



KLE Technological
University
Creating Value
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**School
of
Electronics and Communication Engineering**

**Senior Design Project Report
on
User-Friendly Interface for Dual Health
Risk Prediction: Heart Failure and Diabetes**

by:

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Semester: VII, 2024-2025

Under the Guidance of

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KLE SOCIETY'S
KLE Technological University,
HUBBALLI-580031
2024-2025



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CERTIFICATE

This is to certify that project entitled “User-Friendly Interface for Dual Health Risk Prediction: Heart Failure and Diabetes” is a bonafide work carried out by the student team of “Shyam Desai(01FE21BEC110), Shridhar Naragund (01FE21BEC116), Shashidhar Angadi (01FE21BEC275), Aditya Wali(01FE21BEC306)”. The project report has been approved as it satisfies the requirements with respect to the senior design project work prescribed by the university curriculum for BE (VII Semester) in School of Electronics and Communication Engineering of KLE Technological University for the academic year 2024-2025

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ACKNOWLEDGMENT

We would like to express our sincere gratitude to all the people who have assisted us in the completion of this project. All their contributions are deeply appreciated and acknowledged. We would like to place on record our deep sense of gratitude to Suneetha Budihal, Professor and Head of the Department of School of Electronics and Communication for having the opportunity to extend our skills in the direction of this project. We express our heartfelt gratitude to our guide Kiran M R whose valuable insights proved to be vital in contributing to the success of this project.

by:

Project Team

ABSTRACT

Heart failure and diabetes are among the most prevalent health issues worldwide, significantly influenced by modern lifestyles and dietary habits. The rising mortality and morbidity rates associated with these conditions underscore the need for early prediction and intervention. In this work, we present a comprehensive prediction system leveraging both machine learning (ML) and deep learning techniques. For heart failure prediction, we utilize an artificial neural network (ANN) alongside ML models such as K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Logistic Regression, and Gaussian Naive Bayes. The ANN model demonstrated superior accuracy compared to traditional ML models. For diabetes prediction, we employed advanced ML algorithms, including Random Forest (RF), XGBoost (XGB), and LightGBM, with XGBoost achieving the highest accuracy. Additionally, we designed a user-friendly graphical user interface (GUI) to facilitate intuitive interaction with our predictive models. This GUI enables efficient prediction of both heart failure and diabetes based on user-provided features, aiming to support healthcare professionals and individuals in early risk assessment and management. Our approach achieves higher prediction accuracy compared to existing methods while offering an accessible and practical tool for health risk prediction.

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Chapter 1

Introduction

The heart is a vital organ responsible for pumping blood throughout the body, ensuring the delivery of oxygen and nutrients to tissues. Heart failure occurs when the heart is unable to pump blood effectively, often due to weakened or damaged heart muscles. Factors such as cardiovascular disease (CVD), high cholesterol, hypertension, lack of exercise, alcohol consumption, and smoking significantly contribute to the onset of heart failure. Early detection of this condition is crucial, as it can reduce mortality rates, improve patient outcomes, and enhance quality of life. Advances in medical technology have highlighted the importance of predictive models that can aid in early diagnosis and treatment planning for heart failure, which remains a challenging condition due to its complex nature and varied symptoms.

Deep learning techniques, particularly artificial neural networks (ANN), have proven effective in extracting meaningful patterns from large and complex datasets, enabling accurate predictions. Similarly, traditional machine learning algorithms, such as Support Vector Machines (SVM), Principal Component Analysis (PCA), and Logistic Regression, provide valuable insights for risk assessment. Our work focuses on developing a robust heart failure prediction model, employing both deep learning and machine learning approaches, to assist healthcare providers in diagnosing the condition early and accurately.

Diabetes, another critical health issue, is a chronic condition characterized by elevated blood sugar levels, which can lead to severe complications such as heart disease, kidney failure, and nerve damage. The prevalence of diabetes is increasing worldwide due to lifestyle changes, poor dietary habits, and genetic predispositions. Early detection of diabetes is essential for managing the disease effectively and preventing its progression. Machine learning algorithms like Random Forest (RF), XGBoost (XGB), and LightGBM have demonstrated excellent performance in predicting diabetes by identifying key patterns and risk factors from clinical data. Among these, XGBoost has emerged as the most accurate model in our study.

