minimal training requirements and enhanced provider utilization, our patient-centered digital scribe emerges as a promising solution for automating medical documentation in comparison to conventional and machine learning-based approaches.

This paper delves into the hurdles associated with automating clinical documentation using digital scribes, leveraging advancements in artificial intelligence (AI) and machine learning (ML). It explores the potential of employing speech recognition to replace manual documentation by clinicians or medical scribes. However, the development of digital scribes encounters substantial challenges within the complex clinical environment and conversations. The article identifies and discusses crucial obstacles related to automated speech-based documentation in clinical settings, encompassing recording high-quality audio, transcribing audio through speech recognition, deriving topic structure from conversation data, extracting medical concepts, generating meaningful summaries of conversations, and sourcing clinical data for AI and ML algorithms.[8]

The study by Wenceslao et al. addresses clinician distraction with EMRs during consultations, proposing a real-time speech transcriber plugin for a web-based EMR. Using speech-to-text services, cTAKES, and exploring blockchain for secure recording access, the prototype successfully captures and parses audio conversations. However, usability enhancements, especially in the summarization component, are needed, as identified in a formal evaluation[9]

Going through the previous works, we observed several limitations in the development of automated medical scribes:

- Poor transcription accuracy: Earlier methods struggled to transcribe clinical conversations accurately, particularly in noisy environments or with complex medical terminology.
- Limited contextual understanding: Previous approaches lacked the ability to comprehend the context of medical discussions fully, resulting in inaccuracies or incomplete extraction of medical concepts.
- Manual data annotation: Annotating large datasets for training machine learning models proved costly and time-consuming, thereby limiting the scalability of earlier approaches.
- Inadequate summarization: Earlier methods generated summaries that were either overly verbose, missed critical information, or lacked clinical significance, thereby impacting their usefulness in healthcare settings.
- Privacy and data sharing concerns: Previous research might have encountered challenges in accessing sufficient clinical data for research purposes due to privacy regulations and limitations in data sharing mechanisms.

In triumphant ascent over these formidable challenges, we proudly unveil a groundbreaking model poised to autonomously execute the intricate tasks at hand, seamlessly prefilling Electronic Health Record (EHR) systems. This paradigm-shifting achievement not only surmounts the clinical documentation processes but heralds a new era of efficiency and precision in healthcare information management. The culmination of our endeavors epitomizes a testament to technological prowess and a resolute commitment to revolutionize the landscape of medical documentation.

To address challenges in automating clinical documentation, we utilized Whisper AI for accurate speech-to-text conversion, overcoming noise and terminology complexities. Integration of advanced NLP, including BERT, enabled precise classification of medical dialogue. Leveraging datasets from MIMIC III and MIMIC IV, we ensured robust analysis. The user-friendly interface enhanced accessibility for healthcare professionals. Overall, our approach revolutionizes healthcare documentation, ensuring accuracy, efficiency, and usability. The Methodology is discussed in the following section.

III. Methodology

The paper introduces a groundbreaking automated medical system that utilizes advanced Natural Language Processing technology to extract electronic health records data from conversations between physicians and patients. This system is designed to relieve doctors of the burden of managing electronic health records and represents a cutting-edge solution in healthcare. It can either replace traditional scribing methods or work alongside human scribes as a helpful tool. The system follows a carefully planned processing pipeline, including modules for speech recognition, knowledge extraction, structured data processing, and natural language generation, promising increased efficiency in healthcare. This automated system marks a significant shift in how medical documentation is handled and showcases a remarkable blend of technological innovation, addressing the limitations of human scribing and revolutionizing medical documentation.

Utilizing Whisper AI, we achieved precise conversion of clinical speech to text, capturing doctor-patient conversations accurately. The adaptability of Whisper AI ensures contextual

