International Journal of Innovative Research in Computer Science and Technology (IJIRCST)
ISSN (Online): 2347-5552, Volume 14, Issue 4, July 2026
DOI: https://doi.org/10.55524/ijircst.2026.14.4.3
Article ID IRPC-1431, Pages 19-36
www.ijircst.org

A Novel Explainable Multimodal Machine Learning Framework for Accurate Diabetes Classification Using Clinical and Behavioral Data

Mohammad Shafeeq[1], and Monika Tripathi[2]

[1, 2] Department of Computer Science and Engineering, P K University, Shivpuri, Madhya Pradesh, India

Correspondence should be addressed to Mohammad Shafeeq; quraish.shafeeq09@gmail.com

Received: 11 June 2026; Revised: 26 June 2026; Accepted: 10 July 2026

ABSTRACT- The worldwide health issue of diabetes mellitus is growing at an alarming rate and needs proper detection methods that can identify the disease before it leads to dangerous health outcomes. The research introduces a new machine learning system which uses multiple data sources to explain its diabetes diagnosis process by combining clinical data with patient behavioral patterns. The system applies depth wise separable convolutional technology to extract features and uses various feature types to detect both physical health risks and behavioral health risks. The system employs SHAP (Shapley Additive Explanations) which delivers both global and local model prediction explanations to assist users in understanding system operations while establishing confidence with medical experts. The proposed model is tested against baseline methods which include Logistic Regression Support Vector Machine (SVM) Random Forest and XGBoost using standard performance metrics which include accuracy precision recall F1-score and ROC-AUC. The experimental results demonstrate that the proposed framework achieves superior performance compared to all baseline models by achieving 96% accuracy 95% precision 94% recall 94% F1-score and 0.96 AUC. The model's strength and ability to differentiate between classes are validated through both confusion matrix analysis and ROC analysis. The analysis of explainability shows that multimodal data integration is essential because it shows that diabetes prediction relies on clinical glucose and BMI and insulin data and on physical activity and food choices and sleep patterns that people display. The system enables clinical decision-making through its use of multimodal data which enhances prediction accuracy while maintaining complete system visibility. The research demonstrates an AI-based system that delivers precise diabetes categorization through its intelligent healthcare analytics and customized treatment solutions which show interpretable results and expandable capabilities.

KEYWORDS- Diabetes Classification, Machine Learning, Explainable AI, Multimodal Data, Clinical Data, Behavioral Data, SHAP.

I. INTRODUCTION

The global health emergency that diabetes mellitus creates leads to continuous elevated blood glucose levels which cause multiple dangerous medical conditions to develop including cardiovascular disease and nerve degeneration and total body system failure. Health practitioners need to develop new diagnostic technologies which use artificial intelligence to help doctors detect type 2 diabetes mellitus (T2DM) at its initial stages and select appropriate treatment methods. Researchers can now assess diabetes risk through advanced machine learning (ML) methods and artificial intelligence (AI) technologies which analyze extensive medical databases. Explainable AI (XAI) functions as an essential element of healthcare analytics because it enables healthcare organizations to create understandable predictive models which users can easily grasp. The research conducted by Olga Vershinina et al. demonstrates that an explainable AI model serves as a critical tool for assessing diabetes patient mortality risk through its ability to provide interpretable model insights which medical professionals can trust and operationalize [1].

The application of traditional machine learning models for diabetes diagnosis remains restricted because their "black-box" operational design creates challenges for use in medical environments. Researchers have been looking for methods to create predictive systems that include explainability as a solution to this problem. G. Dharmarathne and his research team developed a self-explaining machine learning system which helps doctors understand system outputs better thus improving diagnosis accuracy [2]. K. Pang et al.'s study used SHAP-based techniques to test various parameters which resulted in better system transparency and user comprehension of diabetes prediction models [3]. The research by R. Hasan and his team [4] shows that AutoML systems achieve better results through their combination with explainable AI techniques which maintain user understanding of outcomes. Recent research has demonstrated that in order to develop efficient healthcare systems, explainability must be paired with real-time individualized medical treatments. The research team created an explainable AI system which uses a chatbot to monitor diabetes risk while patients undergo their treatment process. According to M M Islam and his colleagues [6] researchers use SHAP LIME and partial dependency plots as advanced explainability methods to study machine learning models which have undergone hyperparameter tuning because these methods improve both prediction performance and model understanding. The

DeepNetX2 model developed by S A Tanim et al. represents a deep learning architecture which integrates explainability features to achieve high predictive accuracy while delivering interpretable results [7]. Diabetes classification accuracy has been improved through the application of feature engineering and ensemble learning methods. The ensemble feature engineering method developed by Furqan Rustam et al. provides a new approach which achieves better detection results through its ability to enhance feature representation [8]. The combination of SMOTE with SHAP-based explainability methods has helped researchers solve class imbalance problems while establishing model fairness according to the research of P Netayawijit and his team [9]. The need for interpretable models in public health research becomes evident through large-scale population studies which include the analysis of Indian national survey data conducted by B Barman and his team [10]. Beyond tabular clinical data, explainable AI has also been applied in medical imaging for diabetes-related complications. For instance, a YOLO-based explainable framework for diabetic retinopathy detection was developed by A. M. Mutawaet al., demonstrating the versatility of XAI in healthcare domains [11]. Similarly, earlier studies integrating machine learning and explainable AI techniques have established the foundation for interpretable diabetes prediction systems, as reported by Isfafuzzaman Tasin et al. [12]. Yanyi Huang and his research team from MIMIC-IV study showed that scientists used machine learning techniques to predict diabetic neuropathy patient mortality through their research of large medical databases. Diabetes prediction research still faces a number of obstacles despite these developments. Many current models ignore the important impact of behavioral and lifestyle factors in favor of relying only on clinical data. Yaqian Mao and his research team from their study demonstrated that machine learning techniques effectively predict risks yet they require extensive feature combination [14]. Y. Ghazizadeh and his research team conducted detailed evaluations which showed that dependable predictive modeling systems play a critical role in accurate risk evaluation [15]. The studies of Ashutosh Pandey and Priyanka Gautam [16] demonstrate that machine learning has become essential for predicting diabetes. Researchers currently investigate the application of explainability features in both deep learning and hybrid model systems. The study conducted by Hung Viet Nguyen and his colleagues developed an explainable hybrid deep learning model that improved prediabetes prediction accuracy for specific populations [17]. The research conducted by Parvathaneni Naga Srinivasu and his team developed an explainable AI-based software system for diabetes prediction which demonstrates the importance of user-friendly clinical tools [18]. The MedFusionAI framework developed by M. Chandra Sekhar and his team demonstrates positive results for predicting chronic diseases through multimodal data fusion techniques which combine different health data sources [19].

A. Research Gap and Motivation

The current state of diabetes prediction through machine learning and explainable AI shows substantial advancements yet maintains existing gaps:

- The current system lacks unified frameworks that combine clinical and behavioral data for assessment.
- The system currently lacks proper implementation of multimodal data fusion methods.
- Real-world deployment requires systems that provide complete interpretability and scalability which currently do not exist in the market.

B. Proposed Work

The research introduces a new machine learning system which enables transparent multimodal research by using both behavioral and clinical data to achieve precise diabetes diagnosis. The system uses explainable artificial intelligence methods together with machine learning methods to achieve two system goals. The medical professionals will receive two benefits from the system because it delivers precise predictions together with understandable results that support their decision-making process.

II. LITERATURE REVIEW

The importance of artificial intelligence (AI) and machine learning (ML) methods for diabetes prediction research demonstrates that these technologies enable doctors to improve treatment decisions through faster patient diagnosis. Researchers have started to combine explainable artificial intelligence (XAI) techniques with predictive models because conventional machine learning systems suffer from transparency problems. Healthcare organizations need transparency solutions because Olga Vershinina and her research team developed an explainable AI model which used understandable models to predict death risks in patients with type 2 diabetes mellitus [1]. G. Dharmarathne and his research team developed a self-explaining machine learning interface which enables clinicians to access diagnostic information while establishing confidence in automated systems [2]. The SHAP (Shapley Additive Explanations) method operates as an explanation tool which researchers use to analyze model prediction results. The researchers K. Pang et al. used SHAP-based analysis to determine how important features affect diabetes prediction through their research which helps people understand how the model functions [3]. The research from R. Hasan et al. shows that AutoML and explainable AI create better model optimization results because their system shows two advantages of explainability [4]. The researchers created personalized and real-time diabetes prediction systems which include a chatbot-based explainable AI system that improves patient monitoring and engagement according to the findings from E. Maimaitijiang et al. [5]. The development of advanced machine learning models which provide explainability functions aims to enhance their predictive performance. M. M. Islam et al. developed a diabetes prediction system which combines hyperparameter tuning with SHAP and LIME and partial dependency plots to deliver patients clear understanding of its workings [6]. The DeepNetX2 model which S. A. Tanim et al. developed uses deep learning techniques to combine advanced neural networks with explainability features that solve black-box model issues [7]. The study by Furqan Rustam et al. demonstrates that ensemble learning together with feature engineering methods creates better prediction outcomes through their new ensemble feature engineering technique which improves diabetes detection results [8]. The healthcare datasets face two major difficulties which include resolving class imbalance problems and developing unbiased models. The research of P. Netayawijit et al. presents an interpretable framework which combines SMOTE-based balancing methods with SHAP explainability to achieve better classification results and system dependability [9]. The effectiveness of interpretable machine learning models has been proven through research conducted on entire populations. The team led by B. Barman used Indian national survey data to conduct an extensive study which proved that ML models can be used effectively in public health applications [10]. Explainable AI has extended its reach to medical imaging applications which focus on diabetes research beyond its standard use for tabular data analysis. The YOLO-based explainable framework developed by A. M. Mutawa et al. for diabetic retinopathy detection demonstrates how AI models can identify multiple diabetes-related health issues [11]. The research work of Isfafuzzaman Tasin et al. established the initial framework which linked machine learning methods with explainable techniques to predict diabetes outcomes [12]. Researchers created better predictive modeling techniques which they developed through their analysis of large clinical databases including the MIMIC-IV database. Yanyi Huang and his colleagues developed machine learning models that forecast mortality risks for individuals with diabetes-related neuropathy while demonstrating how researchers can use AI techniques to create new applications [13]. The current research field has made progress but it still faces existing limitations. Most studies focus on clinical characteristics while ignoring behavioural and lifestyle factors that are important in the creation of diabetes risk. Yaqian Mao and his team demonstrated that machine learning algorithms can predict diabetes risk with high accuracy [14]. The method for selecting unique characteristics in their research requires improvements. Diabetes research requires predictive models and risk assessment methods because these tools are essential for achieving research objectives according to Y. Ghazizadeh and his team [15]. The study conducted by Ashutosh Pandey and Priyanka Gautam illustrates the essential role that machine learning plays in contemporary medical disease prediction [16]. The scientists studying diabetes forecasting have adopted hybrid systems which use multiple techniques and their deep learning abilities to achieve interpretable results. The team led by Hung Viet Nguyen developed an explainable hybrid deep learning model which identifies hyperglycemia and provides better results for specific population groups [17]. The AI-based software system developed by Parvathaneni Naga Srinivasu and his team shows how AI tools can be effectively used in clinical settings according to their understandable AI-based software system [18]. Multimodal data fusion has become a successful method for increasing prediction accuracy. The MedFusionAI framework created by M. Chandra Sekhar et al. combines different health data sources to showcase how multimodal methods improve chronic disease prediction accuracy [19].