In this project, we propose a comprehensive system for predicting both heart failure and diabetes, leveraging the strengths of ANN and various machine learning algorithms. Additionally, we have designed a user-friendly graphical user interface (GUI) to make these predictive tools accessible and easy to use for both patients and healthcare professionals. By integrating advanced algorithms with an intuitive interface, our system aims to enhance early detection, support clinical decision-making, and contribute to improved health outcomes for individuals at risk of heart failure and diabetes.

1.1 Motivation

Rising Prevalence of Heart Failure and Diabetes:Increasing rates of heart failure and diabetes worldwide, largely driven by lifestyle factors, highlight the urgent need for early detection and prevention.

High Mortality and Morbidity Rates:Delayed diagnosis often leads to severe complications or death, emphasizing the importance of predictive models for timely intervention.

Complex Nature of Diseases:Heart failure and diabetes involve multifaceted symptoms and risk factors, making them challenging to diagnose with traditional methods.

Need for Accessible Tools:A user-friendly GUI for prediction models can empower healthcare professionals and patients, bridging the gap between advanced analytics and practical application.

Advances in AI and Machine Learning:Emerging machine learning (ML) and deep learning (DL) techniques offer the ability to analyze large datasets, extract meaningful insights, and improve prediction accuracy.

1.2 Objectives

- Implement traditional machine learning algorithms (Logistic Regression, SVM, KNN, Naive Bayes, Random Forest) and a deep learning model (Artificial Neural Network) to predict heart failure.
- Implement machine learning models including Random Forest (RF), XGBoost (XGB), and LightGBM for diabetes prediction.
- Design and implement an intuitive graphical user interface (GUI) to facilitate seamless interaction with prediction models.

1.3 Literature survey

1.3.1 Heart Failure Detection Using Deep Neural Network [1].

- **Heart Disease Prevalence:** Heart disease is the leading cause of death globally, with millions of fatalities each year, highlighting the urgent need for early detection methods to improve survival rates.
- **Deep Learning Approach:** The paper proposes a deep learning-based classifier for heart failure detection, utilizing a deep neural network (DNN) architecture that processes both numerical and categorical features from patient medical records to enhance prediction accuracy.
- **Data Preprocessing Techniques:** Novel preprocessing steps, including normalization and feature encoding, are introduced to prepare the dataset effectively for the DNN model, ensuring that both types of data are appropriately represented for analysis.
- **Grid-Search for Hyperparameters:**The study employs a grid-search method to optimize hyperparameters systematically, avoiding the inefficiencies of trial-and-error approaches commonly used in machine learning model training.

- **Performance Validation:** The proposed DNN model was tested on a standard dataset of 1,025 cases, demonstrating superior performance compared to existing classification methods for heart disease, indicating its potential as a valuable tool for early diagnosis in clinical settings.

1.3.2 Predicting Heart Failure Readmission from Clinical Notes Using Deep Learning [2].

- **Data Source and Methodology:** The study utilizes the MIMIC III database, focusing on discharge summary notes to train the CNN model, which requires no extensive feature engineering due to its ability to process unstructured text data effectively.
- **Performance Comparison:** The CNN model significantly outperforms conventional machine learning models, achieving F1 scores of 0.756 for general readmission and 0.733 for 30-day readmission, compared to random forest models which scored 0.674 and 0.656, respectively.
- **Implications for Healthcare:** The findings suggest that using deep learning techniques on clinical notes can improve the efficiency of predicting hospital readmissions, potentially aiding healthcare providers in targeting resources more effectively to high-risk patients and reducing overall readmission rates.

1.3.3 An Explainable Transformer-Based Deep Learning Model for the Prediction of Incident Heart Failure [7].

- A transformer-based deep learning model, BEHRT, was developed to predict the risk of incident heart failure (HF) within a six-month timeframe using longitudinal electronic health records (EHRs) from the U.K. The study emphasizes creating a model that is both accurate and explainable, addressing a gap in clinical risk prediction.
- The study utilized data from 100,071 patients, including over 13,000 cases of incident HF. It incorporated multiple EHR modalities (diagnoses, medications, age, and calendar year) and demonstrated the superior predictive performance of the BEHRT model compared to other state-of-the-art models like RETAINEX .