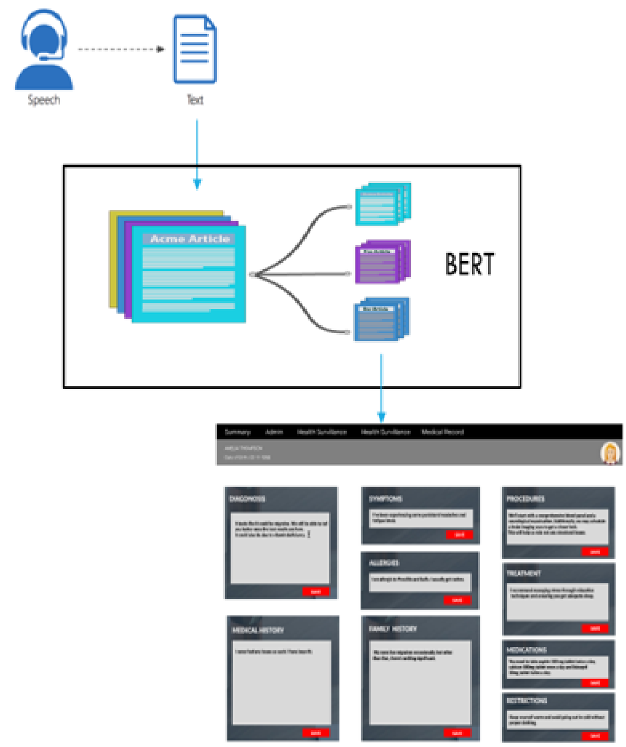

Fig. 1. We use a Speech to Text converter (Whisper AI) to convert the conversation to text. A cutting-edge NLP, BERT model classifies the text into various fields of EHR. The classified text is prefilled into the Application webpage from the backend.

coherence, enhancing transcription quality in healthcare settings.

During the detailed preprocessing stage of examining doctor-patient conversations, a careful combination of advanced Natural Language Processing (NLP) techniques is employed. This seamless blend of lemmatization and stemming plays a crucial role in standardizing language variations by simplifying words to their basic forms. The precise segmentation of sentences breaks down the dialogue into distinct contextual parts. At the same time, systematic tokenization coordinates a thorough organization of linguistic elements. This intricate integration fosters a storytelling approach, ensuring that the conversation resonates effectively with the subtle contextual understanding characteristic of BERT. Such accuracy aids in precise classification and information extraction, particularly in the complex realm of healthcare.

To fulfill our research objectives, we curated a robust dataset by amalgamating information from the MIMIC-III and MIMIC-IV databases. Our database encompasses approximately 2 million datapoints, providing a rich and expansive resource for conducting thorough analyses and investigations. To ensure the fidelity and relevance of our analysis, we embarked on a systematic process of data cleaning and preprocessing. Categorical variables underwent label encoding, an essential step to establish a consistent numerical representation. The Gensim library was adeptly employed for the application of Word2Vec embeddings, capturing subtle semantic relationships within the textual corpus. Complementing this, we implemented count vectorization techniques, transforming the text data into a numerical format that would facilitate subsequent modeling endeavors. These thorough steps in data preparation underscore the methodological robustness of our research, ensuring the extraction of nuanced patterns from the medical dialogue for insightful analysis.

An 80:20 split was performed on the dataset, allocating 80% for training and 20% for testing, to comprehensively evaluate model performance. Utilizing an 80% training set allows for robust model training, while the 20% testing set facilitates rigorous evaluation. The Word2Vec model was instantiated from gensim, with parameters like a window size of 10 and a minimum count of 5 occurrences for a word to be considered. Utilizing 8 worker threads for training enhances efficiency. The vocabulary was built with progress updates every 10 messages, extracting unique words for subsequent analysis. These steps ensure high-quality word embeddings, capturing semantic nuances effectively for downstream tasks.

Embarking on our quest for optimal named entity recognition and text classification, our initial foray involved the deployment of a Support Vector Machine (SVM) model, which exhibited commendable accuracy around 88%. The journey of exploration then unfolded methodically, as we transitioned to the intricacies of Logistic Regression (LR), extracting nuanced insights into linear relationships embedded within the data.

The spectrum of our model selection expanded further with the inclusion of Random Forest (RF), leveraging its ensemble learning prowess to discern intricate patterns and relationships within the complex medical text. This meticulous progression through different Machine Learning (ML) methodologies provided a nuanced understanding of each model's strengths and limitations in the specific context of our objectives.

Venturing into the domain of Deep Learning (DL), our exploration continued with the application of Recurrent Neural Networks (RNN) and Long Short-Term Memory Networks (LSTM). These models, adept at capturing sequential dependencies, enriched our understanding of the contextual nuances inherent in named entity recognition within medical narratives.

Our journey reached its pinnacle by incorporating BERT (Bidirectional Encoder Representations from Transformers), an advanced model based on transformers. This sophisticated architecture, known for its ability to understand context from both directions, significantly boosted our accuracy to new heights, representing a transformative achievement in our research. The fusion of traditional Machine Learning (ML) and cutting-edge Deep Learning (DL) techniques highlighted the depth and breadth of our study, enhancing discussions on superior named entity recognition and text classification in healthcare narratives.

