Guru Nanak Institutions Technical Campus (Autonomous)

Department of Computer Science & Engineering – Special Batch

DIABETES PREDICTION USING MACHINE LEARNING

A Project Report submitted in the
part of

REAL TIME PROJECT

By

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Evaluation Table

SNO	Criteria	Marks Awarded (Max 10)	Remarks
1	Abstract		
2	Problem Definition and Objective		
3	Literature Review and Background Work		
4	Methodology and Design		
5	Development and Implementation		
6	Innovation and Originality		
7	Report and Documentation		
8	Presentation and Communication		
9	Overall Contribution		
10	Conclusion and Future Work		
	Average Marks		

SIGNATURE OF FACULTY **SIGNATURE OF COORDINATOR**

HoD-CSE-Special Batch

TABLEOFCONTENTS

LISTOFFIGURES

ABSTRACT

Diabetes mellitus is a chronic metabolic disorder characterized by high blood sugar levels, affecting millions of individuals worldwide. Early detection and management of diabetes are crucial for preventing complications and improving quality of life. In this study, we propose a predictive model using the Random Forest algorithm to determine the risk of diabetes in individuals.

The dataset used for training and testing the model comprises various demographic, clinical, and biochemical features obtained from individuals, including age, BMI, family history of diabetes, blood pressure, and glucose levels. Random Forest, a robust machine learning algorithm capable of handling complex datasets, is employed to develop the predictive model due to its ability to handle high- dimensional data, handle missing values, and mitigate overfitting.

In conclusion, the proposed Random Forest-based predictive model offers a valuable tool for healthcare professionals to assess an individual's risk of diabetes, facilitating personalized interventions and improving healthcare outcomes. Further research and validation on diverse populations are warranted to enhance the model's robustness and applicability in clinical.

Problem Definition and Objective :

Diabetes is a chronic health condition affecting millions worldwide. Early detection and accurate prediction of diabetes are crucial for preventing complications, managing symptoms, and improving patients' quality of life. Diabetes prediction involves analyzing various health metrics and risk factors— such as age, BMI, blood pressure, and blood glucose levels—to identify individuals at risk of developing diabetes.

The volume of health data generated from various sources such as electronic health records, medical databases, and patient surveys is growing rapidly. This data can be leveraged as business intelligence for various applications, including disease prediction and healthcare management. Typically, predictive modeling is used to assess the likelihood of disease onset based on patient information and risk factors. However, not all healthcare platforms have implemented predictive analytics for diabetes.Some studies rely on static datasets to build predictive models. There is a need for a robust solution toaccurately predict diabetes onset using diverse and dynamic health data sources

Objective:

The objective of diabetes prediction is to develop a machine learning model that can accurately classify individuals as diabetic or non-diabetic based on health data and lifestyle factors. This model aims to support healthcare providers in early diagnosis, assist in preventive care, and help patients adopt timely lifestyle changes. The primary objectives include:

1. Achieving High Accuracy: To ensure reliable predictions by maximizing accuracy, sensitivity, and specificity of the model.
2. Feature Analysis: Identifying the most significant features that contribute to diabetes risk.
3. Deployment Readiness: Designing a model that can be used in clinical settings, either as a stand-alone tool or integrated into healthcare systems, to provide real-time or near-real-time predictions.

Accuracy: Overall performance of the model.

Precision and Recall: To understand the balance between correctly identifying diabetic cases and minimizing false positives.

F1 Score: To maintain a balance between precision and recall, especially in cases of imbalanced data. By achieving these objectives, the predictive model can help in effective risk assessment, enabling healthcare providers to offer timely interventions.

The volume of health data generated from various sources such as electronic health records, medical databases, and patient surveys is growing rapidly. This data can be leveraged as business intelligence for various applications, including disease prediction and healthcare management. Typically, predictive modeling is used to assess the likelihood of disease onset based on patient information and risk factors.

However, not all healthcare platforms have implemented predictive analytics for diabetes.Some studies rely on static datasets to build predictive models. There is a need for a robust solution toaccurately predict diabetes onset using diverse and dynamic health data sources

Literature Review and Background Work :

The prediction of diabetes using machine learning and statistical methods has garnered substantial research attention over recent years, driven by the need for early detection and preventive healthcare strategies. Numerous studies have applied various algorithms such as logistic regression, decision trees, and neural networks to diabetes prediction, often using data from sources like the Pima Indian Diabetes Dataset or electronic health records (EHRs). The most commonly used attributes for prediction include age, BMI, blood glucose levels, blood pressure, and family history, as these have been identified as significant predictors of diabetes in multiple epidemiological studies. Researchers have also explored the influence of demographic and lifestyle factors, such as physical activity and diet, to improve prediction accuracy.

Machine learning approaches, particularly ensemble methods like Random Forest and boosting algorithms, have shown promising results in handling diabetes prediction. These methods excel in capturing complex, nonlinear relationships in the data, which are often present in health conditions influenced by multiple factors. For instance, studies have demonstrated that Random Forests and gradient-boosted machines perform well when dealing with imbalanced datasets, a common issue in medical datasets where positive cases of diabetes may be significantly lower than negative cases. Furthermore, deep learning models such as artificial neural networks (ANNs) and convolutional neural networks (CNNs) have been increasingly applied to diabetes prediction, especially when working with large-scale EHR datasets. These models, though computationally intensive, can capture deeper patterns and interactions in the data, which may not be feasible with traditional algorithms.