1.3.4 Diabetes Prediction using Machine Learning Algorithms[8].

- Diabetes Mellitus is a widespread condition caused by factors like age, obesity, lack of exercise, genetics, poor lifestyle, unhealthy diet, and high blood pressure. It increases the risk of severe complications, including heart disease, kidney failure, stroke, vision problems, and nerve damage.
- Hospitals currently rely on diagnostic tests and clinical data to identify and manage diabetes. Treatment is tailored based on test results, but these approaches lack advanced predictive capabilities.
- Big Data Analytics is pivotal in healthcare, enabling the analysis of vast datasets to uncover hidden patterns and insights. This helps in improving diagnosis, treatment, and prediction accuracy for diseases like diabetes.

1.4 Problem statement

User-Friendly Interface for Dual Health Risk Prediction: Heart Failure and Diabetes

- **Usability and Accessibility:** Design a user-friendly interface that is easily navigable by users of all ages and technical proficiency, ensuring accessibility for people with disabilities.
- **Personalized Health Insights:** Provide personalized health insights and actionable recommendations based on individual risk factors and health data.
- **Predictive Accuracy:** Enhance the predictive accuracy of the model to reliably assess the risk of both heart failure and diabetes.

Chapter 2

System Design

In this section, We will provide a detailed overview of the proposed methodology for heart failure prediction. We will outline the key steps involved in the process, from data collection and preprocessing to model training and evaluation, offering insights into the approach used to achieve accurate predictions.

2.1 Overview of the Proposed Methodology

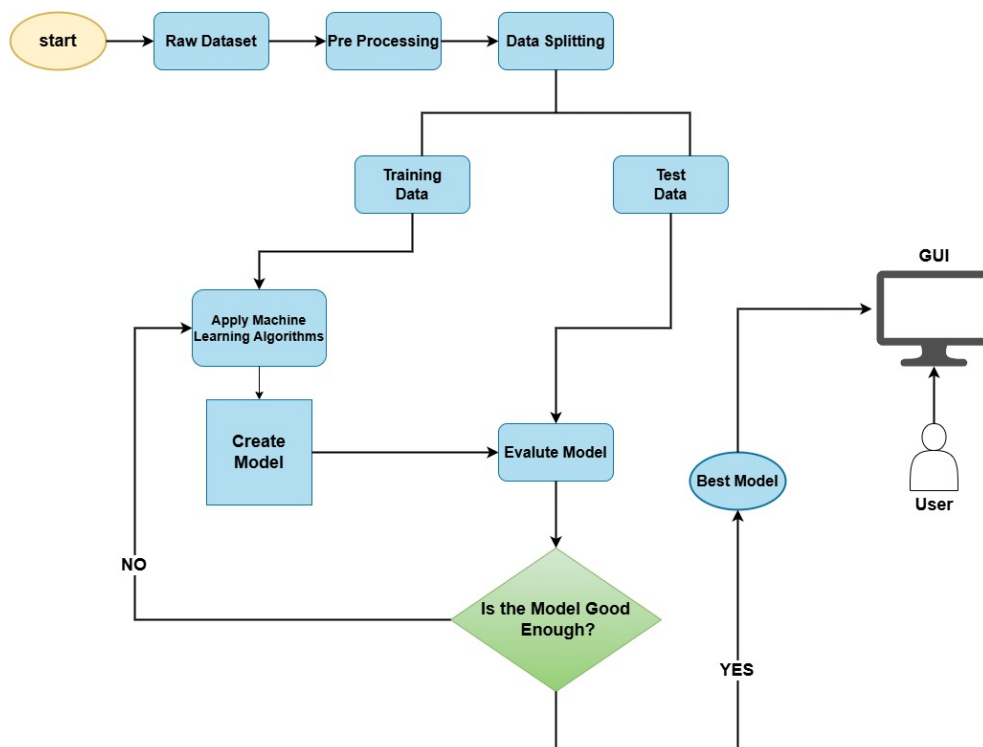


Figure 2.1: The block diagram shows an overview of the proposed method for predicting heart failure and diabetes. It includes steps like data pre-processing, Model training, and prediction. The diagram also highlights real-time prediction and result display, forming a complete prediction system.

