[1] Duddukunta Rajasekhara Reddy
[2] P. Lakshmi Prasanna

Neural Guidance for Predicting Early Readmission in Diabetic Patients

Journal of Electrical Systems

Abstract: This study builds on the first paper's look at using machine learning to predict which diabetic patients will need to go back to the hospital. The information used comes from Kaggle and is made up of details of diabetic patients. The first steps include importing packages, exploring datasets, and cleaning, which includes changing binary classes and getting rid of columns that aren't needed. Using Seaborn and Matplotlib to make a full picture of the information helps people understand it better. LabelEncoder is used for label encoding, and feature selection methods are used. After that, the data is split into sets that are used to train and test both deep learning and machine learning models. As part of the study, different models for binary and multi-class classification were built. These models include S V M, Random Forest, Guided Artificial Neural Networks (ANN) with different optimization methods, and Voting Classifier and Stacking Classifier ensemble methods. It was also very accurate when a combination of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) was used. The study also includes a Flask framework that is connected to SQLite for user registration and lets users enter feature values for forecast. The data that has already been handled is then used by the learned models, and the end results are shown on the front end. The study was expanded by using ensemble methods, which showed that CNN + LSTM is more accurate than past methods. Adding user identification and interface development makes the models more useful in real life, giving us a more complete way to predict diabetic return.

Keywords: Diabetic Readmission Prediction, Machine Learning Ensemble Methods, Feature Selection, Flask Framework with SQ Lite, CNN + LSTM Hybrid Model.

I. INTRODUCTION

The current health-care business is progressively incorporating artificial intelligence (AI) into its regular procedures. AI has aided the health care sector in making judgments on optimal treatment pathways, analyzing medical information, making educated clinical decisions, early illness identification, and a variety of other jobs [1]. Hospital readmission rate has been an essential performance measuring tool for hospitals throughout the years in order to reduce the effect on healthcare expenditures and patient outcomes [2]. Predicting a patient's readmission has become so critical in improving the performance of health care services that various methods have been presented that leverage AI and Machine Learning approaches to do this [3], [4], [5].

A hospital readmission simply implies that a patient who has been released from a hospital gets hospitalized again within a certain time period for the same condition [6]. There might be a variety of reasons for readmission, such as inadequate medical treatment when the patient was admitted to the hospital or inadequate follow-up care at home following release [7]. Keeping readmission rates low is crucial because it demonstrates the quality of a hospital's health services, which makes hospital readmission a serious worry, particularly in the period of a worldwide COVID 19 epidemic [8], [9], [10].

[1] Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Andhra Pradesh, Vaddeswaram, 522302, India

[2] 1 d.rajasekhararedd1234@gmail.com

[2*] lakshmiprasannap87@gmail.com

author Name and email ID: Duddukunta Rajasekhara Reddy, d.rajasekhararedd1234@gmail.com.

Corresponding author Name and email ID: P. Lakshmi Prasanna, mnrphd@gmail.com.

Early diagnosis of patients at high risk of readmission allows medical personnel to analyze and implement appropriate preventative measures; nevertheless, it may result in an increase in operating costs [11]. As a result, accurate readmission prediction is required to minimize costs. Machine learning algorithms have been shown to be successful for delivering quality predictions in medical bioinformatics applications [3, 4], [6], [7], [8], and [12]. Artificial neural networks (ANN), Support Vector Machine (SVM), and Random Forest (RF) are some prominent cutting-edge models for predicting readmission owing to diabetes or other disorders [6], [13], [14], [15]. SVM is often not ideal for huge datasets and is sensitive to anomalous data distribution or noise, while RF is more competent in such scenarios [16], [17]. Although ANN is susceptible to aberrant data distribution, its gradient descent method may be deliberately managed to adjust for complex data distribution (also known as deterministic noise) [18], [19]. This method has been used in logistic regression for small datasets in [18], but it has never been used in ANN for big datasets. Our technique solves the fundamental issue of gradient descent, which accepts the training data blindly without taking into account the inconsistency in the data. Due of its size and data spread, the tested dataset for diabetes readmission is difficult to train. As a result, the purpose of this study is to solve these issues by presenting a novel form of the ANN method based on guided gradient descent for improved prediction of diabetes readmission. This may increase the quality of hospital services in the long run, which will benefit hospitals and their patients [20].