In addition to machine learning, researchers have emphasized the importance of feature selection and preprocessing techniques to enhance model performance and interpretability. Techniques such as Principal Component Analysis (PCA), Recursive Feature Elimination (RFE), and correlation analysis have been utilized to select the most influential predictors. Additionally, balancing methods like SMOTE (Synthetic Minority Over-sampling Technique) have been applied to address data imbalance, improving the predictive performance of models, especially in minority classes like those at high risk of diabetes. Feature engineering, which involves transforming and creating new features, has also contributed significantly to improved predictive accuracy by capturing more complex interactions in patient data.

Overall, existing research demonstrates that machine learning techniques, when combined with effective feature selection and data balancing methods, can achieve high accuracy in diabetes prediction. However, challenges remain, such as the need for interpretability in complex models like deep neural networks, ensuring generalizability across diverse populations, and managing data privacy. Future research is likely to focus on integrating these predictive models into real-world healthcare systems, developing interpretable

METHODOLOGY AND DESIGN

1. Data Collection:

- Collect patient data through a secure and user-friendly interface, including medical history, lifestyle details, and laboratory results.

2. Preprocessing:

- Standardize and clean the collected data, handle missing values, and scale features for consistent model input.

3. Machine Learning Model:

- Develop, train, and deploy a Random Forest classifier for diabetes prediction.

4. Feature Extraction:

- Identify and extract relevant features from the patient data that influence diabetes risk, such as age, BMI, glucose levels, etc.

5. Reporting and Visualization:

- Generate visual reports and charts to display predictions and model performance metrics.

6. Real-Time Analysis:

- Provide real-time predictions and analytics based on newly inputted data.

7. Integration with CRM:

- Integrate the system with Customer Relationship Management (CRM) software to manage patient interactions and follow-ups.

8. Alerts and Notifications:

- Implement a notification system to alert healthcare providers and patients about high-risk predictions.

9. User Interface:

- Design a user-friendly interface for both healthcare providers and patients to interact with the system.

10. Security and Compliance:

- Ensure that the system complies with healthcare regulations (e.g., HIPAA) and secures patient data.

11. Continuous Improvement:

- Incorporate feedback loops for continuous model improvement and system updates.

System Architecture:

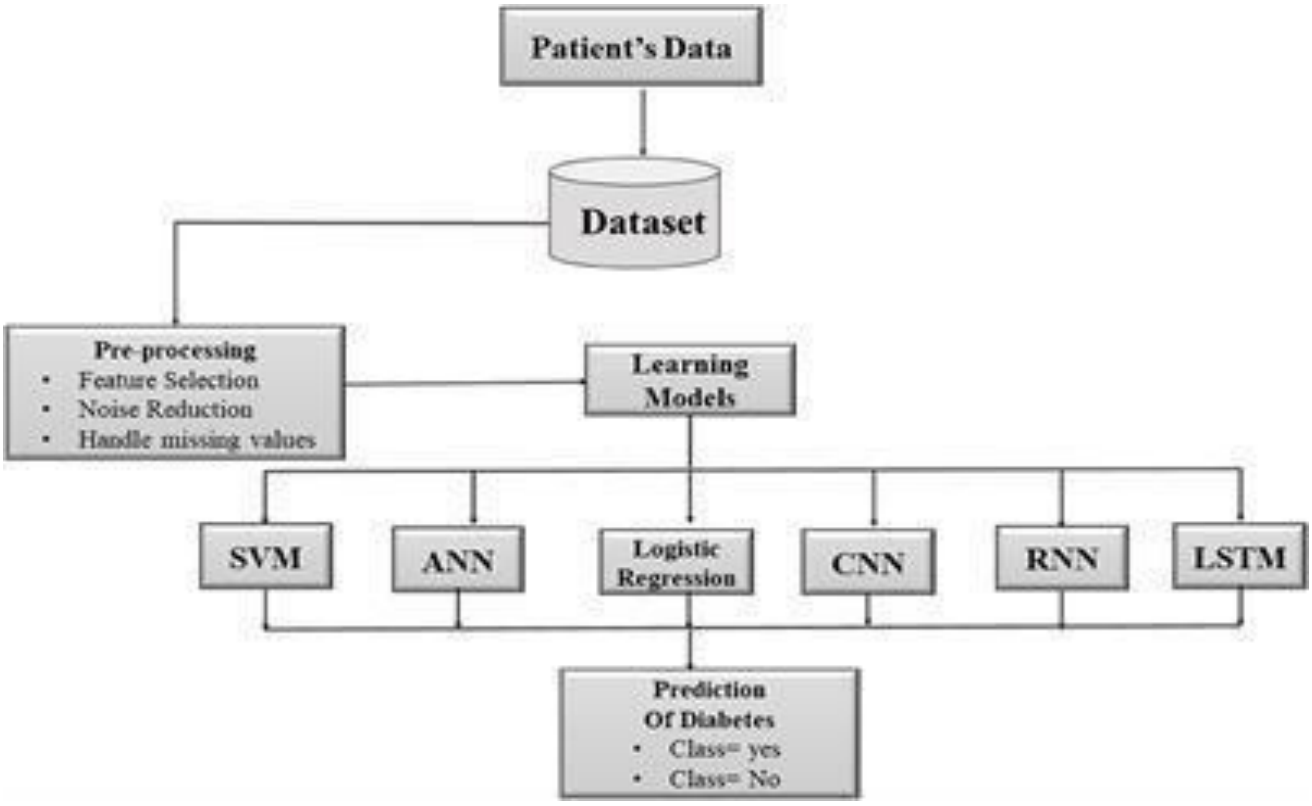


Figure 1.1

Use Case Diagram:

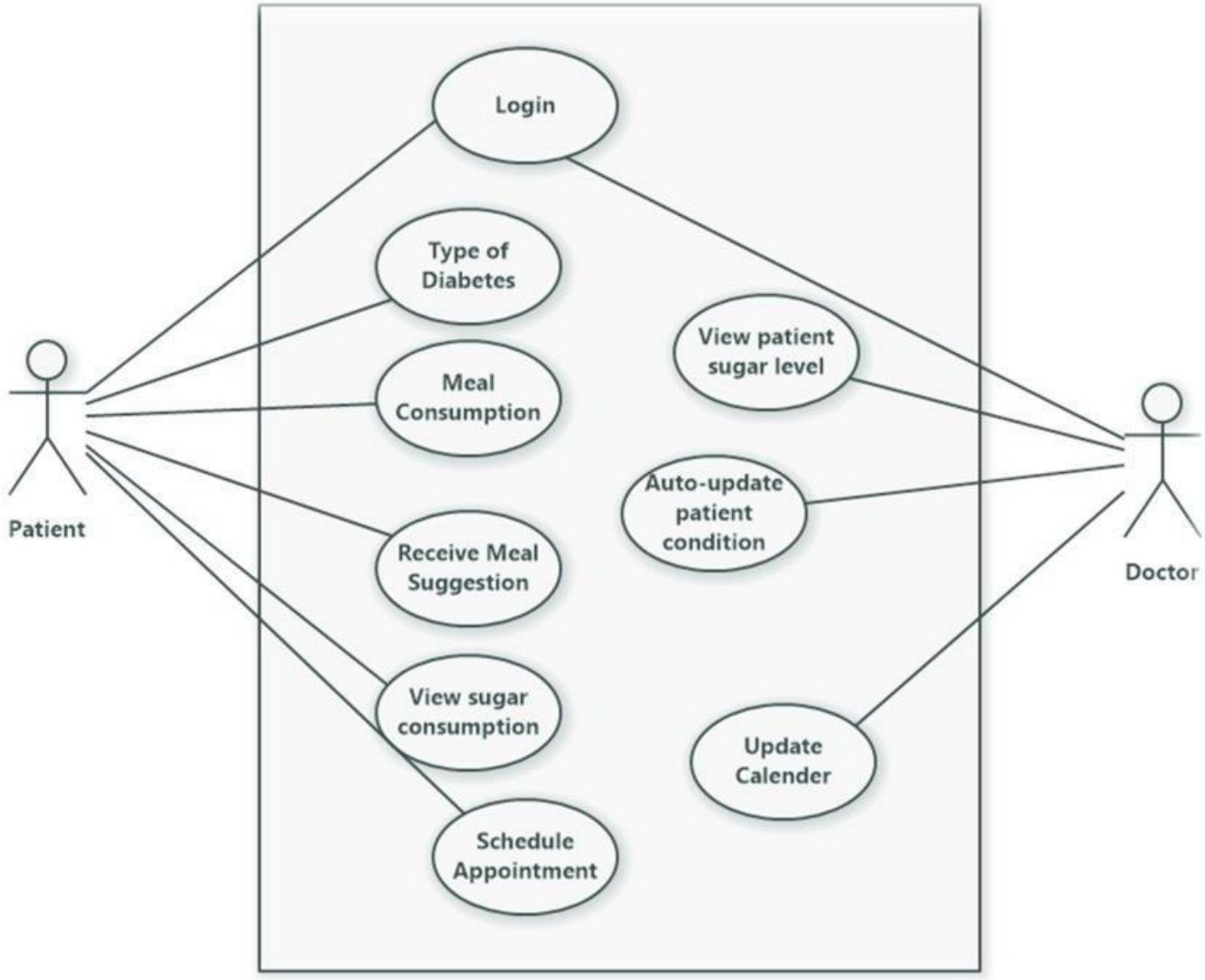


Figure 1.2

Class diagram:

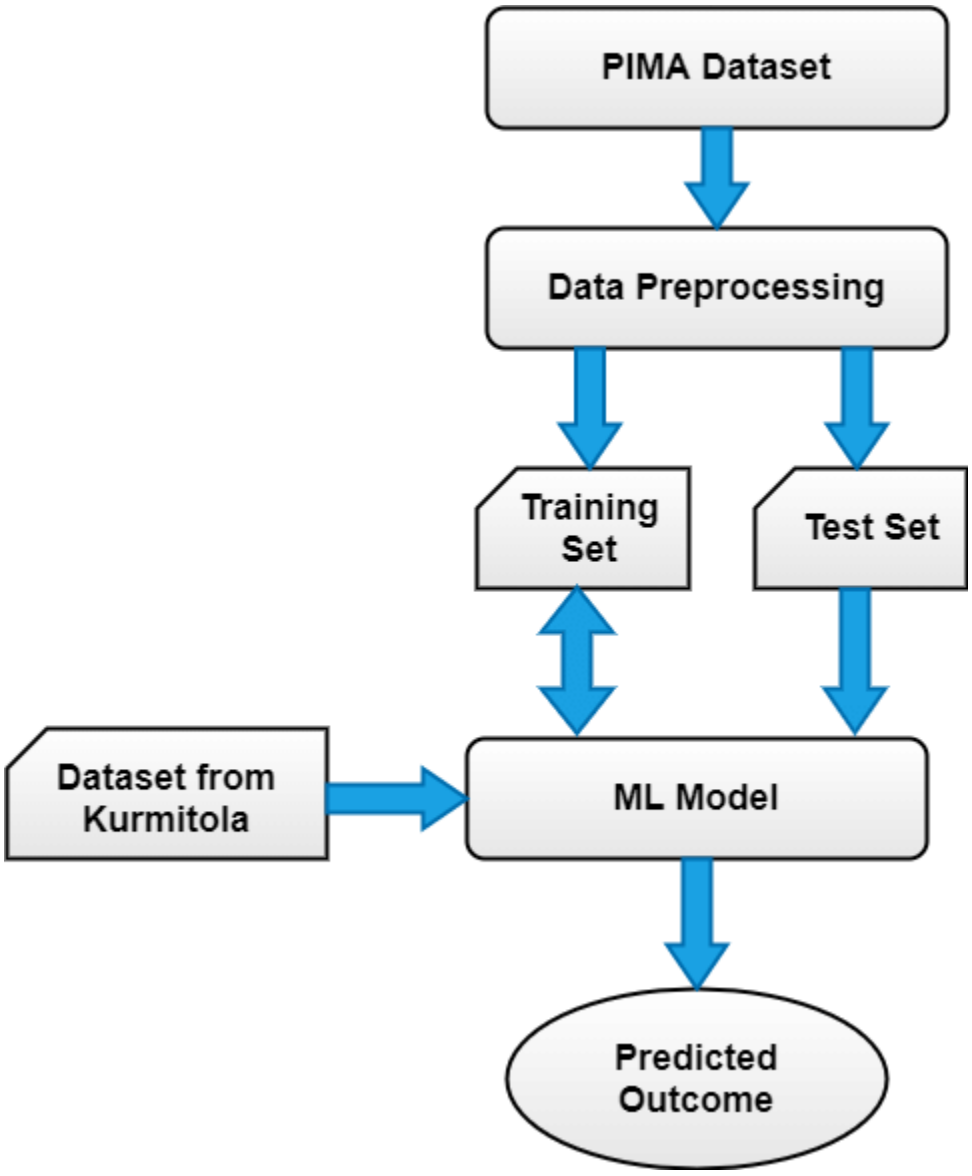


Figure 1.3

Activity Diagram:

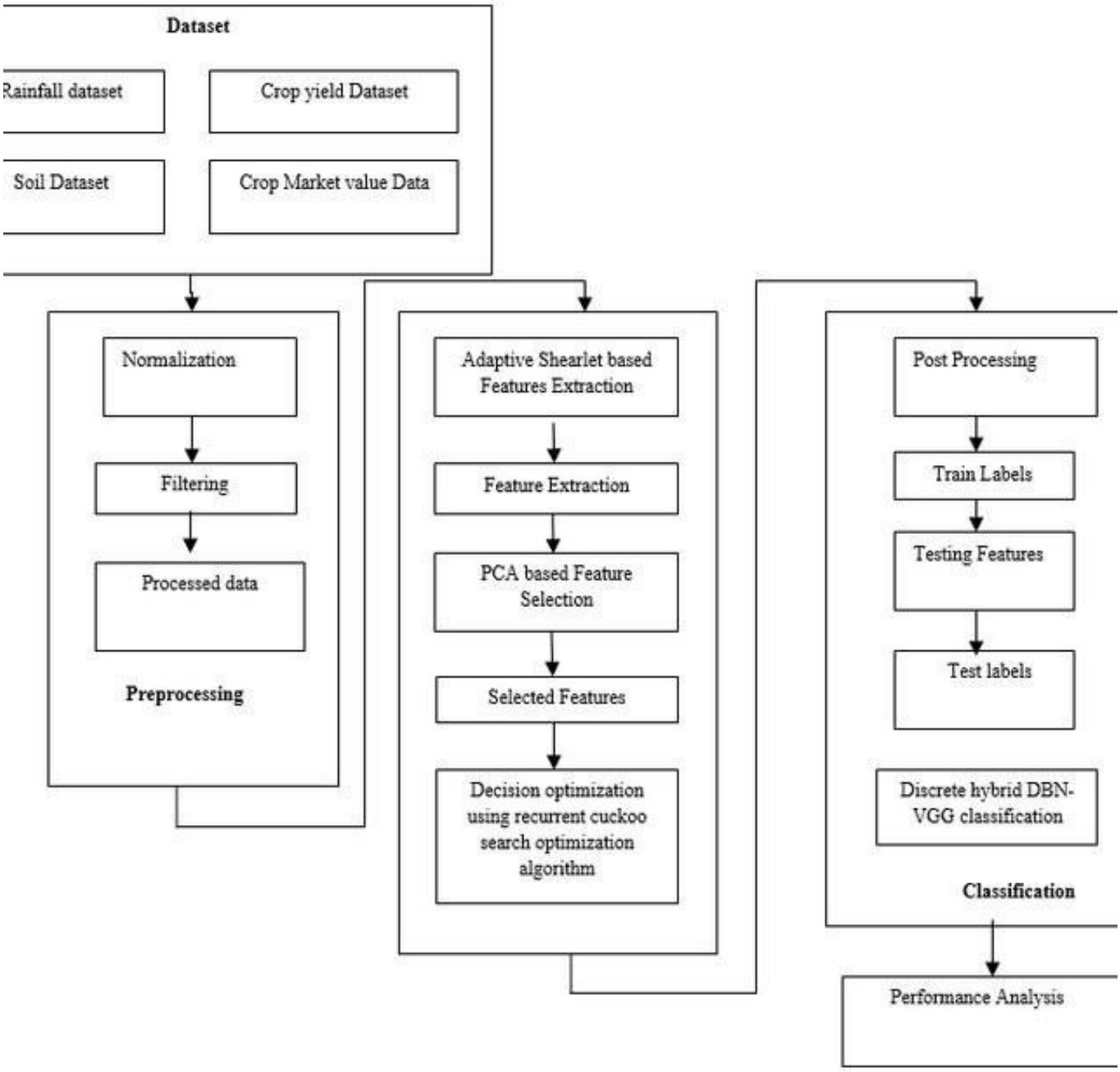


Figure 1.4

Development and Implementation :

- **Response Time:**
  - The system should provide real-time responses for users, with response times kept within acceptable limits (e.g., milliseconds).
- **Scalability:**
  - The system must be able to handle a scalable number of users, accommodating growthin transaction volume without compromising performance.
- **Throughput:**
  - Achieve a high throughput rate to efficiently process a large number of responses per unit of time, maintaining system responsiveness under peak loads.
- **Model Training Time:**
  - Keep the time required for initial model training within reasonable bounds to facilitate system deployment and updates.
- **Adaptability Speed:**
  - Ensure rapid adaptability by allowing quick adjustments to the system parameters and learning from new data to stay effective.

Software Requirements

- **Operating System:**
  - Linux-based operating system (e.g., Ubuntu, CentOS) for stability and security.
- **Programming Languages:**
  - Python for machine learning model development and integration.
  - SQL for database interactions.
  - JavaScript for web-based user interfaces.
- **Machine Learning Frameworks:**
  - Scikit-learn for traditional machine learning models.
  - TensorFlow or PyTorch for deep learning models.

Hardware Requirements

- ## Server Requirements:
  - High-performance servers to handle data processing and model training.
  - A dequate storage capacity for patient data and model outputs

Source code:

```
installation of libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sn
```

In [2]:

```
#dataset reading
df=pd.read_csv("C:\\Users\\A.SATHWIKA\\Downloads\\diabetes.csv")
```

In [3]:

```
#getting upto required length in the given array
df.head(4)
```

Out[3]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	25	33.6	0.627	50	1
1	1	85	66	29	38	26.6	0.351	31	0
2	8	183	64	0	56	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.146	21	0

