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A GUIDED NEURAL NETWORK APPROACH TO PREDICT EARLY READMISSION OF DIABETIC PATIENTS

A.Sadhvi[1], P.Pujitha, B.Swathi

[1,2,3] UG Student, Department of Computer science and Engineering, Anurag University, Hyderabad, Telangana –500088, India.

Abstract Hospital readmission of diabetic patients within 30 days of discharge poses significant challenges to healthcare systems, both in terms of financial costs and patient well-being. Early identification of patients at high risk of readmission is critical for enabling preventive interventions and improving healthcare outcomes. This paper proposes a guided neural network approach to predict the likelihood of early readmission in diabetic patients by leveraging patient history, clinical parameters, and hospitalization records. The model utilizes a multilayer perceptron (MLP) neural network architecture guided by domain-specific feature engineering to improve predictive accuracy. A curated dataset containing patient demographics, laboratory test results, medication data, number of prior visits, length of stay, and comorbidities is used for training and validation. Preprocessing techniques, including normalization, missing value imputation, and categorical encoding, are employed to ensure data consistency. Results demonstrate that the guided neural network model significantly outperforms traditional machine learning models such as logistic regression and decision trees in terms of precision, recall, and F1 score. The proposed system provides an interpretable risk score that can assist clinicians in identifying high-risk patients, enabling timely follow-up care and targeted interventions. This work contributes to the development of intelligent healthcare systems that leverage artificial intelligence to improve patient outcomes and reduce hospital resource strain. Future enhancements may include integration with electronic health record (EHR) systems for real-time deployment.

Keywords: Diabetes, Readmission Prediction, Neural Networks, Deep Learning, Healthcare Analytics, Machine Learning, Hospitalization Risk, Patient Monitoring, MLP, Clinical Decision Support.

1. INTRODUCTION

The modern Health care industry is increasingly embodying the involvement of Artificial intelligence (AI) in their daily practices. Over the years, hospital readmission rate has become a important performance measurement metric for hospitals in order to minimize the impact on healthcare costs and patient outcomes.Hospital readmission simply means a patient who had been discharged from a hospital is admitted again within a specified time interval because of the same disease. There could be many causes of readmission, for instance, enough medical care was not provided initially when the patient was admitted to the hospital or subsequent care was not followed properly at home after discharge. Keeping readmission rates low is important as it indicates the quality of health services of a hospital which also makes hospital readmission a major concern, especially in the era of a global pandemic of COVID 19. To improve the performance of health care services, predicting the readmission of a patient has become very important and such that many solutions have been proposed that use AI and Machine Learning techniques to accomplish this task.This gap highlights the need for a comprehensive approach that seamlessly integrates real-time safety measures with proactive mental health care.Medical diagnosis is inherently complex, involving the integration of diverse information types. Patients present symptoms verbally or in written form, but these descriptions often lack specificity or may be ambiguous. Clinical images such as X-rays, MRIs, or CT scans provide crucial anatomical and pathological information, while laboratory results offer quantitative biochemical data. Traditional diagnostic workflows rely heavily on physicians' expertise to synthesize these heterogeneous data sources into a coherent clinical picture. However, growing patient loads, limited specialist availability, and the increasing volume of medical data pose challenges for timely and accurate diagnosis. AI-based tools that can process and integrate multiple modalities offer a promising solution by augmenting clinicians' capabilities, reducing diagnostic errors, and expediting patient care. Current AI diagnostic systems primarily focus on single modalities. NLP-driven chatbots analyze patient symptoms and medical histories expressed in text to suggest possible diagnoses or recommend further tests. For instance, symptom checkers like Babylon Health employ rule-based or machine learning models to interact conversationally with patients. Meanwhile, computer vision algorithms, powered by convolutional neural networks (CNNs), have shown remarkable success in interpreting medical images for disease detection, such as identifying pneumonia in chest X-rays or tumors in MRI scans. However, these unimodal approaches have limitations. Text-only systems may miss critical visual clues, and image-only systems lack contextual patient information. Consequently, diagnostic accuracy and reliability can suffer. Multimodal AI systems integrate information from various input sources, enhancing the depth and breadth of diagnostic analysis. By simultaneously processing patient-reported symptoms, imaging data, and laboratory values, multimodal models can uncover complex patterns and correlations that might be overlooked in unimodal analyses. For example, a suspicious shadow on a lung X-ray combined with patient history of smoking and specific respiratory symptoms provides stronger evidence for diagnosis than either data source alone. Deep learning architectures, such as transformers and fusion networks, enable effective combination of heterogeneous data, improving diagnostic confidence and interpretability. Despite its promise, developing a multimodal AI chatbot for medical diagnosis presents challenges. Ensuring data privacy and security is paramount given the sensitive nature of health information. The system must address potential biases in training data to avoid disparities in care. Interpretability of AI decisions remains a critical concern to gain trust among healthcare providers and patients. Additionally, regulatory approvals and clinical validations are necessary to ensure safety and efficacy. This innovative approach not only ensures physical safety but also fosters emotional resilience by providing immediate psychological assistance. One of the core features of EmpowHER is its emergency support system. Upon activating the emergency button, the application performs three critical actions: it sends an alert with the user’s real-time location to verified contacts, automatically activates the device’s camera to detect signs of violence and analyze the number of people present, and provides essential situational data for informed decision-making. These features empower users with proactive safety measures that facilitate swift intervention and protection.