The BERT model presented in this paper includes 12 layers, each comprising bidirectional Transformer encoders, enabling comprehensive understanding of contextual relationships within text. With a hidden size of 768 and 12 attention heads, intricate semantic nuances and dependencies can be captured. As shown in Table I, the BERT model was configured with specific parameters.

TABLE I
BERT PARAMETERS

Parameter	Value
Number of Layers	12
Hidden Size	768
Attention Heads	12
Batch Size	64
Max Sequence Length	256
Optimizer	Adam

Gradio, a user-friendly Python library, facilitates the effortless creation of interactive interfaces for machine learning models. With its intuitive design and real-time feedback, Gradio is a valuable System for both developers and non-technical users, streamlining the deployment and testing of machine learning models. Utilizing Gradio, we fashion an accessible front-end to test our ML model. Guarded by an authentication page, entry is reserved for privileged individuals entrusted with recording and classifying conversations. This digital gateway ensures authorized participation in the nuanced orchestration of data transformation and model evaluation, seamlessly blending Gradio's interface sophistication with stringent access control. In this union of art and functionality, our machine learning journey unfolds, elegantly navigating the intricacies of intelligent conversation analysis.[11]

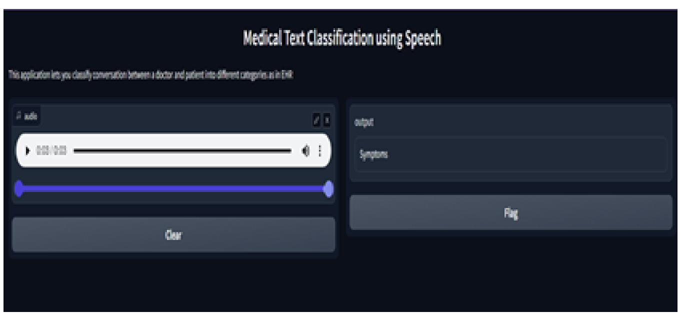

Fig. 2. We use Gradio to test our application. We have a microphone to record the conversations which then classifies each sentence into a field present in the EHR and discards others which are unrelated.

In the landscape of healthcare innovation, our System invites physicians to a domain where spoken words blend into a symphony of data, effortlessly organized and precisely classified. As conversations unfold, this cutting-edge application captures the core of medical dialogue, adeptly sifting through each sentence. With a refined touch, it distinguishes the vital from the trivial, showcasing a model meticulously honed through advanced machine learning. In mere seconds, it categorizes the medical dialogue, seamlessly marrying intelligent conversation analysis with prompt clinical decision-making. Beyond mere recording, this System metamorphoses spoken words into a seamlessly classified fusion of data, casting a scientific radiance over patient-physician interactions.

In today's digital healthcare landscape, our System transcends traditional methods of medical documentation. By capturing and organizing conversations between patients and doctors, it seamlessly integrates with the Electronic Health Record (EHR) Web app to fill in vital information. This marks a significant departure from the past, where doctors spent valuable time manually inputting data or relying on others to do so. With our innovation, the System autonomously records, sorts, and inputs accurate information into the EHR, streamlining the process and alleviating the burden on healthcare professionals. This revolutionary approach not only enhances efficiency but also ensures the accuracy and completeness of patient records. It represents a pivotal shift in healthcare documentation, where advanced automation drives productivity, accuracy, and ultimately, improved patient care.

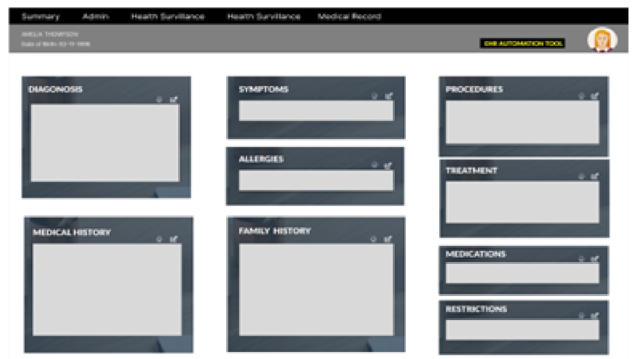

Fig. 3. The Electronic Health Record Application is shown in the figure above.

IV. RESULTS AND DISCUSSIONS

We tested our model by training it on MIMIC III and MIMIC IV [10] datasets and received an accuracy of about 98.97%. We have tried different models and found that the preprocessed data on BERT performed the best. The table II shows the results.The ROC curve for BERT is shown in Figure 4, visually capturing the trade-off between sensitivity and specificity across different decision thresholds in binary classification.