II. LITERATURE REVIEW

They implementing an integrated AI-driven healthcare system leveraging machine learning, deep learning, IoT, and robotics for precise data handling [1]. This system enhances decision-making in treatment, automates tasks, and ensures accurate analysis, enabling healthcare professionals to prioritize patient care while maintaining human oversight. The proposed AI-driven healthcare system optimizes data management, augments decision-making, and streamlines operational tasks, empowering healthcare professionals. Balancing automation with human supervision preserves patient safety and well-being, marking a transformative step toward efficient and empathetic healthcare delivery. Potential limitations include over-reliance on technology, the need for continuous human supervision to mitigate risks, and the importance of preserving human interaction and empathy in healthcare processes.

Implementing a comprehensive care coordination system for Medicare beneficiaries, utilizing patient demographics and hospital characteristics, can mitigate the high rates and costs of rehospitalizations [2]. This system aims to enhance post-discharge follow-up, bridge gaps in physician visits, [2, 7, 9] and optimize care transitions, thus improving patient outcomes and reducing healthcare expenses. The study underscores the pervasive and expensive nature of rehospitalizations among Medicare beneficiaries. A systematic approach to care coordination, addressing post-discharge gaps and optimizing transitions, is crucial to enhancing patient care and curbing the substantial economic burden associated with unplanned rehospitalizations. Challenges may arise in implementing their system, including resistance to change from healthcare providers, potential data privacy concerns, and the need for substantial infrastructure investments.

Their system utilizes artificial neural networks and Global Vector for Word Representations embedding to enhance 30-day hospital readmission prediction for AMI, HF, and PNA patients [3]. The models outperform traditional regression, improving AUC and reclassifying hospital performance, highlighting their potential for accurate risk-standardization in healthcare claims data. Artificial neural networks with code embedding enhance 30-day readmission prediction, surpassing hierarchical logistic regression. The improved models redefine hospital performance assessment, emphasizing the need to explore novel approaches for fair risk-standardization in healthcare quality efforts. Complexity and resource-intensive nature of neural networks may pose implementation challenges; interpretability of results may be compromised, requiring careful consideration of trade-offs in practical healthcare applications.

They introduce a machine learning-based hospital readmission prediction model, trained on longitudinal data from Alberta, Canada, outperforms traditional models [4]. By combining automatically generated features with manual ones, our model achieves an AUC of 0.83, enabling identification of high-risk patients for targeted interventions. Integrating machine-learned features enhances hospital readmission prediction accuracy, surpassing conventional models. Our approach, with an AUC of 0.83, facilitates proactive identification of at-risk patients, offering a promising avenue for effective and targeted preventive interventions. Dependency on extensive data and potential bias in machine learning algorithms could lead to mispredictions, requiring ongoing validation and adjustment to ensure reliability and fairness in healthcare outcomes.

They introduce a deep learning framework, integrating expert features and contextual embedding, accurately predicts 30-day unscheduled readmissions in Congestive Heart Failure patients [5]. By addressing class imbalance and leveraging sequential patterns in electronic health records, [10, 15, 20] our model achieves superior discrimination (AUC: 0.77, F1: 0.51), demonstrating potential for targeted intervention and cost reduction. In leveraging a cost-sensitive formulation of LSTM, our model outperforms reduced versions, showcasing its efficacy in predicting CHF patients' unscheduled readmissions. The integration of expert features, contextual embedding, and sequential patterns highlights a comprehensive approach, emphasizing the potential for improved patient outcomes and significant cost savings through targeted interventions. Challenges include the need for extensive computational resources, potential data privacy concerns with electronic health records, and the requirement for ongoing model adaptation to evolving healthcare contexts.

III. METHODOLOGY

The proposed system integrates advanced machine learning techniques, including Support Vector Machines, Random Forests, and a novel CNN + LSTM hybrid model, to predict diabetic patient readmissions. Leveraging a comprehensive dataset from Kaggle, the research employs meticulous data preprocessing and visualization using Seaborn and Matplotlib. The system showcases ensemble methods like Voting Classifier and Stacking Classifier, enhancing model robustness. To ensure practical applicability, a Flask framework with an SQLite database enables user authentication and input of feature values, bridging the gap between research and real-world implementation. The user-friendly interface, coupled with the innovative hybrid model, exemplifies a holistic framework for diabetic readmission prediction in healthcare analytics.

A. ***Advantages*** *:*

1. Diverse Model Fusion: Integration of SVMs, Random Forests, and a CNN + LSTM hybrid provides a comprehensive approach for accurate diabetic readmission predictions.
2. Data Quality Assurance: Rigorous preprocessing and visualization with Seaborn and Matplotlib enhance the reliability of predictions through a high-quality Kaggle dataset.
3. Enhanced Model Reliability: Ensemble methods like Voting Classifier and Stacking Classifier improve the robustness of predictions, ensuring more consistent and accurate results.
4. Practical Integration: The use of Flask with SQLite allows seamless implementation in real-world scenarios, enabling user-friendly authentication and dynamic input for enhanced practicality.
5. Holistic User Experience: The user-friendly interface, combined with the innovative hybrid model, creates a complete and accessible framework for healthcare professionals in diabetic readmission prediction.