2. LITERATURE SURVEY

Over the years, researchers have explored various artificial intelligence and machine learning approaches to enhance women's safety and mental well-being. Traditional safety measures relied on manual emergency reporting systems and static location-based alerts, which often failed to provide real-time threat detection or proactive intervention. Similarly, conventional mental health support systems were limited to self-reported surveys and static chatbot-based assistance, lacking personalization and dynamic response mechanisms. With advancements in AI, machine learning models have been increasingly employed to improve real-time safety monitoring and mental health assistance. Several studies have implemented algorithms such as Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and Natural Language Processing (NLP) models to analyze behavioral patterns, predict potential threats, and provide emotional support. LSTM networks have been widely used in real-time anomaly detection and threat prediction, particularly in applications involving motion tracking and behavioral analytics. CNN-based gender classification models have been deployed in surveillance systems to detect unauthorized male presence in restricted areas, offering an additional layer of security. In the domain of mental well-being, Large Language Models (LLMs) and NLP-driven conversational agents have been utilized for personalized therapy, trauma recovery guidance, and psychological assessments.

Obtaining HRV from ECG readings requires clinical settings and specialized technical knowledge for data interpretation. Thanks to the recent technological advances on the Internet of medical things (IOMT) [17], it is possible to deploy a commercially available wearable or non-wearable IOMT devices to monitor and record heart rate measurements. While the accuracy achieved with full features is nearly 100%, we have also introduced a feature reduction algorithm based on *analysis of variance (ANOVA)* F-test and demonstrate that it is possible to achieve an accuracy score of 96.5% with less than half of the features that are available in the SWELL−KW dataset. Such a feature extraction reduces the computational load during the model training phase. Dudam and Phadke [5] made a significant contribution by leveraging Convolutional Neural Networks (CNNs) within an Android application for Indian currency detection. Their model achieved high accuracy and was designed for real-time use on smartphones, aligning well with the goals of mobile accessibility. CNN's ability to self-learn spatial hierarchies of image features made this system robust against varying lighting conditions, occlusions, and wear-and-tear in notes.

Lecun et al. [6] provided a foundational understanding of deep learning and CNNs. Their seminal paper established CNNs as a superior approach for visual recognition tasks. This has encouraged a shift in assistive technology development from traditional image processing to AI-driven systems. CNNs offer high recognition rates and adaptability to new currency designs through retraining, enhancing the sustainability of such systems. Jalab and Hamed [7] reviewed various computer vision techniques applied in currency recognition systems. Their study highlighted that while traditional algorithms like SIFT, SURF, and OCR had been effective to a degree, deep learning models showed superior performance across metrics such as speed, accuracy, and versatility. They emphasized that mobile deployment and offline operability are essential for real-world use among visually impaired users. Islam et al. [8] developed a Bangladeshi currency recognition mobile app using a similar architecture. Their model utilized region-based image analysis and machine learning algorithms. Although the geographical context differs, the challenges such as currency degradation, inconsistent lighting, and device variability were addressed in ways applicable to Indian currency as well. Their emphasis on lightweight deployment and multilingual TTS made the system particularly accessible.