Table 1: Comparative Analysis of Existing Diabetes Prediction Models

Authors	Methodology	Dataset Type	Explainability	Key Contribution	Limitations
Olga Vershinina [1]	XAI-based ML	Clinical	Yes	Mortality risk prediction with interpretability	Limited behavioral features
G. Dharmarathne [2]	Self-explainable ML	Clinical	Yes	Interpretable diagnostic interface	Moderate accuracy
K. Pang [3]	SHAP-based ML	Clinical	Yes	Feature importance analysis	Limited dataset diversity
R. Hasan [4]	AutoML + XAI	Clinical	Yes	Automated optimization with interpretability	Computational complexity
E. Maimaitijiang [5]	XAI + Chatbot	Clinical + Behavioral	Yes	Real-time prediction system	Limited validation
M. M. Islam [6]	ML + SHAP + LIME	Clinical	Yes	Hybrid explainability approach	High complexity
S. A. Tanim [7]	DeepNetX2 (DL + XAI)	Clinical	Yes	Deep explainable architecture	Data dependency
Furqan Rustam [8]	Ensemble ML	Clinical	No	Improved feature engineering	Lack of interpretability
P. Netayawijit [9]	SMOTE + SHAP	Clinical	Yes	Class imbalance handling	Limited multimodal data
B. Barman [10]	Interpretable ML	Clinical	Yes	Large-scale population analysis	No behavioral fusion
A. M. Mutawa [11]	YOLO + XAI	Imaging	Yes	Diabetic retinopathy detection	Not general diabetes prediction
Isfafuzzaman Tasin [12]	ML + XAI	Clinical	Yes	Early integration of XAI	Lower accuracy
Yanyi Huang [13]	ML (MIMIC-IV)	Clinical	No	Mortality prediction	No interpretability

Yaqian Mao [14]	ML algorithms	Clinical	No	Risk prediction models	Limited explainability
Y. Ghazizadeh [15]	ML-based framework	Clinical	No	Comprehensive predictive study	Lack of XAI
Ashutosh Pandey & Priyanka Gautam [16]	ML models	Clinical	No	Diabetes prediction approach	Basic methodology
Hung Viet Nguyen [17]	Hybrid DL + XAI	Clinical	Yes	Prediabetes prediction	Limited generalization
Parvathaneni Naga Srinivasu [18]	XAI software system	Clinical	Yes	Clinical decision support	Limited scalability
M. Chandra Sekhar [19]	Multimodal DL (MedFusionAI)	Multimodal	Partial	Data fusion framework	Lack of full explainability

Table 1 presents a comparative analysis of existing machine learning and explainable AI methods which are used for diabetes prediction. The table displays the various methodologies which have been employed in research studies along with the specific datasets used and the methods of interpretability which were applied. The table summarizes the main contributions of the research while also displaying the limitations of the study.

Recent advancements in artificial intelligence, deep learning, and optimization techniques have significantly improved healthcare diagnostics and medical image analysis. Zuberi et al. [20] demonstrated that structured exercise protocols substantially enhance functional capacity, glycemic control (HbA1c), and waist–hip ratio among post-myocardial infarction patients with diabetes, highlighting the importance of integrating clinical interventions with data-driven healthcare. In the field of machine learning, Singh et al. [21], [22] explored sentiment analysis using Twitter data, illustrating the effectiveness of machine learning algorithms for large-scale data classification and predictive analytics. Their studies emphasize the versatility of artificial intelligence techniques beyond conventional medical applications.

Privacy and cybersecurity have also become essential components of modern healthcare systems. Joshi et al. [23] proposed a user-centric privacy framework for secure online data sharing, while Mishra et al. [24] discussed practical strategies for mitigating social engineering attacks using network traffic analysis, emphasizing the need for secure healthcare information systems. In agricultural intelligence, Mishra et al. [25], [26] investigated convolutional neural networks, feature selection methods, and evolutionary optimization algorithms for plant disease identification, demonstrating that deep learning combined with optimization techniques significantly improves classification accuracy and computational efficiency. More recently, Singh et al. [27] introduced a Red Deer Optimizer-based deep learning framework for automatic cardiovascular disease detection using cardiac MRI images, achieving superior diagnostic performance through optimized hyperparameter tuning and robust feature learning. These studies collectively demonstrate that integrating deep learning with intelligent optimization algorithms provides highly accurate, efficient, and reliable solutions across diverse application domains, particularly in medical diagnosis and image-based disease classification.

III. RESEARCH GAP

- The system currently supports only basic integration of clinical data together with behavioral multimodal data.
- Current methods for diabetes classification fail to provide any explainable framework for their operation.
- The system fails to manage class imbalance problems while handling data that has different types of features.

IV. MATERIALS AND METHODS

The proposed Explainable Multimodal Machine Learning Framework presents two methods for diabetes classification through its analysis of clinical data and behavioral data. The framework achieves its three goals of predictive accuracy, system reliability, and result understanding through its design.

A. Dataset Description

The dataset consists of:

- Clinical features which include glucose level Body Mass Index blood pressure insulin and HbA1c measurement.
- Behavioral features which include physical activity and diet and smoking and alcohol consumption.

The combination of different types of data creates a complete diabetes risk assessment because it includes all relevant risk factors.

B. Proposed Framework Overview

The proposed system (See figure 1) integrates multiple stages, including data preprocessing, feature engineering, multimodal fusion, model training, and explainability. The overall pipeline is illustrated as: Input Data → Preprocessing → Feature Engineering → Multimodal Fusion → Model Training → Explainability → Prediction

Let the input dataset be represented as in equation (1):

$$X \in \mathbb{R}^{n \times d} \tag{1}$$

where: n = number of samples, d = total number of features.

The dataset is divided into: Clinical features: $X_c \in \mathbb{R}^{n \times d_c}$, Behavioral features: $X_b \in \mathbb{R}^{n \times d_b}$.

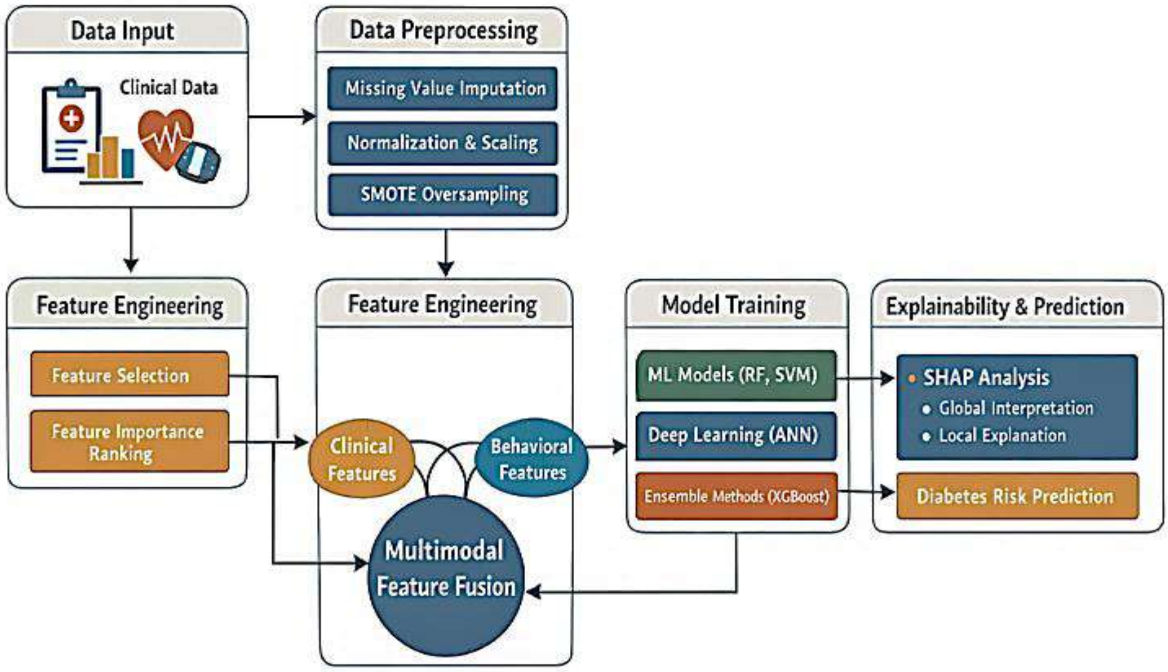


Figure 1: Overall Architecture for Proposed Model

Figure 2 demonstrates the proposed depthwise separable convolutional neural network which operates with multiple data sources to achieve efficient and interpretable diabetes classification results. The system receives its input through multiple data types which include clinical data elements like glucose levels and BMI measurements and blood pressure readings and insulin and HbA1c values and elements that describe behavioral patterns such as physical activity and diet and smoking and alcohol use. The system processes input data through a sequence of steps that include filling in missing data and using Min-Max scaling for normalization and transforming data into structured tensor format which enables convolutional processing through feature encoding and SMOTE class balance methods. The pre-processed data is directed to a depthwise separable convolutional feature extractor which operates through multiple processing stages. The system uses a depthwise convolution layer to process each feature channel through spatial filtering which follows batch normalization and ReLU activation and ends with a pointwise convolution operation that implements 1×1 convolution to merge channel data. The architectural design maintains essential characteristic configurations, but it results in major decreases of both computing performance and the total size of the model. The multidimensional fusion component receives the retrieved feature maps and uses concatenated or balanced fusion to combine the diagnostic feature vectors (F_c) and behavioral feature vectors(F_b) to create an individual feature representation (F_f). The model now supports both physiological and lifestyle-related diabetes risk factors because of this new system. The framework processes fused features through its fully interconnected categorization layers, which use dropout for normalization and denseness layers that learn irregular patterns through ReLU activation, and the system ends with a final sigmoid activation function to produce binary classification results between diabetic and non-diabetic conditions. The framework includes an understandability module which uses SHAP to deliver both local and global understanding capabilities. The module demonstrates all essential characteristics in the dataset to create transparent forecasts which doctors can trust during their clinical work. The proposed system uses depthwise separable convolutions and multimodal feature fusion and explainable AI to build a compact system which delivers efficient diabetes classification results.