The block diagram describes the workflow for building machine learning models to predict two significant health risks: heart failure and diabetes. The process begins by gathering datasets related to these conditions. These datasets are then preprocessed to enhance their quality and relevance. Preprocessing involves steps like handling missing data, removing outliers, selecting essential features, and normalizing values. Once prepared, the data is divided into training and test sets. The training set is used for developing the models, while the test set is reserved to assess their performance.

For predicting heart failure, multiple machine learning algorithms are implemented, including Artificial Neural Networks (ANN), Random Forest, K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Logistic Regression, and Gaussian Naive Bayes. ANN outperforms the others in accuracy and is chosen as the best model for this task. For diabetes prediction, algorithms such as Random Forest, XGBoost (XGB), and LightGBM are utilized. Among these, XGBoost achieves the highest accuracy and is selected as the optimal model. Model selection is based on evaluations conducted using metrics like accuracy, precision, recall, and F1-score.

After training and evaluating the models, the workflow incorporates iterative refinement to address any performance issues. This includes revisiting algorithm techniques to improve outcomes. Once the ANN model for heart failure and the XGBoost model for diabetes are finalized, they are integrated into a user-friendly interface. This interface allows users, including healthcare professionals and patients, to input relevant health data and receive predictions for both heart failure and diabetes risks, making the solution practical and accessible.

Chapter 3

Implementation details

3.1 Specifications

3.1.1 Dataset Description

Heart Failure Clinical Records Dataset:

The Heart Failure Clinical Records dataset from Rana Hospital in Ludhiana, Punjab, India, is a comprehensive collection of patient data used for analyzing and predicting heart failure outcomes. Here are the details of the dataset.,The dataset includes 1886 patient records with 13 features each, covering a wide range of health indicators such as age, anaemia, diabetes, ejection fraction, high blood pressure, platelets, serum creatinine, serum sodium, sex, smoking, time and death event.

Features	Range
Age	40-95
Anaemia	0-1
Creatinine_phosphokinase	23-7861
Diabetes	0-1
Ejection_fraction	14-80
High_blood_pressure	0-1
Platelets	25100-850000
Serum_creatinine	0.5-9.4
Serum_sodium	113-148
Sex	0 (female), 1 (male)
Smoking	0-1
Time	4-285
Death_event	0-1

Table 3.1: Information about the HDD Dataset

Diabetes Dataset:

This dataset is originally from the National Institute of Diabetes and Digestive and Kidney Diseases. The objective of the data set is to diagnostically predict whether a patient has diabetes or not, based on certain diagnostic measurements included in the data set. Several constraints were placed on the selection of these instances from a larger database. In particular, all patients

here are females at least 21 years old of Pima Indian heritage. that is publicly available for machine learning classification, which has been used in this work along with a private dataset. It contains 768 patients' data, and 268 of them have developed diabetes.

Parameter	Description
Pregnancies	Number of times pregnant
Glucose	Plasma glucose concentration measured 2 hours after an oral glucose tolerance test
BloodPressure	Diastolic blood pressure (mm Hg)
SkinThickness	Triceps skin fold thickness (mm)
Insulin	2-Hour serum insulin (μ U/ml)
BMI	Body mass index (weight in kg/(height in m) ²)
DiabetesPedigreeFunction	Diabetes pedigree function
Age	Age (years)
Outcome	Class variable (0 or 1)

Table 3.2: Information about the Diabetes Dataset

3.1.2 Architecture of the proposed ANN

Here, we explain the complete architecture of the ANN used for the heart failure prediction experiment. Basically, the data set consists of 12 characteristics (as mentioned above). It includes the medical record of the 1886 samples in which 1025 heart failure occurred and 861 heart failures did not occur. We divided the whole data set into two sets of which 70% is the training set and the remaining 30% is the test data set.