Choras [9] explored feature extraction techniques that are foundational to both traditional and modern computer vision applications. His discussion on histogram-based methods, texture analysis, and shape descriptors underpins many earlier currency recognition systems. Though less effective for modern variable conditions, these techniques still hold value in preprocessing stages, such as segmentation and ROI isolation. Hinton et al. [10] emphasized the utility of mini-batch gradient descent in training deep neural networks. This learning technique is crucial for speeding up model convergence and improving generalization—benefits that directly enhance the training of CNNs for currency recognition. Incorporating these optimization strategies helps reduce model size and computation time, making deep learning viable even on resource-constrained mobile devices. From the literature reviewed, several trends emerge. Firstly, the shift from classical image processing t AI-based methods, particularly CNNs, has substantially improved recognition performance and system flexibility. Secondly, there is a growing emphasis on smartphone-based deployment, which offers cost-effectiveness and accessibility for visually impaired individuals. Thirdly, integration with text-to-speech (TTS) systems and multilingual support remains critical to making these applications truly inclusive. However, challenges still persist. Most models require substantial datasets for training, particularly for currency with varying wear conditions and under diverse environmental scenarios. Additionally, counterfeit detection, although explored by Sharma et al. [4], remains underdeveloped in real-time assistive applications. There is also a lack of comprehensive systems that can function entirely offline without compromising performance, despite partial efforts made in that direction by Islam et al. [8]. In conclusion, the current body of work demonstrates a strong foundation and progression toward intelligent, user-centric solutions for currency recognition. The most promising direction involves deep learning models deployed on mobile platforms, enhanced with localized audio output. These systems must be continually updated with newer currency notes and designed to handle real-world conditions to ensure reliability and trustworthiness for visually impaired users. Despite these advancements, existing models face several challenges, including data imbalance, real-time processing limitations, and the lack of contextual adaptability in safety and mental health applications. Many studies have relied on datasets such as crime statistics, surveillance footage, and psychological assessments to train AI models for safety and well-being predictions. Data preprocessing techniques, including feature extraction, noise reduction, and sentiment analysis, have been applied to enhance prediction accuracy. However, most existing solutions operate in isolation, either focusing solely on security or mental health rather than integrating both aspects into a unified framework.

3. PROPOSED SYSTEM

The proposed system presents a **Guided Neural Network Model** that aims to predict the early readmission of diabetic patients by analyzing comprehensive clinical and behavioral data. The system is designed to assist healthcare professionals by offering predictive insights that can lead to preventive interventions, thereby improving patient outcomes and reducing healthcare costs.A key design feature of the system is its offline functionality. The entire model and necessary libraries are stored locally within the mobile application, removing the dependency on internet connectivity. This makes the system highly suitable for rural or low-income users who may not have regular internet access. Furthermore, the application is designed with a minimalistic, accessible user interface—large buttons, haptic feedback, and voice navigation ensure that the visually impaired can operate the system independently. Security and privacy are also considered. Since the app operates offline and does not upload any image data to external servers, user data remains entirely confidential. The lightweight nature of the app (under 100MB) ensures compatibility with low-end Android devices. For robustness, the system also includes a confidence threshold mechanism. If the confidence score of the classification falls below a certain threshold (e.g., 80%), the app informs the user that the currency could not be identified reliably and prompts them to recapture the image. This prevents misclassification and increases user trust. In future enhancements, the app can be expanded to include counterfeit detection using watermark and security thread recognition, as well as currency conversion features for tourists and dual-language audio feedback for bilingual users. Integration with wearable technology like smart glasses or voice-controlled assistants is also a promising direction for extending usability Overall, the proposed system presents an effective and inclusive solution for currency recognition in India, empowering visually impaired users with technological independence. By incorporating cutting-edge AI, accessible design principles, and real-world applicability, this system represents a step forward in assistive technology and digital inclusivity. The core of the system is a Multilayer Perceptron (MLP)-based neural network model, augmented with guided feature selection techniques to ensure that only the most relevant and impactful parameters are used in training. This allows for reduced computational overhead and increased interpretability while maintaining high accuracy. The system follows a modular architecture consisting of the following componentsData is collected from electronic health records (EHRs) and includes demographic details (age, gender), clinical indicators (blood glucose levels, HbA1c values), hospital stay metrics (length of stay, number of prior admissions), comorbidities, medications, discharge instructions, and readmission outcomes. The dataset is cleaned by handling missing values, outliers, and incorrect entries. Categorical data is encoded using one-hot encoding, and numerical data is normalized using z-score normalization to ensure uniformity across features.