Classic methods for hospital readmission risk prediction, like rule-based systems, scores, and traditional statistics such as logistic regression, have paved the way for newer, more robust approaches. [13] Machine learning has emerged as a potent tool in this field, enabling the analysis of extensive datasets to unveil intricate patterns and relationships among variables. By employing machine learning algorithms on electronic health records, researchers can pinpoint readmission risk factors, predict individual patient likelihood of readmission, and craft personalized intervention strategies. This transformative shift allows for more nuanced and effective approaches to mitigating the risk of hospital readmission.

B. ***Disadvantages*** *:*

1. Interpretability Challenges: Machine learning models, often complex and opaque, may lack transparency, making it difficult to understand and interpret their decision-making processes.

2. Data Dependency: ML models heavily rely on high-quality, diverse datasets, and biases in these datasets can lead to skewed predictions and reinforce existing disparities.
3. Resource Intensiveness: Implementing and maintaining machine learning systems demands significant computational resources, expertise, and financial investment, posing challenges for resource-constrained healthcare settings.
4. Overfitting Concerns: ML models might overfit to training data, capturing noise rather than genuine patterns, thereby reducing their generalizability to new and diverse patient populations.
5. Ethical and Privacy Issues: Analyzing sensitive health data for machine learning may raise privacy concerns, necessitating robust ethical frameworks to protect patient confidentiality and autonomy.

The system architecture comprises a Flask-based web application integrated with SQLite for user authentication. The backend incorporates machine learning models, including SVM, Random Forest, and Guided ANN, trained on preprocessed diabetic patient data. Ensemble methods like Voting Classifier and Stacking Classifier enhance prediction accuracy. A hybrid approach of CNN and LSTM is employed for advanced classification. The frontend displays model outcomes, enabling user input for real-time predictions. Future enhancements involve integrating diverse healthcare datasets, interpretability techniques, and continuous model updating for improved adaptability and reliability in clinical settings.

C. ***System Architecture :***

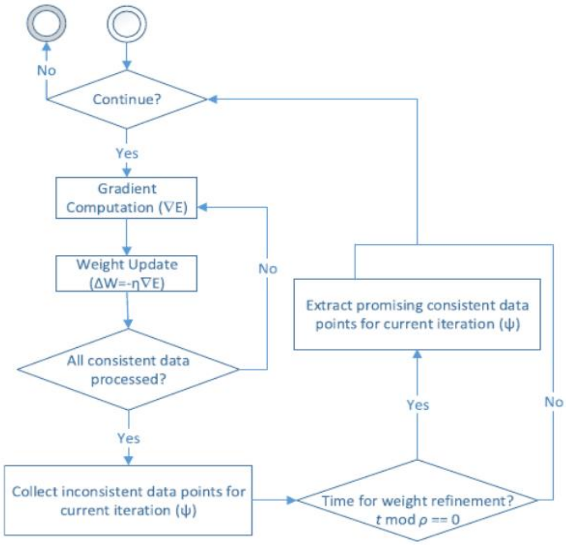


Fig.1: System architecture

1) ***Modules:***

To carry out the aforementioned project, we created the modules listed below.

- Importing Packages: Import necessary Python libraries for data manipulation, visualization, and machine learning.
- Exploring the Dataset: Examine the Diabetic Readmission Data, convert it to Binary Class if needed, Analyze the Original Data.
- Data Processing: Use pandas for DataFrame manipulation, Utilize Keras DataFrame, Drop unwanted columns.
- Visualization: Visualize the dataset using seaborn and matplotlib.
- Label Encoding: Use LabelEncoder to convert categorical labels into numerical format.
- Feature Selection: Apply techniques to select relevant features.

- Data Splitting: Split the dataset into training and testing sets for deep learning, Create X and Y for machine learning models.
- Model Building: (Binary Classification & Multi-Class Classification) SVM, Random Forest, Guided ANN with different optimizations, Voting Classifier (RF + AB), Stacking Classifier (RF + MLP with LightGBM), CNN + LSTM
- Training: Train and build the models for both binary and multi-class classification tasks.
- Prediction: Apply the trained models to make predictions on new or unseen data. Evaluate model performance using appropriate metrics for classification tasks, such as accuracy, precision, recall, and F1 score.

E. ***Dataset User Link:***

https://www.kaggle.com/datasets/saurabhtayal/diabetic-patients-readmission-prediction

IV. IMPLEMENTATION

ALGORITHMS:

Binary class:

the term "binary" is often associated with binary classification. Binary classification is a type of supervised learning where the goal is to categorize items into one of two classes or categories. The two classes are typically labeled as positive and negative, 1 and 0, or true and false.