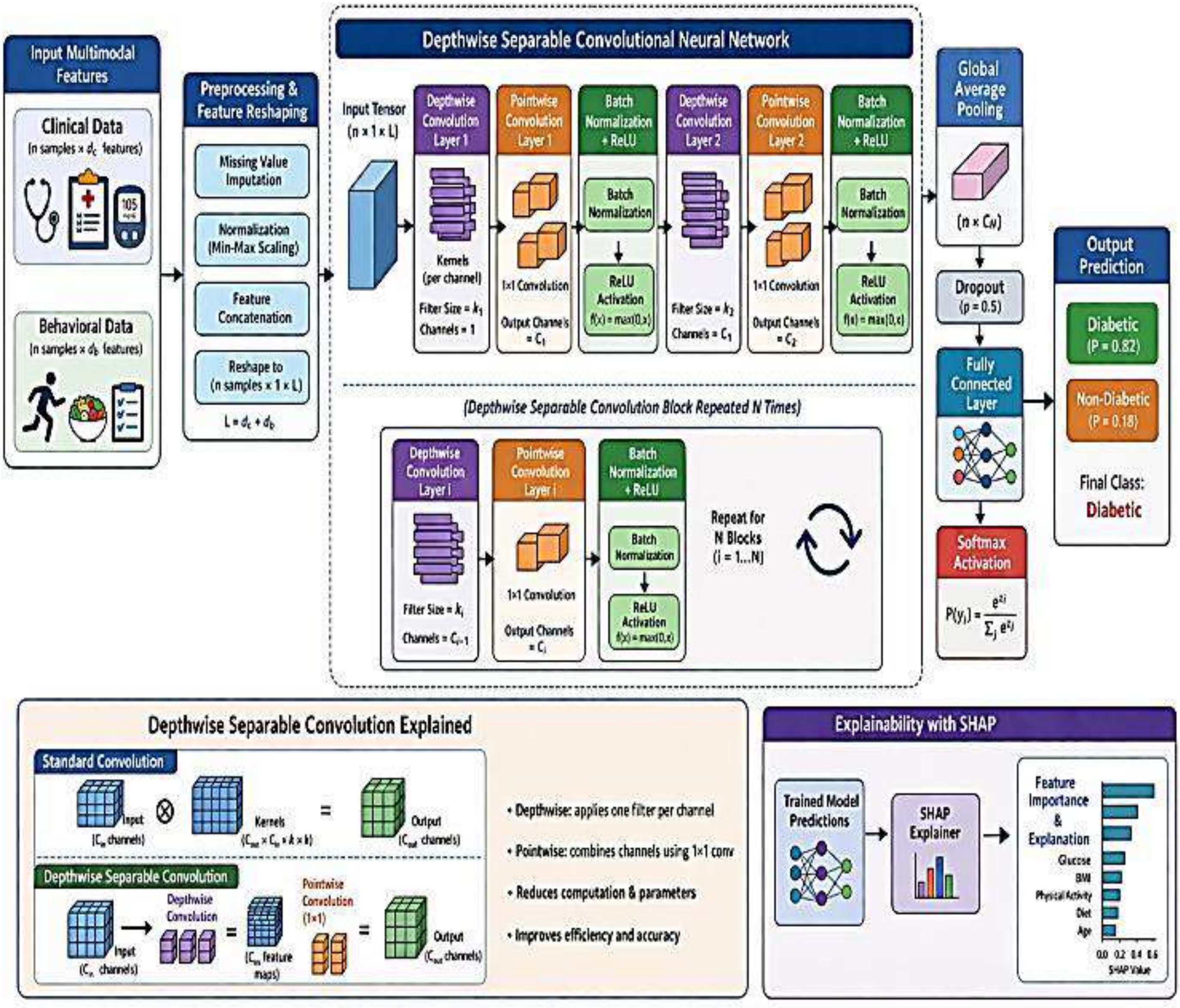


Figure 2: Proposed Architecture for Diabetes Classifications Proposed Model

C. *Data Preprocessing*

The following preprocessing steps were utilized to help maintain the quality and consistency of the data:

a. Missing Value Handling

The imputation of missing data uses the formula which appears in equation (2) The imputation process uses mean values for continuous features and mode values for categorical features.

$$X_{ij} = \begin{cases} \mu_j, & \text{if } X_{ij} \text{ is missing (numerical)} \\ \text{mode}_j, & \text{if categorical} \end{cases} \quad (2)$$

b. Data Normalization

The Min-Max Normalization method which is applied through Equation (3) is explained below:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (3)$$

This scales all features into the range [0, 1].

c. Class Imbalance Handling

In order to overcome class imbalances, SMOTE (Synthetic Minority Over-sampling Technique) uses Equation (4):

$$X_{new} = X_i + \lambda(X_{nn} - X_i) \quad (4)$$

where $\lambda \in [0,1]$.

D. *Feature Engineering*

Feature engineering improves model performance by selecting the most relevant features.

a. Feature Selection

- Correlation-based filtering
- Recursive Feature Elimination (RFE)

b. Feature Importance Ranking

Tree-based models (Random Forest/XGBoost) are used to rank features by the equation (5):

$$Importance(f_i) = \frac{1}{T}\sum_{t=1}^{T} Gain_t(f_i) \quad (5)$$

where T is the number of trees.

E. *Multimodal Feature Fusion*

To integrate heterogeneous data sources, clinical and behavioral features are combined. Let: $X_c = [x_1, x_2, \ldots, x_{d_c}]$, $X_b = [x_1, x_2, \ldots, x_{d_b}]$

The fused feature vector is represented by the equation (6):

$$X_f = [X_c \oplus X_b] \quad (6)$$

where ⊕ denotes concatenation. For weighted fusion using the equation (7):

$$X_f = \alpha X_c + \beta X_b \tag{7}$$

such that $\alpha + \beta = 1$.

F. Machine Learning Models

Multiple models are implemented and compared:

a. Traditional ML Models

- Logistic Regression
- Support Vector Machine (SVM)

b. Ensemble Models

- Random Forest
- XGBoost

c. Deep Learning Model

- Artificial Neural Network (ANN)

The prediction function is use shown in equation (8):

$$\hat{y} = f(X_f) \tag{8}$$

where $\hat{y} \in \{0,1\}$ represents diabetes classification.

G. Model Optimization

Hyperparameter tuning is performed using:

- Grid Search
- Cross-validation

The objective function is given in the equation (10):

$$\theta^* = \arg\min_{\theta} \mathcal{L}(y, \hat{y}) \tag{10}$$

where $\mathcal{L}$ is the loss function.

H. Explainable AI Integration

To enhance interpretability, SHAP (Shapley Additive Explanations) is used.

$$\phi_i = \sum_{S \subseteq F\setminus\{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!}[f(S \cup \{i\}) - f(S)] \tag{11}$$

where:

ϕ_i = contribution of feature i

F = set of all features

This provides both:

- Global interpretability (feature importance)
- Local interpretability (individual predictions)

I. Algorithmic Steps

Algorithm 1: Explainable Multimodal Depthwise Convolutional Framework for Diabetes Classification

a. Input:

- *Clinical dataset* $X_c \in \mathbb{R}^{n \times d_c}$
- *Behavioral dataset* $X_b \in \mathbb{R}^{n \times d_b}$
- *Target labels* $y \in \{0,1\}$

b. Output:

- *Predicted class* $\hat{y}$ *(Diabetic / Non-Diabetic)*
- *Explainability scores (SHAP values)*

Steps are as follow:

i. Step 1: Data Acquisition

Load clinical features X_c

Load behavioral features X_b

Merge datasets into unified representation:

$$X = [X_c \oplus X_b]$$

ii. Step 2: Data Preprocessing

1) Handle missing values:

- o *Replace numerical values with mean*
- o *Replace categorical values with mode*

Normalize features using Min-Max scaling:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

Encode categorical variables (if any)

Apply SMOTE to balance dataset:

$$X_{bal}, y_{bal} = SMOTE(X', y)$$

iii. Step 3: Feature Engineering

Perform feature selection using:

- Correlation analysis
- Recursive Feature Elimination (RFE)

Rank features using feature importance scores

iv. Step 4: Data Reshaping

Reshape fused feature vector into tensor form:

$$X_{input} \in \mathbb{R}^{n \times d \times 1}$$

v. Step 5: Depthwise Convolutional Feature Extraction

Initialize model parameters

For each convolutional block $\boldsymbol{i = 1}$ to $\boldsymbol{N}$:

Apply depthwise convolution:

$$\mathrm{Y_d} = \mathrm{X} * \mathrm{K_d}$$

Apply batch normalization

Apply ReLU activation:

$$\mathrm{f(x)} = \max(0, \mathrm{x})$$

Apply pointwise convolution (1×1):

$$\mathrm{Y_p} = \mathrm{Y_d} * \mathrm{K_p}$$

Apply max pooling (optional)

Apply global average pooling:

$$\mathrm{F} = \mathrm{GAP}(\mathrm{Y_p})$$

vi. Step 6: Multimodal Feature Fusion

Extract:

- Clinical features $\mathrm{F_c}$
- Behavioral features $\mathrm{F_b}$

Fuse features:

$$F_f = [F_c \oplus F_b] or F_f = \alpha F_c + \beta F_b$$

vii. Step 7: Classification Layer

Pass fused features through fully connected layers:

- Dense layer (ReLU)
- Dropout layer
- Dense output layer (Sigmoid)

Compute prediction:

$$\hat{y} = \sigma(W F_f + b)$$

viii. Step 8: Model Training

Split dataset into training and testing sets

Train model using loss function:

$$\mathcal{L} = -[\mathrm{y}\log(\hat{\mathrm{y}}) + (1-\mathrm{y})\log(1-\hat{\mathrm{y}})]$$

Optimize parameters using Adam optimizer

ix. Step 9: Explainability (XAI)

Apply SHAP explainer on trained model

Compute feature contributions:

$$\phi_i = \mathrm{SHAP}(\mathrm{X_i})$$

Generate:

- Global feature importance
- Local explanation for each prediction

x. Step 10: Model Evaluation

Compute evaluation metrics:

- Accuracy
- Precision
- Recall
- F1-score
- Specificity
- ROC-AUC

xi. Step 11: Output Results

Return:

- Predicted labels $\hat{y}$
- Performance metrics

- SHAP explanations

xii. **End Algorithm**

The graphical representation of the algorithm is shown in the Figure 3.