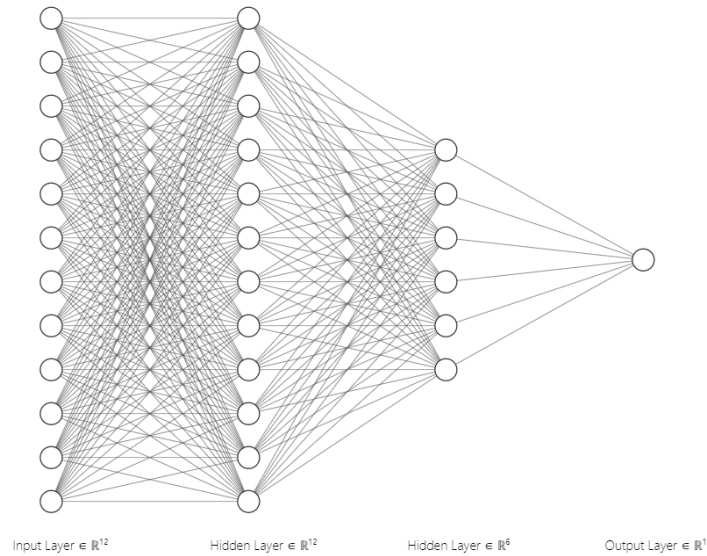


Figure 3.1: Architecure of the proposed ANN

Neural Network Configuration:

- Input layer: Twelve units
- First hidden layer: Twelve units
- Second hidden layer: Six units
- Final layer: One unit
- Epochs: 500
- Loss function: Binary Cross Entropy

Table 3.3: Details of Hyper-Parameters

Hyper-parameter	Values
Activation function	ReLU
Optimizers	Adam
Loss function	Binary cross-entropy
Epochs	500

3.1.3 Design and Functionality of GUI

We created an easy-to-use web application to predict the risk of heart failure and diabetes. It is built using the Streamlit library, which makes it interactive and simple for users. The application asks users to enter specific details.

For heart failure, the application uses an Artificial Neural Network (ANN) model saved in a file called model.pkl. For diabetes, it uses an XGBoost model saved in another file, like diabetes model.pkl. These files store the trained models in the backend to make accurate predictions.

Users enter their health details into the application, and the models process this information to predict the risks of heart failure and diabetes. The web application also has a section explaining how to use it and how it works. Finally, it shows the results in a clear and user-friendly way, making it helpful for both patients and healthcare providers.

Chapter 4

Results and Discussions

4.1 Analysis and explanations related to heart failure prediction:

In our model, the dataset was divided into 70% for training and 30% for testing to ensure robust evaluation. Using the Artificial Neural Network (ANN) model, we achieved a high training accuracy of 97.16%, indicating that the model effectively learned the patterns within the training data. The validation accuracy of 95.08% reflects the model's ability to generalize well to unseen data during the training process. Finally, the model attained a testing accuracy of 97.70%, demonstrating its strong performance and reliability in predicting outcomes on entirely new data, highlighting its efficacy in real-world applications.

CONFUSION MATRIX =

$$\begin{bmatrix} 239 & 1 \\ 12 & 314 \end{bmatrix}$$

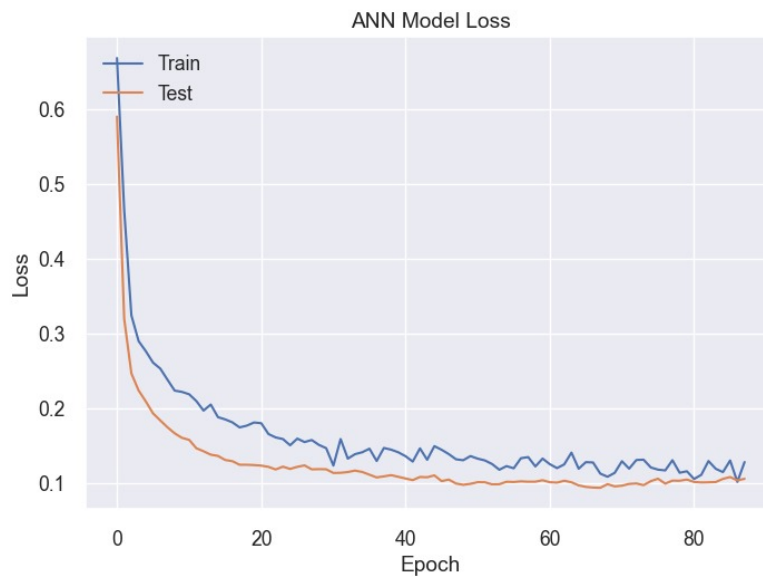


Figure 4.1: Overview of training (blue) and testing (orange) loss curves, both decreasing and stabilizing, indicating good model performance.