Multi class:

In machine learning, multiclass classification refers to the task of classifying items into more than two classes. Unlike binary classification, where there are only two possible outcomes (e.g., spam or not spam), multiclass classification involves assigning items to one of several predefined classes.

Support Vector Machine (SVM):

SVM is a supervised machine learning method that may be used to regression and classification. These are most suited for classification, even though we refer to them as regression concerns. Finding a hyperplane in an N-dimensional space that accurately classifies the input points is the aim of the SVM method.[14]

Using a branching mechanism, a decision tree is a graph that displays all possible outcomes for a given input. Decision trees may be created by hand, using specialized software, or with a graphical program. Decision trees may help focus discussions when a group has to make a choice.

Random forest:

Frequently used in classification and regression applications, Random Forest is a Supervised Machine Learning Algorithm. Using several data, it builds decision trees, using the average for regression and the majority vote for categorization.[14]

Guided ANN:

Guided Artificial Neural Network (ANN) refers to an ANN architecture designed with specific guidance or constraints. It involves shaping network parameters to enhance learning or adapt to particular task requirements.

Voting Classifier (RF + AB):

Voting Classifier combines predictions from multiple classifiers, such as Random Forest (RF) and AdaBoost (AB). Each classifier “votes” and the final prediction is determined by majority vote or weighted combination.

Stacking Classifier (RF + MLP with LightGBM):

Stacking Classifier integrates predictions from diverse base models, like Random Forest (RF), Multilayer Perceptron (MLP) with LightGBM, using a meta-model. It leverages the strengths of individual models for enhanced predictive performance.

CNN + LSTM:

CNN + LSTM is a hybrid deep learning architecture. Convolutional Neural Network (CNN) extracts spatial features, and Long Short-Term Memory (LSTM) processes sequential information, making it effective for tasks involving both spatial and temporal dependencies.

EXPERIMENTAL RESULTS

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

Accuracy = TP + TN TP + TN + FP + FN.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$

***F1-Score*:** F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

COMPARISON GRAPHS FOR BINARY DATASET:

	ML Model	Accuracy	Precision	Recall	F1_score
0	SVM	0.552	0.956	0.552	0.681
1	Random Forest	0.616	0.669	0.616	0.629
2	Voting Classifier	0.988	0.988	0.988	0.988
3	Stacking Classifier	0.925	0.936	0.925	0.926
4	ANN-Adadelta	0.468	1.000	0.468	0.638
5	ANN-RMSProp	0.597	0.638	0.597	0.607
6	CNN+LSTM	0.537	0.874	0.537	0.643