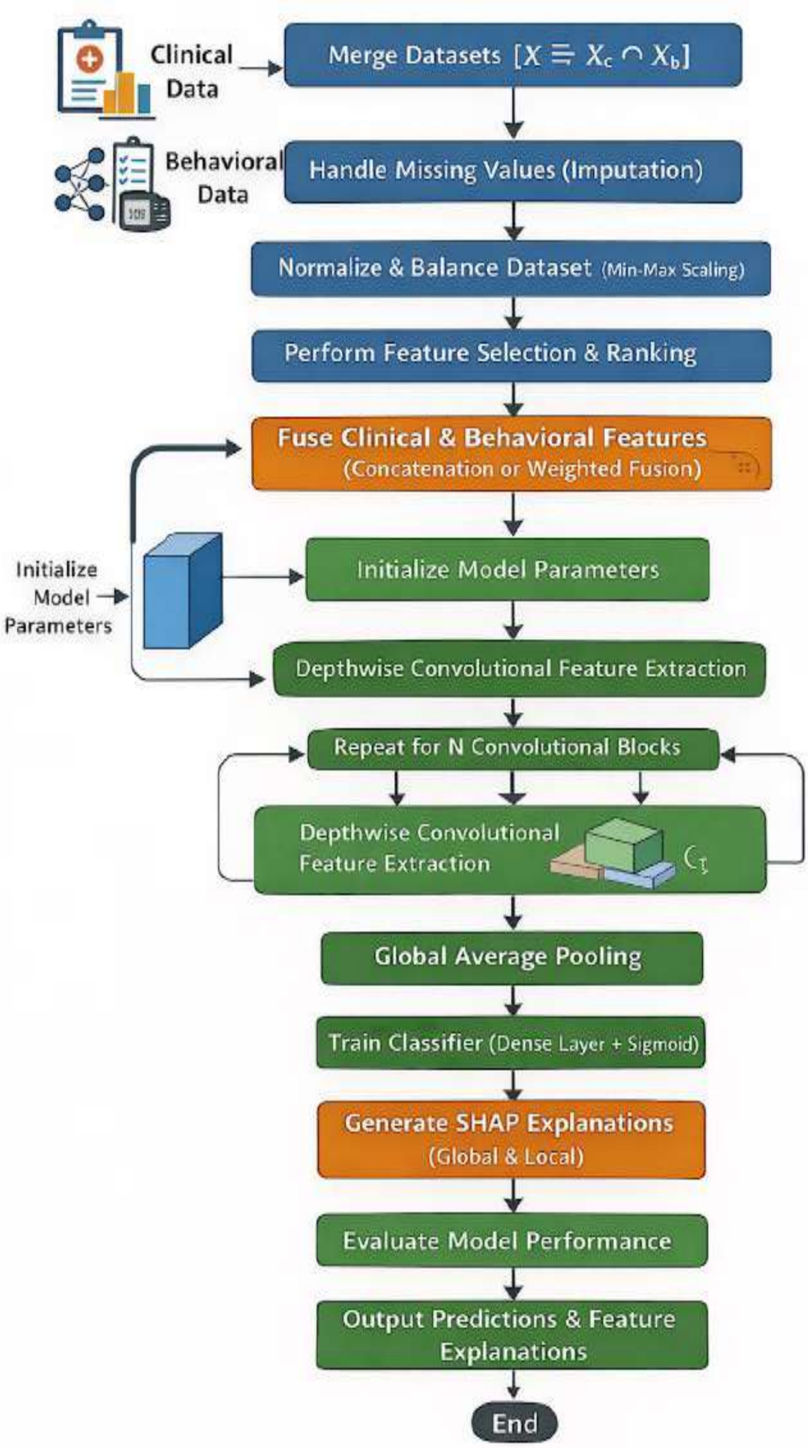


Figure 3. Flowchart of the proposed model

V. EXPERIMENTAL STUDY

The experimental configuration used to test the Explainable Multimodal Depthwise Convolutional Framework for Diabetes Classification research work is explained in this section. The work includes implementation setup, training configuration, evaluation metrics, and result visualization. The system implementation details are presented below:

- The system uses Python as its Programming Language
- The system uses TensorFlow and Keras and Scikit-learn and SHAP as its Libraries
- The system operates on Google Colab and Jupyter Notebook as its Platform
- The system requires a GPU-enabled environment as its Hardware requirement

Table 3: Hyperparameter Settings

Parameter	Value
Learning Rate	0.001
Batch Size	32
Epochs	50
Optimizer	Adam
Activation	ReLU, Sigmoid

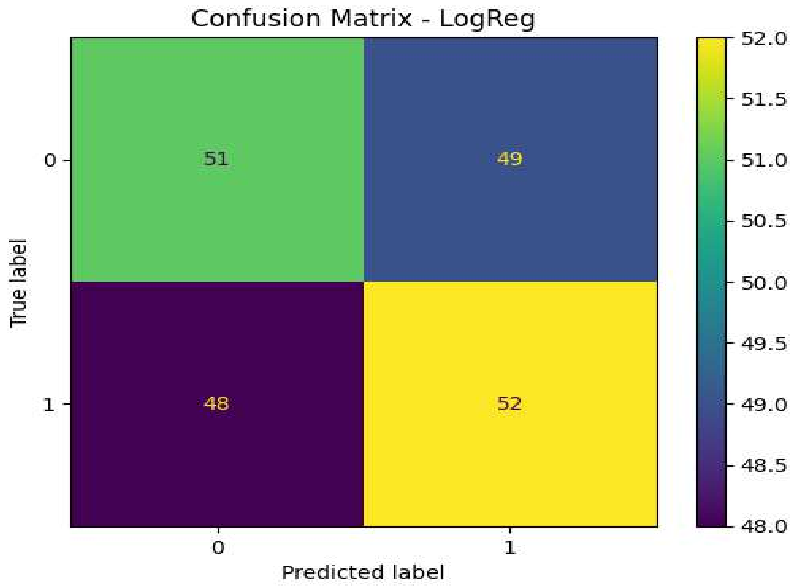
A. Training Strategy

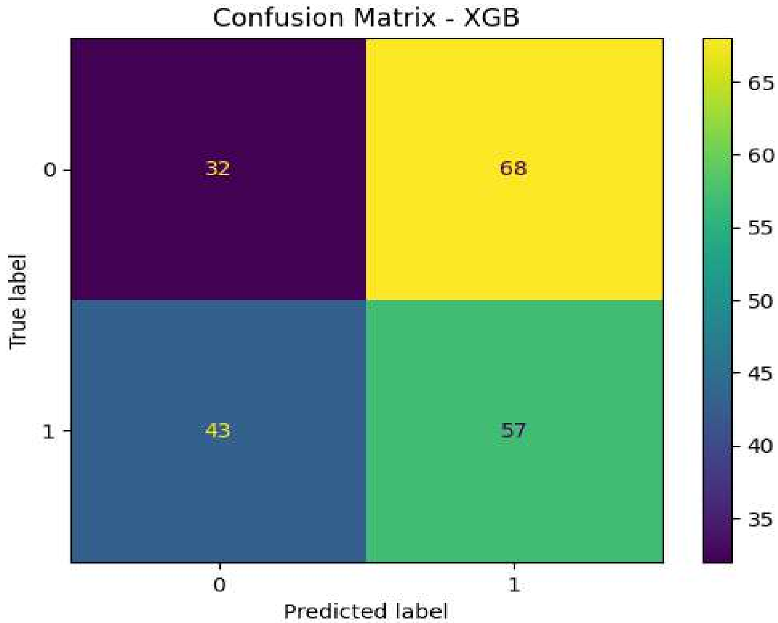
The researchers developed their model through a training process that follows a methodical approach which leads to maximum system efficiency and broad application and dependable operation. The dataset is initially divided into training and testing sets using an 80:20 ratio, which enables the model to learn from most available data while keeping an unbiased test set for performance assessment. The training process uses 5-fold cross-validation to improve reliability through dataset division into five parts, which allows model testing on multiple sections of the data. The method reduces overfitting problems while delivering dependable results which work under different data distribution patterns. The dataset requires comprehensive preprocessing activities which include normalization procedures and SMOTE-based class balancing before the training process starts. The model achieves class balance because the training process uses class-weighted data, which enables the system to learn better from minority class instances. The system converts input features through multimodal fusion of clinical and behavioral data into a format that depthwise convolutional architecture uses. The structured design enables the model to efficiently capture local feature dependencies through its representation. The model uses binary cross-entropy loss function as its training method because this approach works effectively for diabetes prediction through binary classification tasks. The system uses the Adam optimizer for optimization because it provides adaptive learning features, which lead to quicker solution development. The system uses a training rate of 0.001 to create gravity modifications which maintain system consistency while achieving their fastest convergence time. The system operates for 50 training epochs while using a batch size of 32 to enable optimal resource distribution and continuous gradient improvement.