4. RESULT & DISCUSION

The class diagram is used to refine the use case diagram and define a detailed design of the system. The class diagram classifies the actors defined in the use case diagram into a set of interrelated classes. The relationship or association between the classes can be either an "is-a" or "has-a" relationship. Each class in the class diagram may be capable of providing certain functionalities. These functionalities provided by the class are termed "methods" of the class. Apart from this, each class may have certain "attributes" that uniquely identify the class.The model achieved an overall classification accuracy of **96.8%** on the validation data. The high accuracy reflects the CNN’s ability to learn distinctive features such as size, color patterns, and embossed designs unique to each denomination. Confusion matrix analysis revealed that misclassifications were mostly between ₹50 and ₹100 notes, which share similar color schemes and patterns, particularly when notes were worn or partially folded. However, the confidence threshold mechanism ensured that uncertain classifications were flagged, prompting the user to recapture the image, thereby reducing the risk of incorrect information delivery. Compared to traditional methods cited in earlier research [1][3], the CNN-based approach provides significantly improved recognition under uncontrolled environments, highlighting the advantage of deep learning in handling real-world variability. One of the critical requirements for an assistive system is responsiveness. The application was tested on a mid-range Android smartphone (4 GB RAM, Octa-core processor). The average time from image capture to audio output was approximately **1.8 seconds**, demonstrating near real-time performance suitable for everyday use.

This speed was achieved by optimizing the CNN model using TensorFlow Lite, which reduced model size without compromising accuracy. Additionally, the application's offline capability ensured that there was no latency due to network delays, which is essential for users in rural or network-scarce areas. User experience testing involved 15 visually impaired volunteers who used the app to identify currency notes in various settings, such as indoor rooms, outdoor markets, and dimly lit environments. Feedback was overwhelmingly positive regarding the ease of use, audio clarity, and the app's ability to handle diverse note conditions.

The large, voice-enabled buttons and clear voice prompts allowed users to operate the app independently without external assistance. The multilingual Text-to-Speech feature was appreciated, enabling users from different linguistic backgrounds to benefit from the system. Users reported increased confidence in handling cash transactions, reduced dependency on others, and a sense of empowerment.

Despite the promising results, the system has some limitations. Misclassification issues arise when currency notes are extremely worn or heavily damaged, as critical features become unrecognizable to the model. Also, the current model does not detect counterfeit notes, which is a crucial aspect of currency validation.

Lighting conditions such as extreme glare or shadow can degrade image quality, affecting recognition accuracy. Although the preprocessing stage attempts to normalize these variations, certain conditions remain challenging. Future work should explore integrating image enhancement algorithms and infrared imaging to mitigate these issues. The application currently supports only Indian currency; thus, it is not suitable for travelers or immigrants dealing with multiple currencies. Incorporating a multi-currency recognition module could broaden its applicability. Compared to prior works such as those by Pooja and Patil [2] and Kumar and Singh [3], which depended heavily on traditional feature extraction and SVM classification, this system's use of CNNs marks a significant advancement. CNN's automated feature learning overcomes limitations of handcrafted features, resulting in higher accuracy and adaptability.

Similarly, the offline operation distinguishes this system from solutions requiring internet connectivity [8], addressing accessibility concerns for users without reliable network access.

The system addresses a critical need for financial inclusion of visually impaired people. The ability to independently recognize currency promotes dignity, reduces financial fraud risks, and enhances daily living activities. Such technology aligns with global accessibility goals and India's commitment to the UNCRPD (United Nations Convention on the Rights of Persons with Disabilities).

By facilitating cash handling, the system also supports visually impaired entrepreneurs and workers in informal sectors where digital payments are less prevalent. Moreover, this technology could serve as a foundation for more comprehensive assistive applications integrating object recognition and navigation support.