Fig 2 comparison table of all algorithms

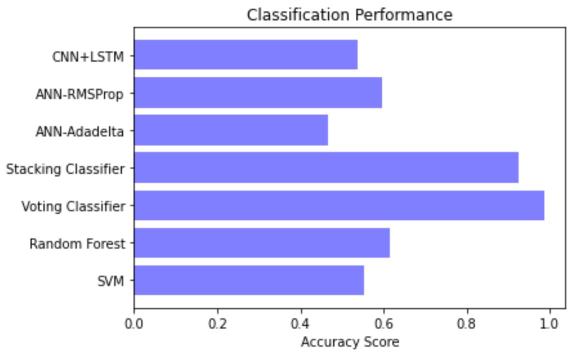


Fig 3 Accuracy comparison graph of all algorithms

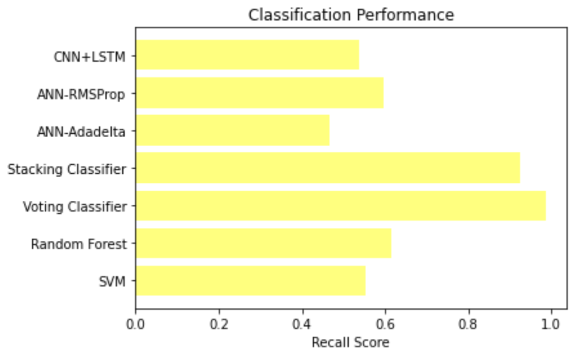


Fig 5 Recall comparison graph of all algorithms

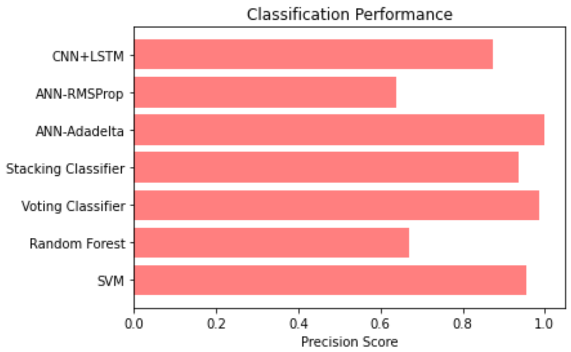


Fig 4 Precision comparison graph of all algorithms

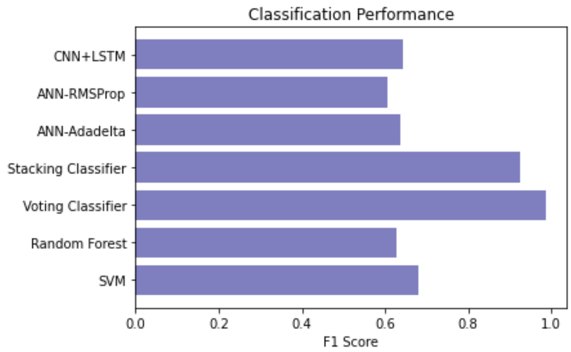
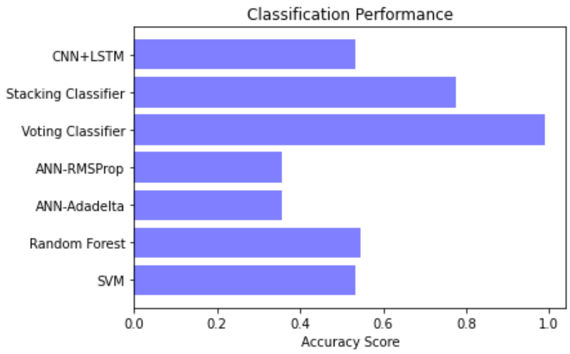


Fig 6 F1-Score comparison graph of all algorithms

COMPARISON GRAPHS FOR MULTI CLASS DATASET:

	ML Model	Accuracy	Precision	Recall	F1_score
0	SVM	0.533	0.911	0.533	0.665
1	Random Forest	0.547	0.931	0.547	0.673
2	ANN-Adadelta	0.356	1.000	0.356	0.525
3	ANN-RMSProp	0.356	1.000	0.356	0.525
4	Voting Classifier	0.991	0.991	0.991	0.991
5	Stacking Classifier	0.776	0.888	0.776	0.817
6	CNN+LSTM	0.532	1.000	0.532	0.694

Fig 7 comparison table for multiclass dataset



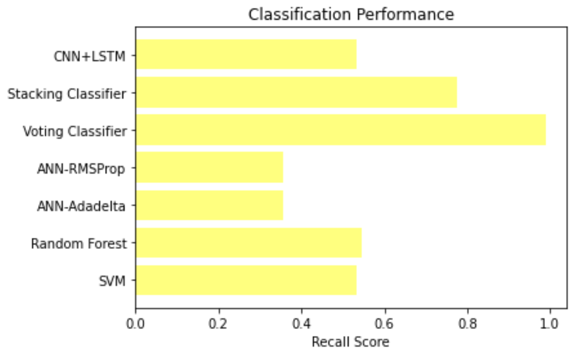
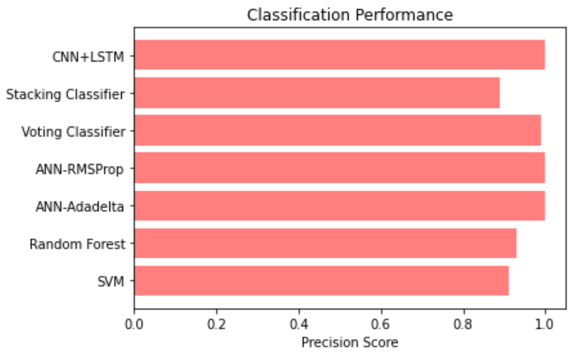