TABLE II
MODEL PERFORMANCE METRICS

Model	**Accuracy**	**Precision**	**Recall**	**Specificity**	**F1**
SVM	88.14%	87.75%	87.90%	87.81%	0.87
RF	76.89%	76.80%	76.95%	76.84%	0.76
LR	91.66%	91.63%	91.72%	91.62%	0.91
RNN	91.34%	91.28%	91.40%	91.34%	0.91
LSTM	93.48%	93.45%	93.52%	93.44%	0.93
BERT	98.97%	98.94%	99%	98.92%	0.98

BERT showed the highest accuracy with an F1 score of 0.98 compared to other models. This high F1 score underscores the superior performance and accuracy achieved by our model compared to its counterparts.[9]

BERT demonstrates strong performance, accurately predicting about six classes with a perfect rate of 100%. For the remaining classes, it also performs well, with high numbers of correct predictions and very few mistakes. This shows that BERT is effective in identifying instances across various classes. However, there are still some misclassifications, seen through false positives and false negatives. Despite these errors, BERT maintains overall accuracy, with an error rate of just around 1.03%. This means that it only makes incorrect predictions for about 1.03% of instances on average.

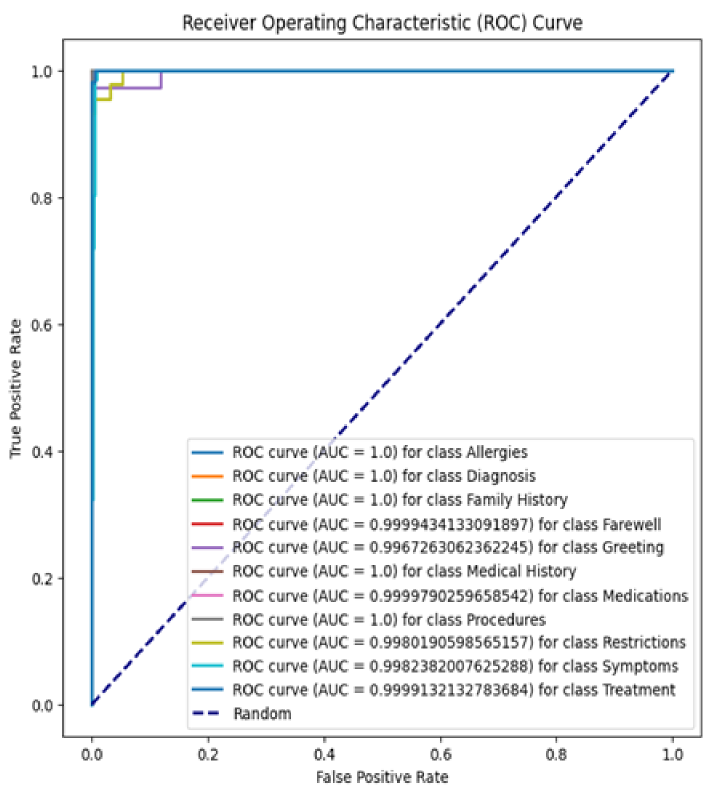

Fig. 4. ROC curve for multiclass classification

Our cutting-edge System demonstrated a remarkable surge in efficiency, eclipsing traditional typing and dictation methods by an extraordinary margin of 90%. It is imperative, however, to adopt a more comprehensive perspective, acknowledging that the projected overall savings hover around 65%. This nuanced consideration considers the inclination of physicians to augment notes beyond immediate patient discussions, thus influencing the holistic gains realized by our pioneering patient-centered digital scribe. This nuanced insight transcends mere speed metrics, offering a supreme understanding of the System's profound impact on the landscape of medical documentation practices which is much faster than method stated in [7].

In the operational framework of this Software System, the physician's procedural steps unfold with precision.

1) Upon the patient's arrival, the physician initiates the recording process by activating the record button on the System before the conversation between the physician and patient begins. Figure 5

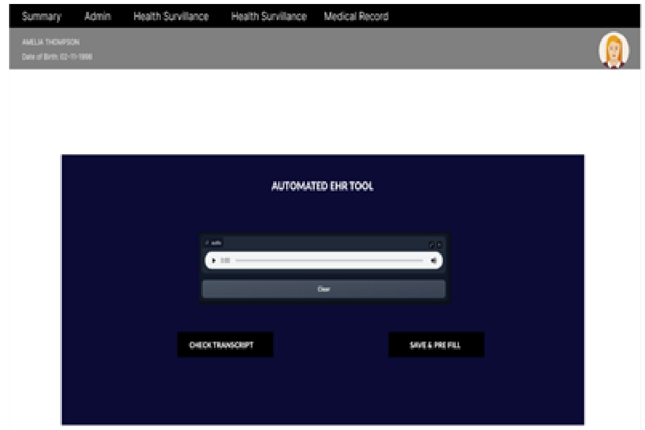

Fig. 5. Records the conversations between the physician and patient.