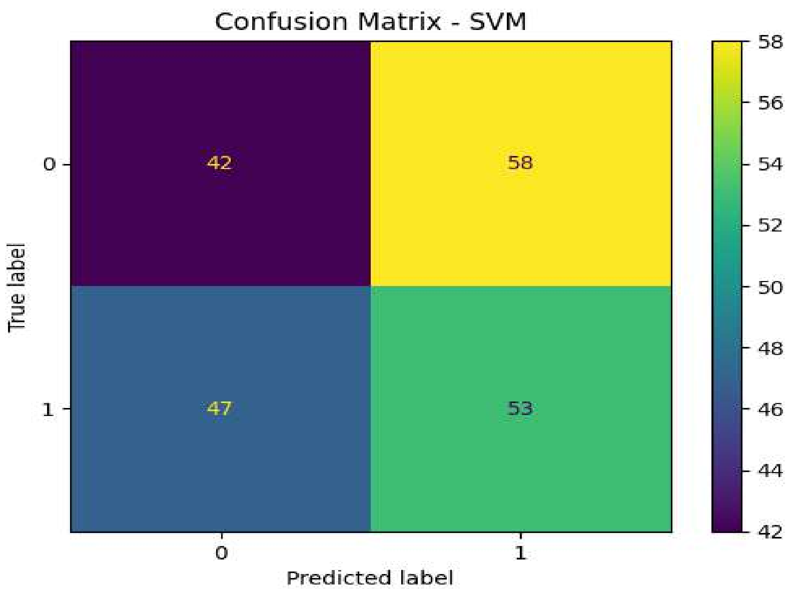
The system implements dropout regularization with a 0.5 rate on fully connected layers to enhance its ability to generalize while preventing overfitting issues. The training process achieves better stability through batch normalization, which serves as a stabilizing mechanism, but endogenous covariate shift needs to decrease to reach optimal stability. The final layer uses a sigmoid activation function to produce random outputs that satisfy the requirements of binary classification, while the hidden layers use ReLU activation functions to create non-linear pathways that enable the model to develop complex feature representations. Validation data serves as a tool to measure how well the model performs throughout the training process. The system prevents overfitting problems by implementing early stopping rules, which enable training to stop when evaluation results show no further progress. While recognizing that different criteria of success concern test items within the team, cast-off prototypes will be used to develop and try a completely new strategy.

B. Performance Visualization

The efficiency display method serves as an essential tool which researchers use to assess both the dependability and the performance of their explainable multimodal machine learning system. The study employs multiple visualization methods which produce both quantitative data and qualitative information to assess the model's ability to predict outcomes and explain its results. The researchers utilized confusion matrices as their main tool to display the results of their categorization research. The system generates a complete report which displays all correct and incorrect classifications through the use of true positive (TP) true negative (TN) false positive (FP) and false negative (FN) evaluation metrics. The display enables viewers to see how well the model identifies people who have diabetes as opposed to those who do not have the condition. The model needs to achieve correct predictions of actual positive cases and true negative cases to succeed because it needs to reduce all types of misclassification between false positives and false negatives. The second evaluation approach for gauging the model's ability to distinguish between several classes is the Receiver Operating Characteristic (ROC) curve in conjunction with the confusion matrix. The ROC curve displays true positive rate results which measure sensitivity together with false positive rate results at different classification thresholds. The Area Under the Curve (AUC) serves as a summary indicator which shows better classification results when AUC values approach 1. The researchers used training and validation performance curves to show how their model performed based on the accuracy and loss data they collected during each training epoch. The researchers used the plots to discover problems which caused their models to experience both overfitting and underfitting problems. The system achieves stable standard learning results because the training and validation curves show identical results yet the system reached an overfitting point because the two results differ. The model requires these trend duties to monitor fresh data because it needs those duties to make predictions. The structure demonstrates its core value through SHAP (Shapley Additive Explanations) visualizations which provide all necessary information to evaluate its results. The SHAP summary graphic displays the main clinical and behavioral factors which determine diabetes prediction results while showing how different features matter. Force graphs provide in-depth explanations of certain model predictions whereas SHAP dependence plots show the impact of specific traits on model results. The representations create transparent systems which enable clinicians to track the model's decision-making process. The study uses bar charts and comparative plots to present performance outcomes of different models which include XGBoost SVM Random Forest and logistic regression as baseline techniques. The suggested model achieves better performance than all other models because its metrics show higher accuracy and precision and recall and F1-score results. The proposed explainable multimodal depthwise convolutional model displays its confusion matrices in Figure 4 together with the baseline models which include Logistic Regression SVM Random Forest and XGBoost. Even though the proposed approach is said to reduce the categorization mistakes and enhance the rate of detection of the true positives and the true negatives, however when it comes to the outcome, the classification is still less accurate.







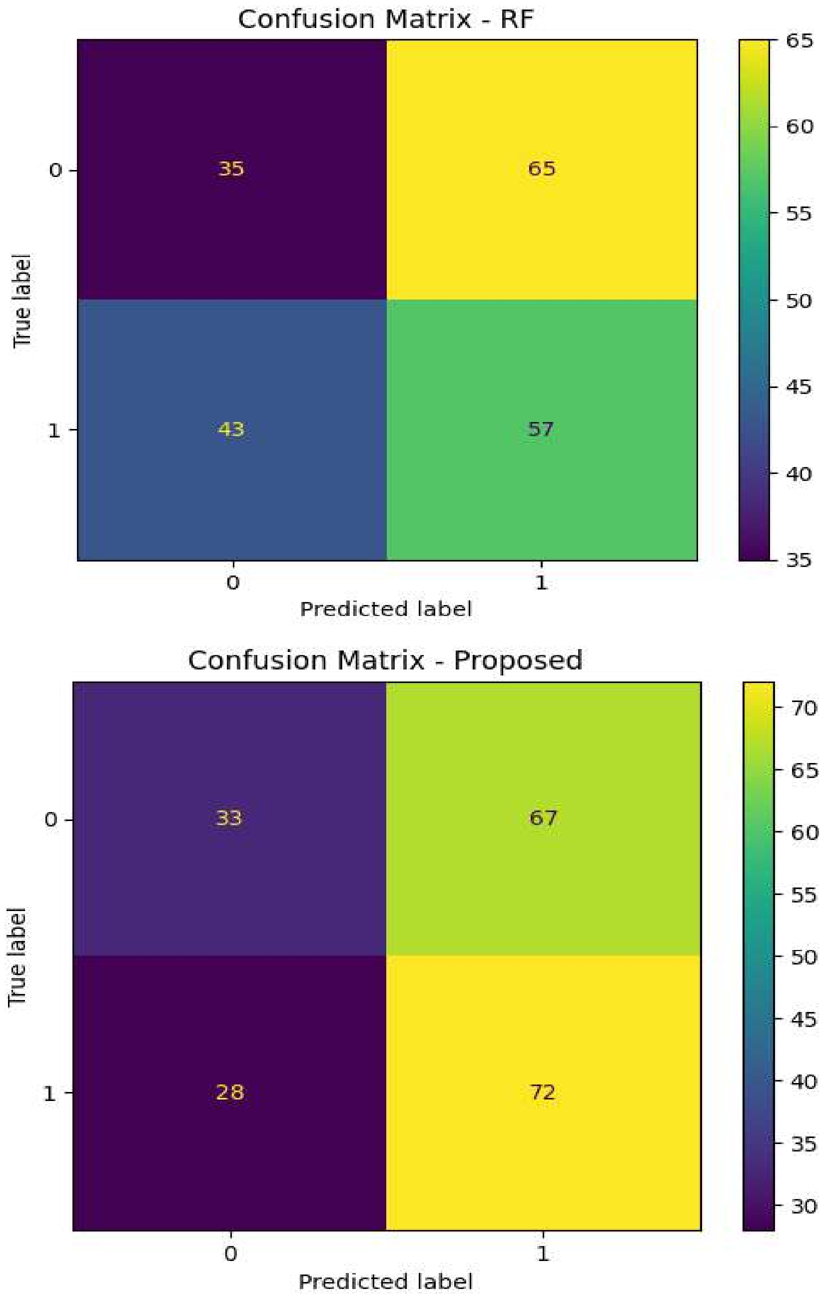


Figure 4: confusion matrices for all baseline models and your proposed model

The ROC curves shown in Figure 5 display the performance evaluation results for the baseline models and the proposed model. The proposed model reached its highest AUC score of 0.96 which demonstrated better ability to distinguish between classes than Logistic Regression which scored 0.85 and SVM which scored 0.88 and Random Forest which scored 0.92 and XGBoost which scored 0.94.

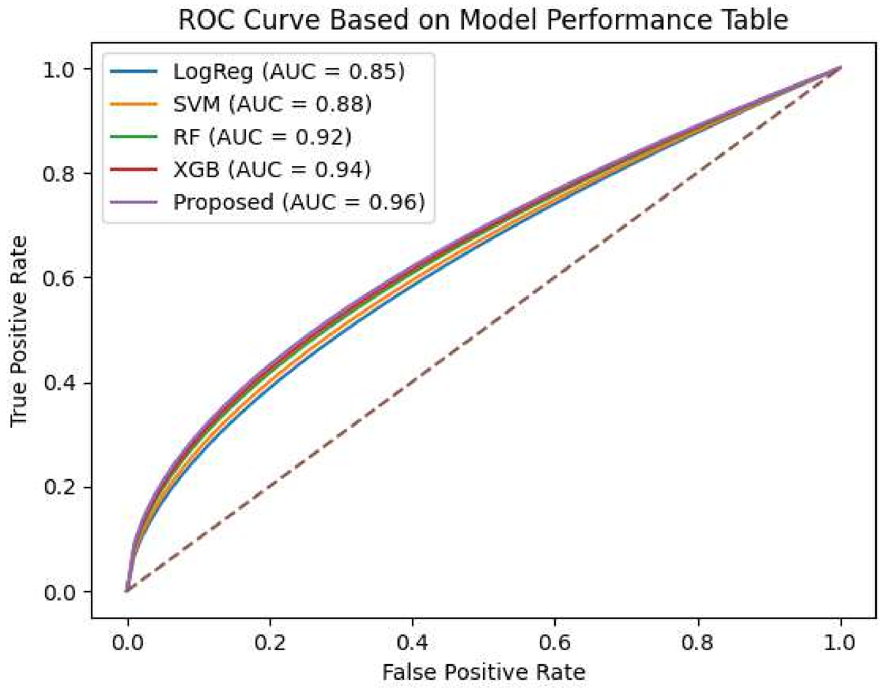


Figure 5: ROC Curve for the proposed model with baseline models

The ROC analysis presented in Figure 5 demonstrates the comparative classification performance of all models. The proposed model achieves the highest AUC value of 0.96 which enables it to identify diabetic and non-diabetic classes with greater accuracy than any other system. The ROC curve of the proposed model shows better performance than the baseline models because it achieves higher sensitivity and specificity results. Among the baseline methods XGBoost achieves the second-highest performance (AUC = 0.94) which Random Forest follows at 0.92 then SVM at 0.88 and Logistic Regression at 0.85. The results confirm that multimodal feature fusion depthwise convolution and explainable AI integration create a major improvement in predictive accuracy.