Fig 8 accuracy graph for multiclass dataset

Fig 10 recall graph for multiclass dataset



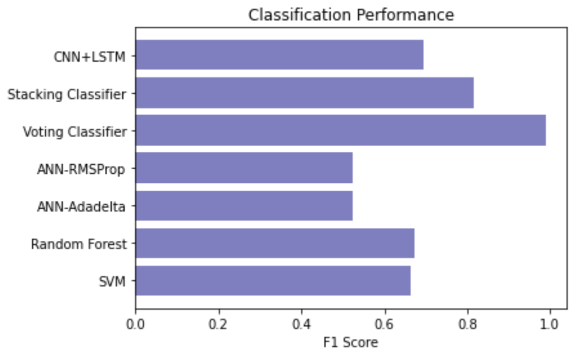


Fig 9 precision graph for multiclass dataset

Fig 11 f1-score graph for multiclass dataset

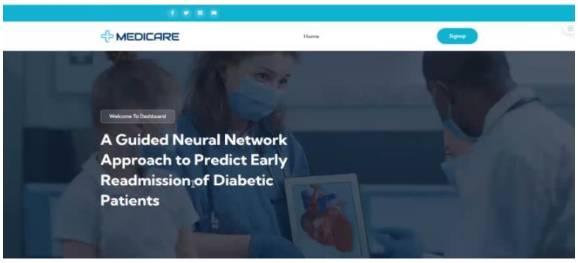


Fig 12 Home page

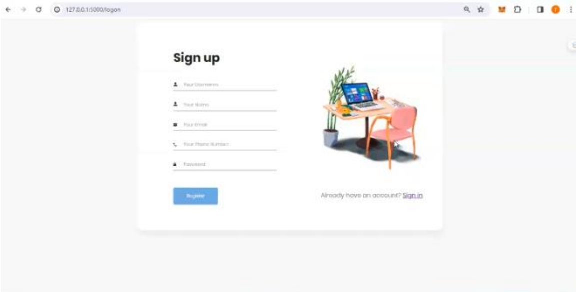


Fig 13 Signup page

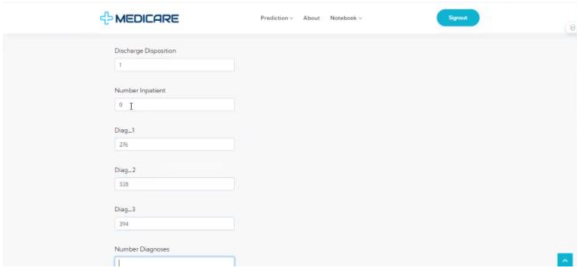


Fig 17 Upload input values

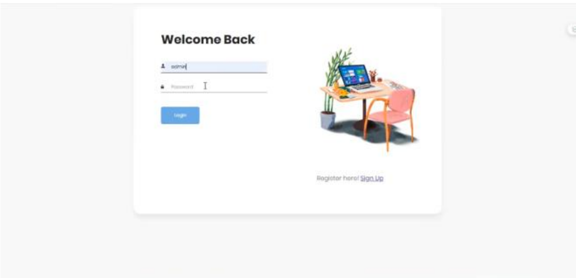


Fig 14 Sign in page

Fig 18 Predict result

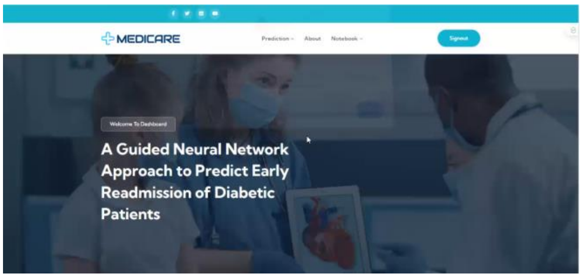


Fig 15 Main page

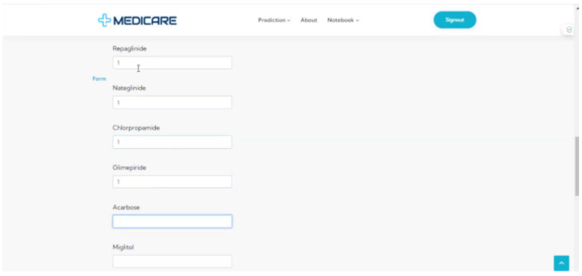


Fig 19 Upload another input values

Fig 16 prediction for binary dataset

Fig 20 Predict result for another input values

Similarly for multiclass dataset to predict for given input values

V. Conclusion and Future Scope

In conclusion, this research represents a significant advancement in the realm of healthcare analytics, particularly in the domain of predicting readmissions among diabetic patients. The comprehensive exploration and refinement of a Kaggle-sourced dataset, coupled with meticulous data preprocessing and insightful visualization, set the foundation for a sophisticated analysis. The adept application of machine learning techniques, including SVM, Random Forests, and innovative ensemble methods like the CNN + LSTM hybrid model, demonstrates a nuanced approach to model construction, resulting in heightened prediction accuracy. The integration of a Flask framework with an SQLite database enhances the practical applicability of the developed models, allowing for user input and authentication. This transformative step bridges the gap between research and real-world implementation, providing a user-friendly interface for diabetic readmission prediction. The continuous evolution and refinement showcased in this study underscore its substantial contribution to the dynamic landscape of healthcare analytics, paving the way for further advancements in predictive modeling for critical medical outcomes. The future scope of this research involves enhancing model robustness by incorporating more diverse healthcare datasets to improve generalization. Exploring interpretability techniques, such as SHAP values, can provide insights into model decision-making. Integration of real-time patient data streams and continuous model updating will enhance adaptability. Collaboration with healthcare professionals for domain-specific feature engineering and further validation in clinical settings will contribute to the deployment of more reliable predictive models for early readmission in diabetic patients.