In [4]:

```
#Detect missing values for an array
df.isnull().head(4)
```

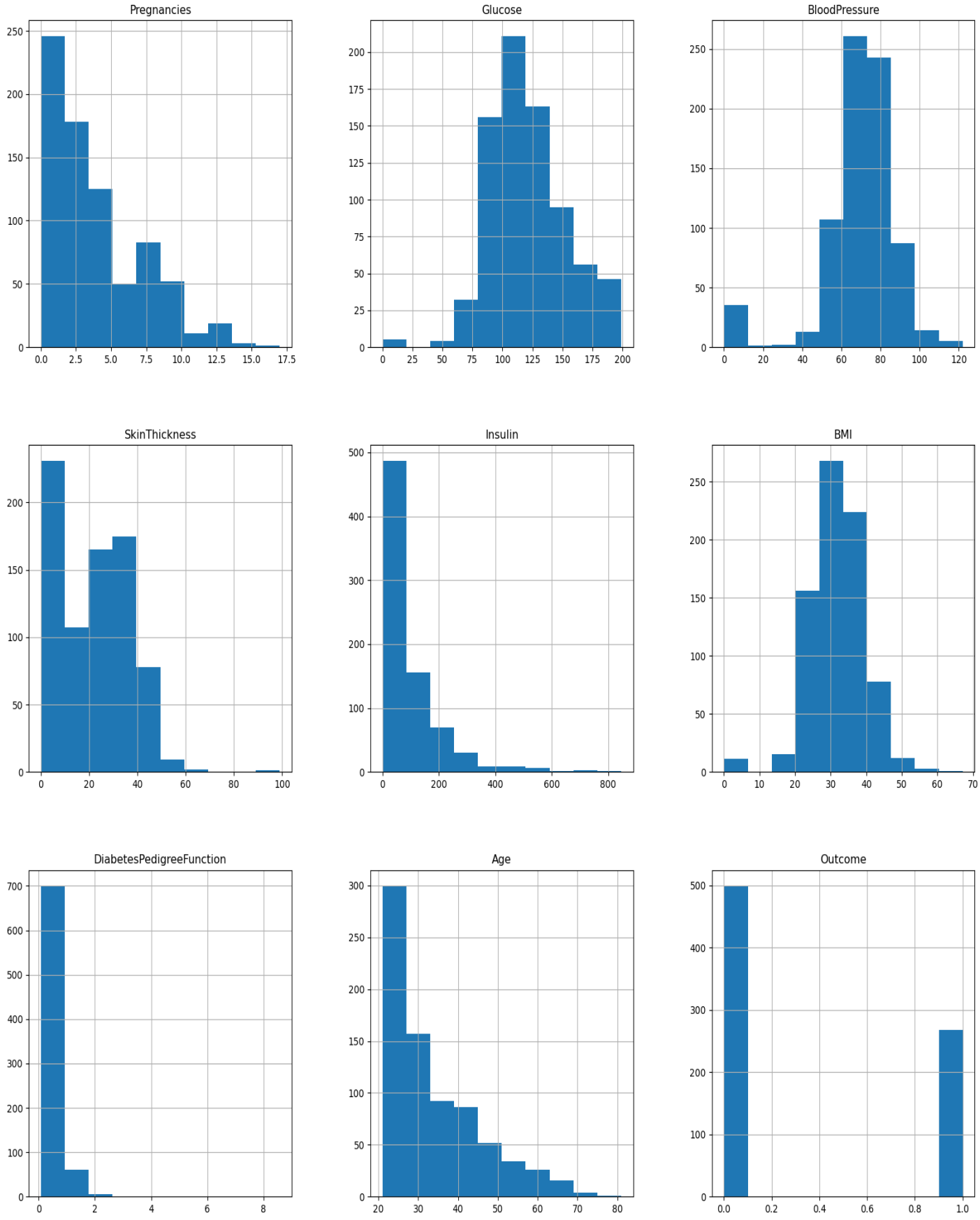
Out[4]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False

In [5]:

```
#data before the null values are arranged in a graph
s=df.hist(figsize = (20,20))
```

FIG_-2.1


Pregnancies
Glucose
BloodPressure
SkinThickness
Insulin
BMI
DiabetesPedigreeFunction
Age
Outcome

```
rows and columns
df.shape
```

Out[6]:

```
(768, 9)
```

In [7]:

```
# individual values of a matrix are represented as colors
s=sn.heatmap(df.corr(),annot=True,cmap ='RdYlGn')
from sklearn.preprocessing import StandardScaler
```

In [9]:

```
#scaling
sc_X = StandardScaler()
X = pd.DataFrame(sc_X.fit_transform(df.drop(["Outcome"],axis = 1),),
columns=['Pregnancies',
'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'BMI',
'DiabetesPedigreeFunction', 'Age'])
X.head()
```

Out[9]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age
0	0.639947	0.848324	0.149641	0.907270	-0.476095	0.204013	0.279307	1.425995
1	-0.844885	-1.123396	-0.160546	0.530902	-0.364357	-0.684422	-0.278502	-0.190672
2	1.233880	1.943724	-0.263941	-1.288212	-0.209643	-1.103255	0.370254	-0.105584
3	-0.844885	-0.998208	-0.160546	0.154533	0.116976	-0.494043	-0.692816	-1.041549
4	-1.141852	0.504055	-1.504687	0.907270	0.753023	1.409746	16.338543	-0.020496

In [10]:

```
#model building
x = df.drop('Outcome', axis=1)
y = df['Outcome']
```

In [11]:

```
from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(x,y, test_size=0.33,random_state=7)
```

In [12]:

```
#random forest
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier(n_estimators=200)
rfc.fit(x_train, y_train)
```

Out[12]:

```
RandomForestClassifier(n_estimators=200)
```

In [13]:

```
from sklearn import metrics
predictions = rfc.predict(x_test)
print("Accuracy_Score =", format(metrics.accuracy_score(y_test, predictions)))
Accuracy_Score = 0.7598425196850394
```