the loss curves of the ANN model during training and testing across multiple epochs. Initially, both losses start high and decrease rapidly as the model learns from the data, stabilizing after a few epochs. The training loss is slightly lower than the testing loss, indicating that the model generalizes well without significant overfitting. The minimal gap between the two curves further reflects a well-trained model with balanced performance on both training and testing datasets.

In the dataset, there are 1886 samples, and we used 30% for testing in our model. 30% of 1886 is approximately 565.8, which is rounded to 566. In our model, we used a confusion matrix for these 566 samples. A confusion matrix explains the performance of machine learning and deep learning algorithms. From the model's predictions, it shows the number of accurate and inaccurate predictions. It includes the following four outcomes: true positive (T.P.), true negative (T.N.), false positive (F.P.), and false negative (F.N.). In our case, the positive class is 1 (heart failure occurs), and the negative class is 0 (heart failure does not occur). Based on our confusion matrix, the following values are obtained:

- T.P. = 314: The model correctly predicted that heart failure occurs.
- T.N. = 239: The model correctly predicted that heart failure does not occur.
- F.P. = 1: The model predicted that heart failure occurs, while it actually does not.
- F.N. = 12: The model predicted that heart failure does not occur, while it actually does.

The accuracy is given by:

$$\text{Accuracy} = \frac{T.N. + T.P.}{F.P. + F.N. + T.P. + T.N.}$$

$$\text{Accuracy} = \frac{239 + 314}{1 + 12 + 314 + 239} = 0.977$$

The error rate is:

$$\text{Error rate} = 1 - \text{Accuracy} = 1 - 0.977 = 0.023$$

Precision is calculated as:

$$\text{Precision} = \frac{T.P.}{T.P. + F.P.}$$

$$\text{Precision} = \frac{314}{314 + 1} = 0.996$$

Recall is calculated as:

$$\text{Recall} = \frac{T.P.}{F.N. + T.P.}$$

$$\text{Recall} = \frac{314}{314 + 12} = 0.963$$

Model	Accuracy
ANN	97.703180
Random Forest	97.173145
K-Nearest Neighbour	96.466431
Support Vector Machine	89.399293
Logistic Regression	86.572438
Gaussian Naive Bayes	85.865724

Figure 4.2: The experimental results of the algorithm used for heart failure prediction.

4.2 Analysis and explanations related to Diabetes prediction:

4.2.1 Diabetes Prediction Using XGBoost

1. **Significance of Diabetes Prediction:** Early prediction of diabetes is crucial for preventing complications and reducing healthcare costs. XGBoost, a powerful gradient-boosting algorithm, excels in handling structured data, making it ideal for accurate and reliable diabetes prediction.
2. **Preprocessing and Feature Selection:** Effective preprocessing, such as handling missing values, normalizing data, and addressing imbalances (e.g., using SMOTE), is essential for robust predictions. XGBoost's inherent feature importance metrics help identify critical factors like glucose levels, BMI, and age, enhancing model interpretability and performance.
3. **Model Optimization and Performance Metrics:** Hyperparameter tuning (e.g., learning rate, tree depth, and estimators) improves model performance while avoiding overfitting. Metrics such as accuracy, precision-recall, and AUC-ROC are used to evaluate the model's effectiveness in distinguishing diabetic and non-diabetic cases.
4. **Comparative and Interpretability Analysis:** XGBoost's performance is compared with other models (e.g., logistic regression and random forests) to highlight its efficiency in handling large datasets and missing values. Tools like SHAP values are employed to explain feature contributions, building trust and insights into risk factors.
5. **Challenges and Implications:** The proposed model aids healthcare providers in making informed decisions, paving the way for personalized interventions. Challenges, including data privacy, variability in healthcare datasets, and overfitting risks, need to be addressed for successful deployment in clinical practice.