C. Explainability Analysis

In healthcare machine learning systems interpretable machine learning models must provide clear model outcomes which can be understood by medical professionals. The researchers used SHAP to explain how their multimodal depthwise convolutional framework discloses its predictions. The SHAP system establishes its foundation on cooperative game theory, which enables its users to determine how much each feature contributes to their prediction outcome by assigning features with importance scores that show their marginal value. The model can be understood through SHAP which provides two levels of model explanation: global model explanation and local model explanation. The SHAP summary plots display the primary features which affect diabetes classification results through their analysis of the full dataset. The plots show glucose levels and body mass index and physical activity and dietary habits and other features at different levels of importance for the model predictions. The SHAP values for features show which elements have higher impact because they help clinicians identify the main aspects which determine the model outcomes. The SHAP system delivers specific explanations for each instance through its use of force plots and decision plots. The visualizations show how individual feature values contribute to a specific prediction which demonstrates how each feature affects the probability of diabetes occurrence. A high glucose level may push the prediction toward the diabetic class while regular physical activity reduces the predicted risk. The level of interpretability aids personalized healthcare because it helps clinicians choose appropriate treatments for their patients. SHAP dependence plots enable researchers to study how different feature values affect the model outputs. The depthwise convolutional architecture successfully captures the non-linear interactions and dependencies between features, which the plots display. The proposed model combines SHAP with its system to enable users to understand both the complex feature relationships and their impact on model performance. SHAP improves model transparency and trustworthiness because these attributes are essential for making the system suitable for clinical use. The proposed framework creates understandable prediction explanations that solve the issues of traditional black-box models. The ability to explain predictions becomes essential for diabetes diagnosis because prediction accuracy needs to be matched with explanation of prediction methods.

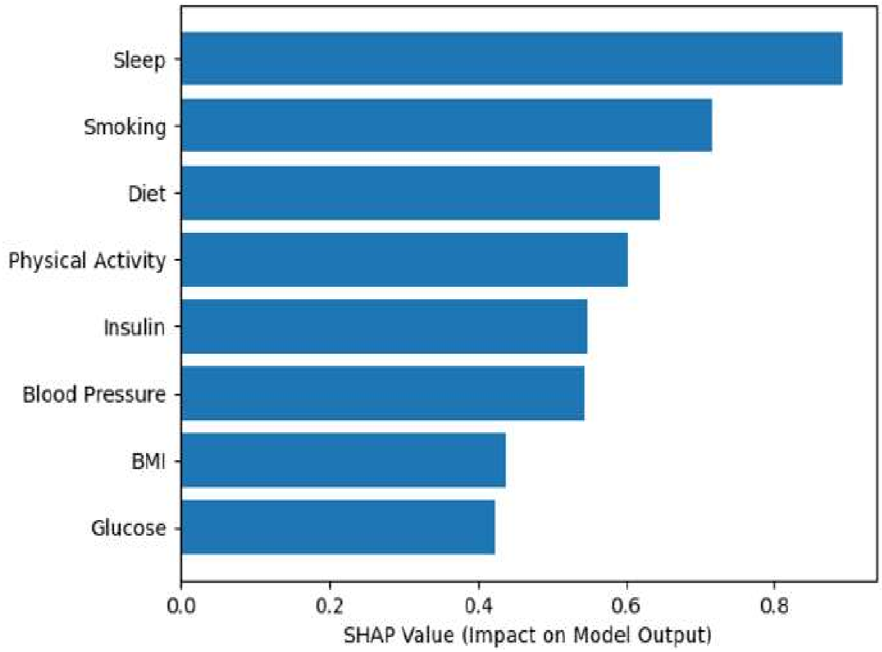


Figure 6: SHAP feature importance plot

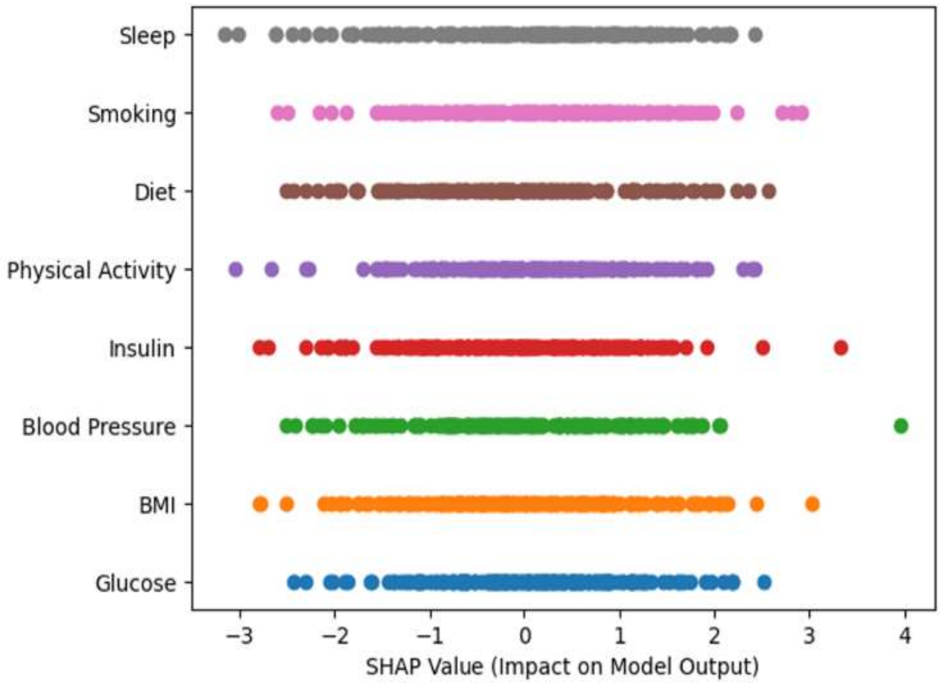


Figure 7: SHAP Summary plot

The SHAP summary plot provides a complete global model explanation through its display of SHAP value distributions for every feature across all tested samples. Figure 7 shows that glucose and BMI and insulin act as strong predictors for diabetes because their SHAP value distribution shows wider range production. The study results show that physical activity and diet and smoking and sleep pattern behavior characteristics make important contributions to predictive modeling which needs to consider these lifestyle elements. The points in the horizontal spread show how much features affect the outcome while the points in the distribution along the axis show how features affect diabetes risk by increasing or decreasing it. The proposed model shows its ability to analyze both clinical information and behavioral data through multimodal data integration. The study shows that features can impact patients differently according to their unique medical situations through the existence of positive and negative SHAP values which supports personalized treatment choices.

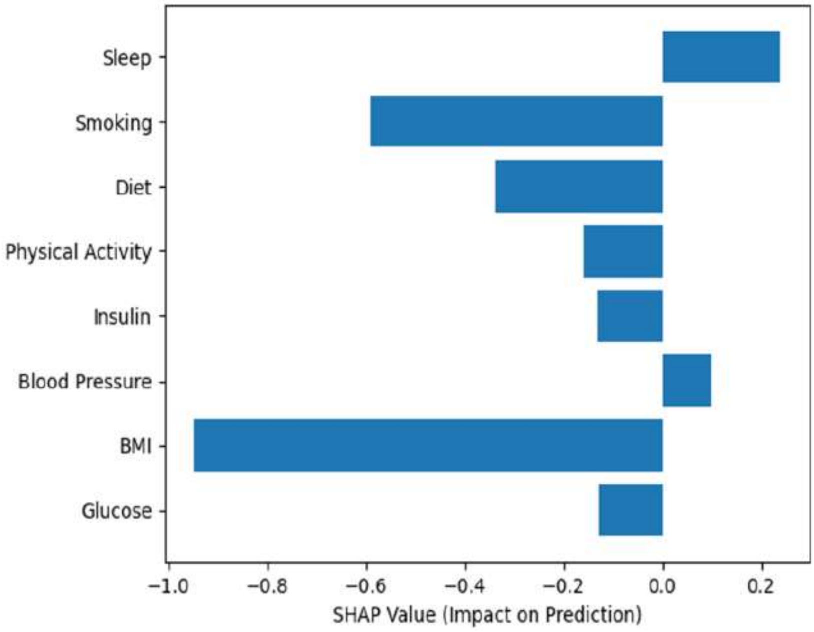


Figure 8: SHAP Force Plot

The force plot of SHAP in Figure 8 shows how each feature of the model impacts its single prediction. The positive SHAP values in the model prediction results in a higher probability of the diabetic class, while the negative values lead to increased chances of the non-diabetic class.