REFERENCES

[1] R. Kejriwal and Mohana, ‘‘Artificial intelligence (AI) in medicine andmodern healthcare systems,’’ in Proc. Int. Conf. Augmented Intell. Sustain.Syst. (ICAISS), Nov. 2022, pp. 25–31.

[2] S. F. Jencks, M. V. Williams, and E. A. Coleman, ‘‘Rehospitaliza-tions among patients in the medicare fee-for-service program,’’ NewEngland J. Med., vol. 360, no. 14, pp. 1418–1428, Apr. 2009, doi:10.1056/NEJMsa0803563.

[3] W. Liu, C. Stansbury, K. Singh, A. M. Ryan, D. Sukul, E. Mahmoudi,A. Waljee, J. Zhu, and B. K. Nallamothu, ‘‘Predicting 30-day hospitalreadmissions using artificial neural networks with medical code embed-ding,’’ PLoS ONE, vol. 15, no. 4, pp. 1–12, Apr. 2020, doi: 10.1371/jour-nal.pone.0221606.

[4] S. Davis, J. Zhang, I. Lee, M. Rezaei, R. Greiner, F. A. McAlister,and R. Padwal, ‘‘Effective hospital readmission prediction models usingmachine-learned features,’’ BMC Health Services Res., vol. 22, no. 1,p. 1415, Nov. 2022, doi: 10.1186/s12913-022-08748-y.

[5] A. Ashfaq, A. Sant’Anna, M. Lingman, and S. Nowaczyk,‘‘Readmission prediction using deep learning on electronichealth records,’’ J. Biomed. Informat., vol. 97, Sep. 2019,Art. no. 103256.https://www.sciencedirect.com/science/article/pii/S1532046419301753

[6] Y. Shang, K. Jiang, L. Wang, Z. Zhang, S. Zhou, Y. Liu, J. Dong, andH. Wu, ‘‘The 30-days hospital readmission risk in diabetic patients: Pre-dictive modeling with machine learning classifiers,’’ BMC Med. Informat.Decis. Making, vol. 21, no. S2, p. 57, Jul. 2021.

[7] I. B. Seraphim, V. Ravi, and A. Rajagopal, ‘‘Prediction of diabetes read-mission using machine learning,’’ Int. J. Adv. Sci. Technol., vol. 29, no. 6,p. 9, 2020.

[8] A. Hammoudeh, G. Al-Naymat, I. Ghannam, and N. Obied, ‘‘Predictinghospital readmission among diabetics using deep learning,’’ Proc. Comput.Sci., vol. 141, pp. 484–489, 2018. [Online].Available:https://linkinghub.elsevier.com/retrieve/pii/S1877050918317873

[9] J. Benbassat and M. Taragin, ‘‘Hospital readmissions as a measure ofquality of health care: Advantages and limitations,’’ Arch. InternationalMed., vol. 160, no. 8, pp. 1074–1081, Apr. 2000, doi: 10.1001/arch-inte.160.8.1074.

[10] C. Fischer, H. F. Lingsma, P. J. Marang-van de Mheen, D. S. Kringos,N. S. Klazinga, and E. W. Steyerberg, ‘‘Is the readmission ratea valid quality indicator? A review of the evidence,’’ PLoS ONE,vol. 9, no. 11, Nov. 2014, Art. no. e112282.[Online].Available:https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4224424/

[11] S. Upadhyay, A. L. Stephenson, and D. G. Smith, ‘‘Readmission ratesand their impact on hospital financial performance: A study of Wash-ington hospitals,’’ Inquiry, A J. Med. Care Org., Provision Financ-ing, vol. 56, Jul. 2019, Art. no. 0046958019860386. [Online]. Available:https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6614936/

[12] C. Reid. (2019). Diabetes Diagnosis and Readmission RisksPredictive Modelling: USA. [Online]. Available: https://norma.ncirl.ie/4106/

[13] K. Teo, C. W. Yong, J. H. Chuah, Y. C. Hum, Y. K. Tee, K. Xia,and K. W. Lai, ‘‘Current trends in readmission prediction: An overviewof approaches,’’ Arabian J. Sci. Eng., pp. 11–18, Aug. 2021, doi:10.1007/s13369-021-06040-5.