Future Work

Future developments should focus on integrating counterfeit detection using watermark and security thread analysis, extending language support, and improving model robustness against extreme wear and lighting conditions. Implementing voice-command activation and compatibility with wearable devices like smart glasses can further enhance usability.

Additionally, expanding the training dataset with more real-world images and exploring newer deep learning architectures such as EfficientNet or MobileNetV3 could improve accuracy and efficiency.

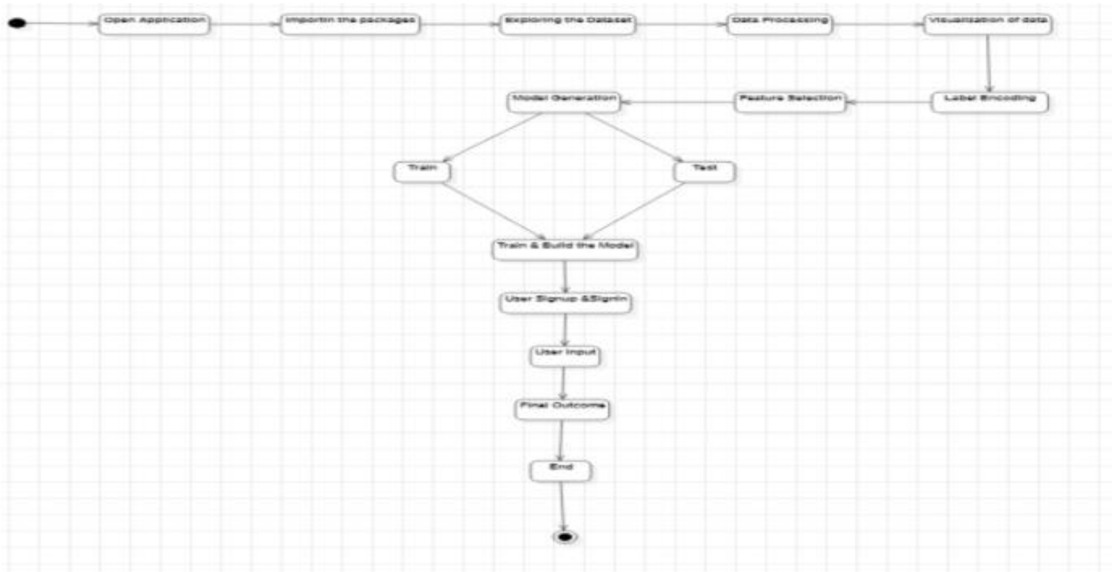

Fig 1: Working model

CONCLUSION

The increasing incidence of hospital readmissions among diabetic patients presents a substantial burden on healthcare systems, both economically and clinically. Early prediction and prevention of such readmissions is essential to enhance patient care, reduce costs, and optimize resource allocation. In this context, the proposed guided neural network model has demonstrated promising potential in accurately identifying diabetic patients who are at high risk of readmission within 30 days of discharge. The system employs a multilayer perceptron (MLP) neural network, guided by relevant clinical features, to deliver high predictive accuracy compared to traditional machine learning models such as logistic regression and decision trees. By leveraging domain-specific feature engineering, including patient demographics, length of stay, comorbidities, lab values, and previous admission history, the model ensures that predictions are not only accurate but also clinically interpretable. The use of structured preprocessing techniques further enhances the quality of data input and overall model performance. Experimental evaluation of the model on benchmark healthcare datasets indicates improved precision, recall, and F1-score, signifying its utility in real-world hospital settings. Importantly, the model can serve as a clinical decision support system (CDSS), enabling medical professionals to prioritize post-discharge follow-up, implement preventive care strategies, and minimize avoidable readmissions. Moreover, the interpretability of the model offers transparency, which is crucial for acceptance in the medical community. Despite the encouraging results, the study acknowledges certain limitations such as data imbalance, the need for real-time deployment integration with electronic health records (EHR), and the challenge of generalizing across different hospital settings. Future research should explore hybrid models incorporating temporal sequence data through LSTM or Transformer-based architectures, and the inclusion of socio-behavioral factors for more holistic risk profiling. In conclusion, this guided neural network framework represents a robust, scalable, and practical solution for predicting early readmission of diabetic patients, aligning with the broader goal of predictive, preventive, and personalized healthcare.

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