4.3 Experimental Results

Prediction Form

Age

45

-

+

Sex

☒ Male

☐ Female

Anaemia ?

☒ Yes

☐ No

Creatinine phosphokinase (mcg/L)

4000

-

+

Diabetes

Yes

▼

Ejection fraction %

39

-

+

High blood pressure

☒ Yes

☐ No

Platelets (kiloplatelets/mL)

48099.99

-

+

Serum creatinine (mg/dL)

6.28

-

+

Serum sodium (mEq/L)

117

-

+

Smoking

☒ Yes

☐ No

Time (follow-up-period)

55

-

+

Prediction of Survival in Patients with Heart Failure

How does it work ?

Complete all the questions and the Deep learning model(Artificial Neural Network) will predict the survival of patients with heart failure

These are the values you entered

```
{  "Age" : 45  "Sex" : "Male"  "Anaemia" : "Yes"  "Creatinine phosphokinase (mcg/L)" : 4000  "Diabetes" : "Yes"  "Ejection fraction %" : 39  "High blood pressure" : "Yes"  "Platelets (kiloplatelets/mL)" : 48099.99  "Serum creatinine (mg/dL)" : 6.28  "Serum sodium (mEq/L)" : 117  "Smoking" : "Yes"  "Time" : 55}
```

Predict

Results

The patient will live

Figure 4.3: Overview of the heart failure prediction GUI: the first image shows the user input interface, and the second image displays the results generated after processing the input.

Enter the Following parameters :

Pregnancies:

0

Glucose :

0.044

BloodPressure :

12

Triceps skin fold thickness (mm):

16

Insulin :

5

Body mass index :

23

DiabetesPedigreeFunction :

4

Age :

23

predict

Figure 4.4: (a) User Input Interface

diabete Disease Prediction



No need to fear. You have no dangerous symptoms of the diabete disease

Back Home

Figure 4.5: (b) Results Display Interface

Figure 4.6: Overview of the diabetes prediction GUI: (a) shows the user input interface, and (b) displays the results generated after processing the input.

Chapter 5

Conclusions and Future Scope

5.1 Conclusion

In this study, we developed a comprehensive prediction system that leverages advanced machine learning and deep learning techniques to predict two critical health conditions—heart failure and diabetes. For heart failure prediction, an artificial neural network (ANN) demonstrated superior accuracy compared to traditional machine learning models like KNN, SVM, Logistic Regression, and Gaussian Naive Bayes. Similarly, for diabetes prediction, the XGBoost algorithm emerged as the most effective model, outperforming alternatives such as Random Forest and LightGBM.

Our approach incorporated a user-friendly graphical user interface (GUI), enabling seamless interaction with the predictive models. This interface is designed to support healthcare professionals and individuals by providing an intuitive platform for early risk assessment and management. The high accuracy and accessibility of our system indicate its potential for significant real-world impact in aiding timely diagnosis and treatment.

The success of this project demonstrates the power of integrating machine learning algorithms with practical applications to address pressing healthcare challenges. It sets the stage for future advancements, including scaling the system for other diseases, optimizing algorithms for faster responses, and improving accessibility through mobile applications. This project serves as a step forward in leveraging technology for better healthcare outcomes.

5.2 Future scope

- **Expansion to Other Diseases:** Enhance the application by integrating predictive models for additional diseases like hypertension, kidney diseases, or cancer. This will make the tool more comprehensive and increase its utility.
- **AI Model Optimization:** Regular updates with new and diverse datasets will enable the models to adapt to changing healthcare trends and improve predictions. Additionally, optimizing algorithms will reduce processing time, ensuring quicker responses for users and a seamless experience.
- **Mobile App Development:** Developing a mobile-friendly version of the web application ensures that users can access predictions and health insights conveniently on their smartphones. This increases accessibility, especially for users in remote areas or those who prefer using mobile devices over desktops, enhancing the application's reach and usability.

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