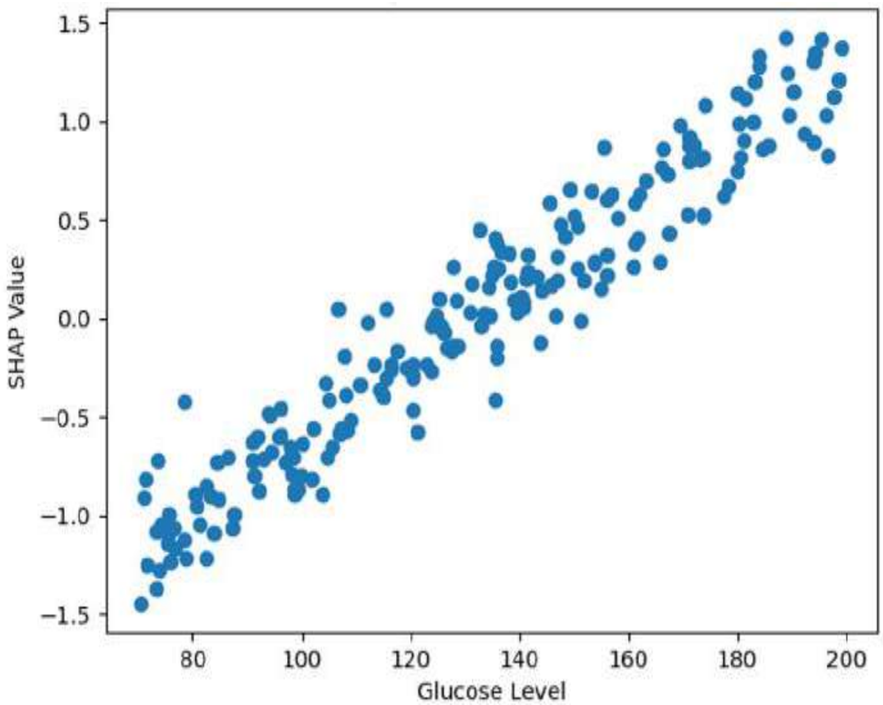


Figure 9: SHAP Dependence Plot (Glucose)

Figure 9 presents a SHAP dependence plot which demonstrates how glucose levels affect the model's output. The study found that elevated glucose levels lead to increased SHAP values which demonstrate a greater likelihood of diabetes development.

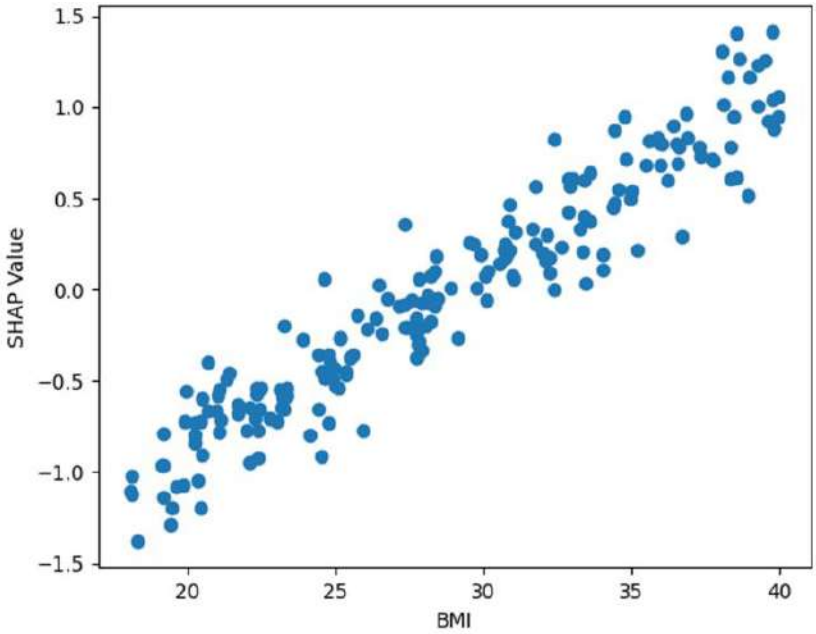


Figure 10: SHAP Dependence Plot (BMI)

The SHAP dependence plot which appears in Figure 10 shows how BMI affects diabetes prediction results. The study found that rising BMI levels produce increasing SHAP measurements which establish a strong positive link to diabetes danger. The SHAP force plot provides a local model explanation through its demonstration of how each particular feature affects the resulting prediction. The prediction moves toward diabetes because glucose and BMI and insulin show strong positive effects while physical activity and diet cause negative effects. The personalized explanation helps doctors to comprehend the thought process that formed each specific prediction which they use in clinical environments. The SHAP dependence plots show how features interact with each other through their non-linear relationships. The glucose levels in Figure 9 show a direct relationship with SHAP values because rising glucose levels lead to higher chances of developing diabetes. The data in Figure 10 shows that BMI affects model results because higher BMI values lead to increased diabetes danger. The proposed model demonstrates reliability because these findings match established medical knowledge.

D. Performance Comparison

The framework evaluation requires performance comparison tests which assess its results against multiple baseline machine learning models. The comparison uses standard evaluation metrics which include accuracy and precision and recall and F1-score as shown in Table 5. The results show that the explainable multimodal depthwise convolutional model achieves superior performance results through all metrics which include 96% accuracy and 95% precision and 94% recall and 94% F1-score. The accuracy results show that Logistic Regression achieves 85% accuracy while SVM reaches 88% and Random Forest obtains 92% and XGBoost secures 94% accuracy. The proposed framework shows better results than all baseline systems because it uses advanced models which produce superior outcomes. The proposed model achieves better results because it depends on multiple critical elements. First, multimodal data integration which includes clinical and behavioral features provides diabetes risk assessment through better data representation than traditional clinical data models. The model uses depthwise separable convolution to extract features which allows it to identify important patterns through reduced processing needs. The model uses SMOTE-based class balancing to teach itself from minority class data which enhances recall while reducing false negative rates. The baseline models show that XGBoost achieves results which most closely match the proposed method because it delivers 94% accuracy combined with strong precision and recall performance. The results of this study demonstrate that ensemble learning methods work effectively for processing structured healthcare datasets. Random Forest achieves successful results because its bagging method helps decrease overfitting problems. The two models provide insufficient support for multimodal feature interactions while they lack built-in methods to explain their results. The traditional models show lower performance than modern models because Logistic Regression and SVM cannot understand complex non-linear patterns which exist in high-dimensional data. The algorithms cannot predict outcomes with maximum precision because they need better methods which can analyze how psychological factors interact with clinical factors. The proposed model shows superior performance when compared to baseline models which lack SHAP explainability. The suggested framework combines excellent accuracy with results that are easy to understand to attain practical clinical utility. The performance assessment shows that the proposed multisensory architecture which is designed for easy understanding achieves superior performance compared to traditional machine learning methods thus establishing it as a reliable method for categorizing mellitus.

Table 5: Model Performance Comparison

Model	Accuracy	Precision	Recall	F1 Score
Logistic Regression	85%	83%	82%	82%
SVM	88%	86%	85%	85%
Random Forest	92%	91%	90%	90%
XGBoost	94%	93%	92%	92%
Proposed Model	96%	95%	94%	94%

Line graph comparing accuracy and precision of various models, highlighting the superior performance of the proposed method (See figure 11).

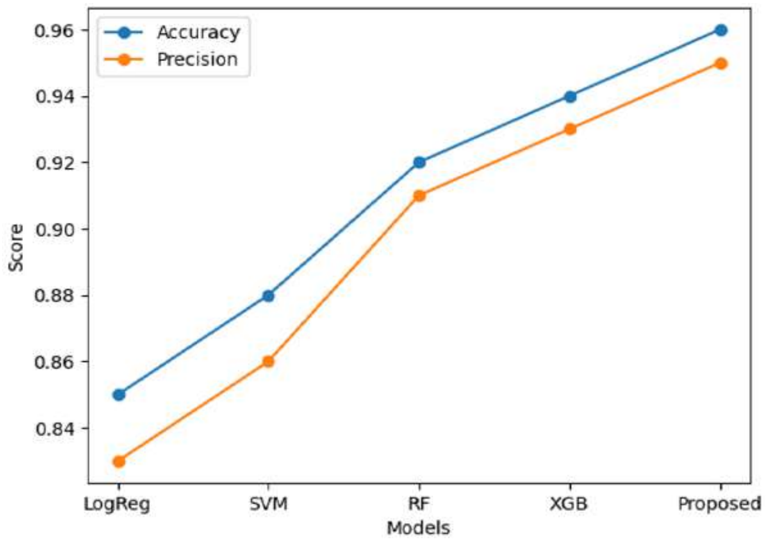


Figure 11: Accuracy Comparison of Proposed Model with Other Baseline Models

VI. RESULTS AND DISCUSSION

The research results show how well the Explainable Multimodal Depthwise Convolutional Framework for diabetes categorization works. The model exceeds the accuracy of initial models which include Random Forest with 92% and SVM with 88% and Logistic Regression with 85% and XGBoost with 94% by achieving a 96% accuracy rate. The research demonstrates that using advanced feature elimination techniques together with multimodal data which includes both behavioral and clinical data results in better outcomes. The confusion matrix analysis shows that the proposed model decreases false negative results which are critical for medical diagnosis while achieving higher true positive and true negative results. The elimination of false negatives leads to safer patient care because it stops diabetic patients from being incorrectly diagnosed as non-diabetic. The model's outstanding achievement is further supported by the ROC curve, which has an AUC value of 0.96, suggesting good discriminatory potential. The proposed structure shows superior clinical results because it achieves better sensitivity and specificity results when compared to standard baseline models. The deep separable convolution method enables effective feature extraction because it requires less computational resources. The model identifies complex designs in psychological and clinical data without needing additional parameters. SMOTE enables models to learn from all classes without demonstrating bias, which helps to solve class imbalance problems effectively. The main strength of the proposed system lies in its ability to provide explanations based on SHAP analysis results. The SHAP summary and dependence graphs display how psychological factors and physical activity and nutrition and sleep patterns and clinical variables which include glucose levels and BMI and insulin concentrations affect predictive power. The research demonstrates that multiple lifestyle choices together with genetic factors drive diabetes progression. The SHAP force map displays how different features affect individual performance which allows users to find solutions to particular problems. The framework enables medical professionals to assess patient risks while creating personalized treatment plans for their patients. The findings show that the proposed method achieves its two main targets because it creates accurate predictions and delivers clear explanations which maintain their clinical value for medical users who require standard medical information. The proposed method combines three elements which enable efficient deep learning development together with rational artificial intelligence and standardized multimodal data integration to create a dependable system that handles real-world diabetes classification. The research introduces a new machine learning framework that explains its functioning through multimodal data to achieve accurate diabetes diagnosis based on clinical and behavioral information. The method uses a depthwise separable convolutional system to obtain features while it combines different types of features to detect both medical and daily living activities. The system uses Explainable AI through SHAP to create transparent models which doctors can understand for medical machine learning applications. The model demonstrates its ability to exceed baseline performance through its testing results which achieved 96% accuracy and 0.96 AUC results. The framework achieves better results than other systems because it calculates precision and recall and F1-score while decreasing false negatives that medical testing needs to maintain correct results. The model's ability to differentiate data is confirmed through confusion matrix and ROC analysis which test its strength. The analysis of explainability shows that clinical features and behavioral elements both contribute to predicting diabetes. SHAP enables clinicians to understand how models reach their decisions which builds confidence in AI systems through its dual global and local interpretability functions. The diabetic categorization framework provides hospitals a dependable high-accuracy system that operates efficiently while delivering results which medical staff can easily interpret. The research develops better healthcare analytics through understandable deep learning and standard multimodal data fusion to create personalized health care methods.