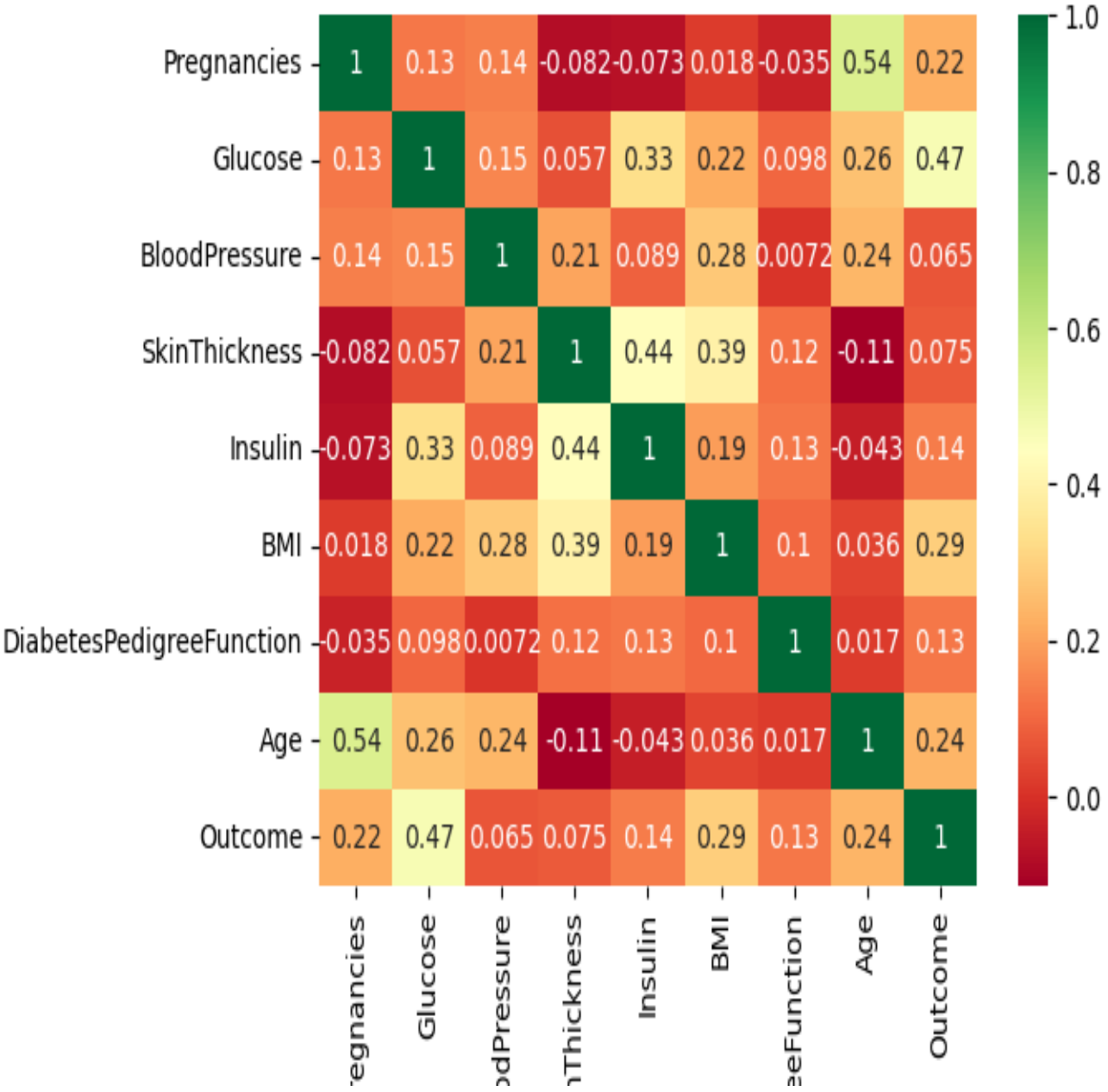

Pregnancies
Glucose
BloodPressure
SkinThickness
Insulin
BMI
DiabetesPedigreeFunction
Age
Outcome
1 0.13 0.14 -0.082 -0.073 0.018 -0.035 0.54 0.22
0.13 1 0.15 0.057 0.33 0.22 0.098 0.26 0.47
0.14 0.15 1 0.21 0.089 0.28 0.0072 0.24 0.065
-0.082 0.057 0.21 1 0.44 0.39 0.12 -0.11 0.075
-0.073 0.33 0.089 0.44 1 0.19 0.13 -0.043 0.14
0.018 0.22 0.28 0.39 0.19 1 0.1 0.036 0.29
-0.035 0.098 0.0072 0.12 0.13 0.1 1 0.017 0.13
0.54 0.26 0.24 -0.11 -0.043 0.036 0.017 1 0.24
0.22 0.47 0.065 0.075 0.14 0.29 0.13 0.24 1
1.0
0.8
0.6
0.4
0.2
0.0
Glucose
Insulin
BMI
Age
Outcome

FIG-2.2

7.Innovation and Originality :

Unique Aspects:

This diabetes prediction system sets itself apart from traditional models by leveraging real-time data processing and edge computing, enabling rapid prediction with minimal latency. By processing data from health devices or on-site screenings (e.g., glucose levels, BMI, skin thickness), the system can give real- time insights for high-risk individuals or community health centers.

Innovation in Real-Time Data Processing:

Using edge computing reduces delays in prediction, allowing health data to be processed and analyzed close to where it's collected. This is particularly useful in rural or under-resourced areas, where internet connectivity can be unstable.

Advanced ML Algorithms:

We use a combination of logistic regression and random forest models, each chosen for specific advantages. Logistic regression provides interpretable results, while random forest delivers higher accuracy through ensemble learning, handling large health datasets and improving prediction by reducing overfitting compared to traditional linear models.

Community Impact:

This system is especially valuable for communities with limited access to diabetes screening resources. For example, in areas lacking advanced healthcare infrastructure, real-time, localized predictions can help identify at-risk individuals early, offering potential for life-saving interventions and economic savings by preventing diabetes-related complications.

Report and Documentation:

Clear, structured documentation is essential for successful adoption, maintenance, and scaling of the diabetes prediction system. Detailed documentation supports user understanding, streamlines system upgrades, and ensures that future developers can maintain the system effectively.