2) A detailed and comprehensive conversation ensues between the physician and the patient, addressing the presented medical concerns. The patient articulates their health-related issues, delving into aspects such as family and medical history, medication details, and potential side effects.
3) The physician asks clarifying questions and patient continues to provide information. The physician conducts a physical examination to further inform the diagnostic process and treatment.
4) With the conversation concluded, the physician brings the recording to a halt.
5) The System seamlessly transcribes the entire dialogue, autonomously populating the EHR system with pertinent and accurate data.
6) The physician reviews the prefilled data, ensuring accuracy, and has the flexibility to make necessary adjustments before saving the finalized information. Figure 6.

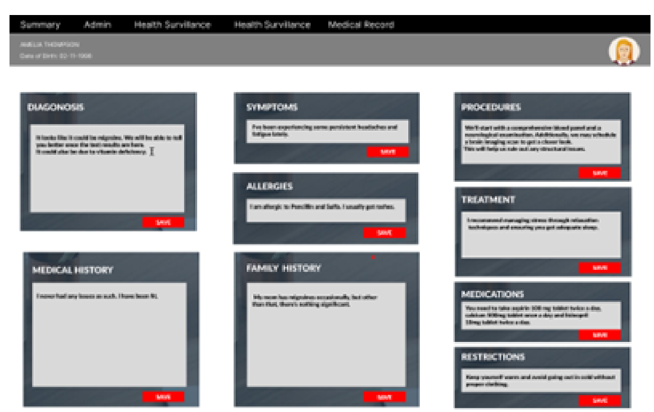

Fig. 6. The data has been prefilled and now the physician can look into each section and make changes as required and submit each section.

7) The Electronic Health record is rightly populated and saved for future reference. Figure 7

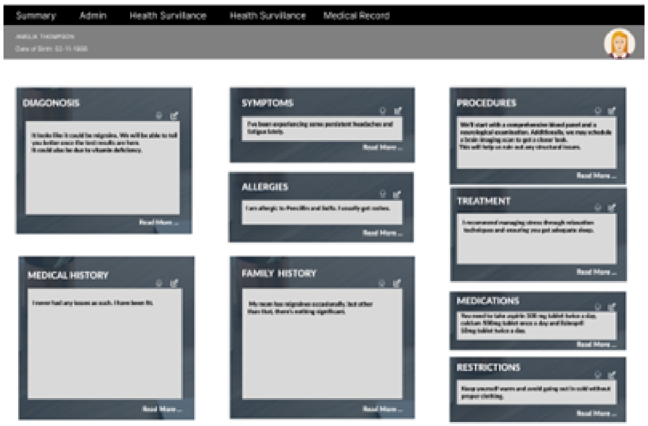

Fig. 7. Prefilled and saved patient data for future reference stored in an Electronic Health record..

V. CONCLUSION AND FUTURE WORK

In conclusion, this paper presented an Automated Electronic Health Record (EHR) System that transcends conventional boundaries. This cutting-edge solution not only transcribes the intricate dialogues between healthcare providers and patients but also harnesses advanced clinical text classification methodologies to adeptly categorize and auto-fill pertinent information into the specific sections of an Electronic Health Record. By endowing physicians with the ability to meticulously review and validate prefilled data before integration, our System ensures an unparalleled level of precision and dependability. This transformative innovation empowers healthcare professionals, fostering a heightened sense of confidence in delivering optimal patient care and streamlining their daily workflows. With an outstanding classification accuracy surpassing 97%, our System exemplifies unparalleled efficacy, eclipsing traditional manual data entry processes by saving over 90% of the time invested. The incorporation of MIMIC III and MIMIC IV datasets further substantiates the credibility and adaptability of our classification model, reinforcing the System's significance in revolutionizing healthcare practices.

As we chart our course forward, we aspire to enrich our EHR System by integrating advanced diagnostic decision support features. Our roadmap includes the incorporation of a summarization System and various other cutting-edge medical assistive technologies. Additionally, our future endeavors involve the augmentation of our dataset, aiming to train and optimize our models further, exploring novel approaches to achieve accuracy levels nearing perfection.

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