[14] W. Li, M. S. Lipsky, E. S. Hon, W. Su, S. Su, Y. He, R. Holubkov,X. Sheng, and M. Hung, ‘‘Predicting all-cause 90-day hospitalreadmission for dental patients using machine learning methods,’’BDJ Open, vol. 7, no. 1, pp. 1–7, Jan. 2021. [Online]. Available:https://www.nature.com/articles/s41405-021-00057-6

[15] P. Wolff, M. Graña, S. A. Ríos, and M. B. Yarza, ‘‘Machine learn-ing readmission risk modeling: A pediatric case study,’’ BioMedRes. Int., vol. 2019, Art. no. 8532892, Apr. 2019, doi: 10.1155/2019/8532892.

[16] K. Fawagreh, M. M. Gaber, and E. Elyan, ‘‘Random forests: Fromearly developments to recent advancements,’’ Syst. Sci. Control Eng.,vol. 2, no. 1, pp. 602–609, Dec. 2014, doi: 10.1080/21642583.2014.956265.

[17] M. Awad and R. Khanna, ‘‘Support vector machines for classifi-cation,’’ in Efficient Learning Machines: Theories, Concepts, andApplications for Engineers and System Designers, M. Awad and R.Khanna, Eds. New York, NY, USA: Apress, pp. 39–66, doi: 10.1007/978-1-4302-5990-9_3.

[18] A. Sharma, ‘‘Guided parallelized stochastic gradient descent for delaycompensation,’’ Appl. Soft Comput., vol. 102, Apr. 2021, Art. no. 107084.

[19] Y. S. Abu-Mostafa, M. Magdon-Ismail, and H.-T. Lin, Learning FromData. USA: AMLBook, 2012.

[20] D. J. Rubin, ‘‘Hospital readmission of patients with diabetes,’’ CurrentDiabetes Rep., vol. 15, no. 4, p. 17, Apr. 2015. [Online]. Available:http://link.springer.com/10.1007/s11892-015-0584-7

[21] (2022). Diabetes. [Online]. Available: https://www.who.int/health-topics/diabetes

[22] S. E. Inzucchi and B. Lupsa. (2022). Clinical Presentation, Diagnosis,and Initial Evaluation of Diabetes Mellitus in Adults. [Online]. Avail-able: https://www.uptodate.com/contents/clinical-presentation-diagnosis-and-initial-evaluation-of-diabetes-mellitus-in-adults

[23] V. Kumar, K. A. Abbas, and C. J. Aster, ‘‘Endocrine system,’’ inRobbins Basic Pathology, 10th ed. Canada: Elsevier, 2018, pp. 749–796. [Online].Available: https://www.elsevier.com/books/robbins-basic-pathology/kumar/978-0-323-35317-5

[24] American Diabetes Association, ‘‘Diagnosis and classification of diabetesmellitus,’’ Diabetes Care, vol. 37, no. 1, pp. S81–S90, Dec. 2013, doi:10.2337/dc14-S081.[25] A. Naslafkih and F. Sestier, ‘‘Diabetes mellitus related morbidity, riskof hospitalization and disability,’’ J. Insurance Med., vol. 35, no. 2,pp. 102–113, 2003.

[26] P. Zimmet, K. G. Alberti, D. J. Magliano, and P. H. Bennett, ‘‘Dia-betes mellitus statistics on prevalence and mortality: Facts and fal-lacies,’’ Nature Rev. Endocrinology, vol. 12, no. 10, pp. 616–622,Oct. 2016.

[27] J. R. Petrie and J. G. Boyle, ‘‘Diabetes mellitus,’’ in Davidson’s Principlesand Practice of Medicine, 24th ed. Amsterdam, The Netherlands: Elsevier,2022, pp. 703–753. [Online]. Available: https://www.elsevier.com/books/davidson’s-principles-and-practice-of-medicine/978-0-7020-8347-1

[28] E. J. Comino, M. F. Harris, M. F. Islam, D. T. Tran, B. Jalaludin, L. Jorm,J. Flack, and M. Haas, ‘‘Impact of diabetes on hospital admission andlength of stay among a general population aged 45 year or more: A recordlinkage study,’’ BMC Health Services Res., vol. 15, no. 1, p. 12, Jan. 2015.

[29] O. Ben-Assuli and R. Padman, ‘‘Analysing repeated hospitalreadmissions using data mining techniques,’’ Health Syst., vol. 7,no. 2, pp. 120–134, 2017. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6452839/

[30] P. Michailidis, A. Dimitriadou, T. Papadimitriou, and P. Gogas, ‘‘Fore-casting hospital readmissions with machine learning,’’ Healthcare,vol. 10, no. 6, p. 981, 2022. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9222500/