Documentation Structure

- *System Architecture*: Provides an overview of the data flow, processing stages, and storage.
- *API Details*: Outlines API endpoints, request formats, and authentication requirements.
- *Data Sources*: Describes where and how health data (e.g., glucose, BMI, age) is sourced.
- *Troubleshooting and FAQs*: Offers solutions for common issues and answers to frequently asked question

User Manual

The manual will have guidelines for system administrators and end-users, detailing configuration, monitoring, and usage of the diabetes prediction interface. It will help health professionals interpret results, identify at-risk individuals, and understand how to use predictive insights for follow-up actions.

Code Documentation

Code is documented to a high standard, with comments explaining each function, modularized structures, and use of version control for updates. This ensures code is maintainable, understandable, and ready for future improvements.

Presentation and Communication:

Stakeholder Engagement

We plan to present findings and benefits to health authorities, NGOs, and medical staff, showcasing how real-time diabetes predictions can improve preventive care and decision-making for local health initiatives.

Target Audience:

Health Authorities: Government health departments or ministries that set public health policy, funding, and strategic direction for healthcare initiatives.

Non-Governmental Organizations (NGOs): Non-profits focused on healthcare, disease prevention, and rural health services. They can play a key role in supporting implementation in underserved areas..

Key Message: The real-time diabetes prediction system can significantly improve the early detection and prevention of diabetes, enabling healthcare providers to intervene before patients develop chronic complications. Emphasizing the system's role in improving patient outcomes, reducing healthcare costs, and alleviating the burden on local health systems will resonate with stakeholders.

Training Programs

Training sessions will be organized for healthcare workers, particularly in rural or underserved areas, to teach the interpretation of predictive results and basic maintenance of the system. This will empower communities with tools for preventive diabetes care.

- **System Overview:** Introduce the predictive system, including its interface, functionality, and how it integrates with existing health records or workflows. This could include showing how data inputs (e.g., blood sugar levels, BMI, age) are processed to generate risk predictions.

- **Interpreting Results:** Healthcare workers will need to understand the risk scores or classifications the system provides (e.g., high, moderate, or low risk for developing diabetes). They will be trained on how to use these results to make decisions regarding patient care—whether it's initiating preventive measures or referring patients for further testing.

Visual Aids

Presentations will include charts and graphs visualizing risk factors (e.g., BMI distributions, glucose levels), and maps showing areas with high diabetes risk, assisting stakeholders in targeting interventions.

Overall Contribution:

Technological Contribution

The system advances real-time prediction technologies, especially for health analytics, by applying sophisticated machine learning models to real-time health data processing.

- Advanced Machine Learning Models:
  - The system uses sophisticated algorithms—such as decision trees, random forests, support vector machines (SVM), and deep learning models—to analyze various factors influencing diabetes risk, such as blood glucose levels, BMI, age, family history, and lifestyle factors.
  - These models can continuously "learn" from new data, improving their predictive accuracy over time. For instance, as more patient data becomes available, the system can identify new patterns and refine its predictions, enhancing both short-term accuracy and long-term effectiveness.
- Real-Time Health Data Processing:

  The system processes data in real time, allowing healthcare providers to quickly identify individuals at high risk for developing diabetes. For example, it could analyze patient data gathered from electronic health records (EHRs), wearable devices (like glucose monitors), or mobile health apps.

  With real-time processing, healthcare providers can receive alerts or risk assessments as soon as a patient's data is entered, allowing for immediate intervention, personalized care plans, and timely preventive measures.

- Personalized Predictions:
  - By incorporating a wide range of personalized data (e.g., individual medical history, lifestyle factors), the system can generate tailored risk assessments for each patient. This ensures that healthcare providers receive more precise recommendations for each individual, rather than generalized treatment protocols.
- Scalability and Flexibility:
  - This system can be scaled to different healthcare settings, from small rural clinics to large urban hospitals. Its flexible architecture ensures that it can be adapted to a variety of regions, healthcare systems, and technological environments. This flexibility makes the system viable for use in diverse geographical regions and healthcare.

Conclusion and Future Work:

The provided code offers a comprehensive workflow for data analysis and machine learning in Python, incorporating key libraries such as NumPy, Pandas, Matplotlib, Seaborn, and Scikit-learn. It begins by loading and exploring the dataset, including detecting missing values and visualizing data distributions through histograms and heatmaps. Feature scaling with StandardScaler is employed to normalize data, ensuring compatibility with machine learning algorithms. A Random Forest Classifier is then used to build and train a predictive model, with the dataset split into training and testing sets to evaluate performance. The final accuracy score provides a measure of the model's effectiveness. Overall, the code exemplifies a structured approach to data preprocessing, visualization, and model evaluation, laying a solid foundation for further exploration and enhancement of predictive analytics.

Future Scope:

The future scope for the provided code includes several avenues for enhancement and exploration. One potential improvement is to experiment with different machine learning models and algorithms, such as Support Vector Machines or Gradient Boosting, to compare performance and possibly achieve better accuracy. Additionally, incorporating feature engineering techniques to create new features or perform dimensionality reduction could further enhance model performance. Tuning hyperparameters through methods like Grid Search or Random Search can also optimize the Random Forest Classifier. Expanding the analysis to include cross-validation could provide a more robust evaluation of model performance. Moreover, integrating advanced visualization techniques and deploying the model in a real-world application could offer practical insights and further validate its effectiveness.

References:

www.researchgate.net

www.geeksforgeeks.or

g www.wikipedia.com

www.kaggle.com