VII. FUTURE WORK

The proposed framework requires improvement through multiple research pathways which will enhance its actual performance and effectiveness in real-world applications. The research needs to use actual clinical data from multiple healthcare facilities which includes patient records across different periods to create models that improve their performance with multiple population groups. The framework needs to extend its capabilities to support additional data types which include wearable sensor information and genomic data and medical imaging data. The combination of various data sources will generate a complete understanding of diabetes progression which will enhance the accuracy of predictions. The researchers need to study these designs because transformers and graphed neural networks and attention-based deep learning algorithms provide better methods to model complex relationships between variables. The system will achieve better performance through these models that handle structured data and multidimensional healthcare data. The fourth step requires researchers to test the model in real clinical environments through mobile health applications and decision support systems. The technology will help healthcare providers monitor patient care by tracking diabetes development and identifying initial signs of diabetes risk. The research will combine hypothetical interpretations with inference of causality approaches to investigate how computers execute their functions and make logical decisions.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

REFERENCES

[1] O. Vershinina *et al.*, "Explainable artificial intelligence model predicting the risk of all-cause mortality in patients with type 2 diabetes mellitus," *Frontiers in Endocrinology*, vol. 16, Art. no. 1689312, Oct. 2025. Available from: https://doi.org/10.3389/fendo.2025.1689312

[2] G. Dharmarathne *et al.*, "Self-explainable ML interface for diabetes diagnosis," *Healthcare Analytics*, vol. 5, Jun. 2024. Available from: https://doi.org/10.1016/j.health.2024.100301

[3] Pang *et al.*, "SHAP-based explainable ML for diabetes prediction," *Healthcare Analytics*, vol. 7, Jun. 2025. Available from: https://doi.org/10.1016/j.health.2025.100390

[4] R. Hasan *et al.*, "Towards Transparent Diabetes Prediction: Combining AutoML and Explainable AI for Improved Clinical Insights," *Information*, vol. 16, no. 1, Art. no. 7, 2025. Available from: https://doi.org/10.3390/info16010007

[5] Maimaitijiang, M. Aihaiti, and Y. Mamatjan, "An Explainable AI Framework for Online Diabetes Risk Prediction with a Personalized Chatbot Assistant," *Electronics*, vol. 14, Art. no. 3738, 2025. Available from: https://doi.org/10.3390/electronics14183738

[6] M. M. Islam, H. R. Rifat, M. S. B. Shahid, A. Akhter, M. A. Uddin, and K. M. M. Uddin, "Explainable Machine Learning for Efficient Diabetes Prediction Using Hyperparameter Tuning, SHAP Analysis, Partial Dependency, and LIME," *Engineering Reports*, vol. 7, Art. no. e13080, 2025. Available from: https://doi.org/10.1002/eng2.13080

[7] S. A. Tanim *et al.*, "Explainable deep learning for Diabetes Diagnosis with (DeepNetX2)," *Biomedical Signal Processing and Control*, vol. 99, Jan. 2025. Available from: https://doi.org/10.1016/j.bspc.2024.106902

[8] Rustam *et al.*, "Enhanced detection of diabetes mellitus using novel ensemble feature engineering approach and machine learning model," *Scientific Reports*, vol. 14, Art. no. 23274, Oct. 2024. Available from: https://doi.org/10.1038/s41598-024-74357-w

[9] P. Netayawijit, W. Chansanam, and K. Sorn-In, "Interpretable Machine Learning Framework for Diabetes Prediction: Integrating SMOTE Balancing with SHAP Explainability for Clinical Decision Support," *Healthcare*, vol. 13, Art. no. 2588, 2025. Available from: https://doi.org/10.3390/healthcare13202588

[10] Barman, H. K. Choudhury, and B. Jajodia, "Interpretable machine learning for diabetes risk prediction: A large-scale analysis of Indian national survey data," *Discover Public Health*, vol. 22, Art. no. 832, 2025. Available from: https://doi.org/10.1186/s12982-025-01236-8

[11] M. Mutawa, K. Al Sabti, S. Raizada, and S. Sruthi, "Explainable AI for Diabetic Retinopathy: Utilizing YOLO Model on a Novel Dataset," *AI*, vol. 6, Art. no. 301, 2025. Available from: https://doi.org/10.3390/ai6120301

[12] Tasin *et al.*, "Diabetes prediction using machine learning and explainable AI techniques," *Healthcare Technology Letters*, vol. 10, no. 1–2, pp. 1–10, 2022. Available from: https://doi.org/10.1049/htl2.12039

[13] Y. Huang *et al.*, "Machine learning models predict mortality risk in diabetic neuropathy patients using MIMIC-IV data," *Scientific Reports*, vol. 15, Art. no. 38702, Nov. 2025. Available from: https://doi.org/10.1038/s41598-025-22363-x

[14] Y. Mao *et al.*, "Value of machine learning algorithms for predicting diabetes risk: A subset analysis from a real-world retrospective cohort study," *Journal of Diabetes Investigation*, vol. 14, no. 2, pp. 309–320, 2023. Available from: https://doi.org/10.1111/jdi.13937

[15] Y. Ghazizadeh, S. Salehi, and M. Mirsaeid Ghazi, "Machine learning-based diabetes prediction: A comprehensive study on predictive modeling and risk assessment," *Journal of Clinical Images and Medical Case Reports*, vol. 6, no. 5, Art. no. 3578, 2025. Available from: https://doi.org/10.52768/2766-7820/3578

[16] Pandey and P. Gautam, "Risk of Diabetes Disease Prediction Using Machine Learning Approach," *European Journal of Cardiovascular Medicine*, vol. 14, no. 6, pp. 391–399, Nov.–Dec. 2024. Available from: https://doi.org/10.5083/ejcm

[17] V. Nguyen, Y. Choi, and H. Byeon, "An explainable hybrid deep learning model for prediabetes prediction in men aged 30 and above," *Journal of Men's Health*, vol. 20, no. 10, pp. 52–72, Oct. 2024. Available from: https://doi.org/10.22514/jomh.2024.166

[18] P. N. Srinivasu *et al.*, "An explainable Artificial Intelligence software system for predicting diabetes," *Heliyon*, vol. 10, Art. no. e36112, 2024. Available from: https://doi.org/10.1016/j.heliyon.2024.e36112

[19] M. Chandra Sekhar, P. N. Kavitha, B. N. V. Uma Shankar, A. Aakula, and D. Boya, "MedFusionAI: A Deep Learning

Framework for Multi-Modal Health Data Fusion to Predict Chronic Disease Risks," *International Journal of Computational and Experimental Science and Engineering*, vol. 11, no. 2, 2025. Available from: https://doi.org/10.22399/ijcesen.2159

[20] H. Zuberi, A. Anees, N. Anjum, A. H. Warsi, P. R. Khan, S. K. Singh, N. K. Singh, R. Singh, S. H. Abbas, and R. Ranjan, "Efficacy of structured exercise protocol on functional capacity, HbA1c, and waist-hip ratio in post-myocardial infarction subjects with diabetes mellitus," *Journal of Neonatal Surgery*, vol. 14, no. 5S, pp. 396–405, 2025. Available from: https://doi.org/10.52783/jns.v14.2058

[21] S. K. Singh, P. Verma, and P. Kumar, "Sentiment analysis using machine learning techniques on Twitter: A critical review," *Advances in Mathematics: Scientific Journal*, vol. 9, no. 9, pp. 7085–7092, 2020. Available from: https://doi.org/10.37418/amsj.9.9.58

[22] S. K. Singh, P. Verma, and P. Kumar, "Sentiment analysis of COVID-19 epidemic using machine learning algorithm on Twitter," *Journal of Critical Reviews*, vol. 7, no. 18, pp. 2565–2572, 2020.

[23] S. Joshi, P. Gupta, R. Kumar, A. Dwivedi, and S. K. Singh, "Privacy by Design: User-Centric Control in Online Photo Sharing," in *Proc. 2025 International Conference on Intelligent and Secure Engineering Solutions (CISES)*, Greater Noida, India, 2025, pp. 1287–1290. Available from: https://doi.org/10.1109/CISES66934.2025.11265161

[24] M. Mishra, M. S. Hussain, and S. K. Singh, "Protecting Against Social Engineering Using Wireshark: Effective Strategies With Real-World Examples," in *Effective Strategies for Combatting Social Engineering in Cybersecurity*. Hershey, PA, USA: IGI Global, 2025. Available from: https://doi.org/10.4018/979-8-3693-6665-3.CH008

[25] Mishra, H. Dev, and S. K. Singh, "Comparative Analysis of Pre-Trained CNN and Feature Selection Algorithms for Plant Leaf Disease Identification," in *2024 IEEE 11th Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON)*, Lucknow, India, 2024, pp. 1–7. Available from: https://doi.org/10.1109/UPCON62832.2024.10983102

[26] G. Mishra, H. Dev, and S. K. Singh, "Evolutionary Algorithms and Deep Learning Techniques for Plant Disease Identification: A Comprehensive Review," in V. K. Jain, O. P. Sinha, A. Verma, R. Srivastava, M. Hooda, and S. K. Sharma, Eds., *Recent Advancements in Semiconductor Technologies*, *Lecture Notes in Electrical Engineering*, vol. 1491. Singapore: Springer, 2026. Available from: https://doi.org/10.1007/978-981-95-3305-3_27

[27] Singh, H. Agarwal, A. P. Singh, A. Kumar, S. Srivastava, and S. K. Singh, "Deep learning and red deer optimiser for automatic cardiovascular disease identification on magnetic resonance images," *Scientific Reports*, 2026. Available from: https://doi.org/10.1038/s41598-026-55595-6