Intelligent Ensemble-Based Decision Support System for the Classification and Management of Type 2 Diabetes Mellitus (T2dm) Subtypes Using Clinical Data

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ABSTRACT

Type 2 Diabetes Mellitus (T2DM) presents as a significant public health problem, which requires accurate diagnosis and personalized management to reduce disease complications, thus, improving patient outcome. This paper presents an intelligent ensemble-based decision support system for classification and management of T2DM subtypes using clinical data collected from the University of Nigeria Teaching Hospital (UNTH) and Parklane Hospital, Enugu State, Nigeria. A total number of 23,300 validated patient's records were integrated and used in this study. Seven Machine Learning (ML) classifiers namely: Random Forest (RF), Multi-Layer Perceptron (MLP), Support Vector Machine (SVM), Naïve Bayes (NB), K-Nearest Neighbour (KNN), Extreme Gradient Boosting (XGBoost) and Decision Tree (DT) were trained and evaluated. The three best performing classifiers were combined using a stacking ensemble approach with XGBoost as the meta-classifier. In addition, a clinical decision support recommendation framework was designed and deployed to provide management recommendations for Normal, Mild Age-related Diabetes (MARD), Mild Obesity-related Diabetes (MOD), Severe Insulin-deficient Diabetes (SIDD) and Severe Insulin-resistant Diabetes (SIRD) patients. The experimental results revealed that the proposed stacking ensemble achieved an overall classification accuracy of 98.18% with excellent precision, recall, and F1-scores for all diabetes classes. The results further indicate that ensemble approach can be employed to achieve enhanced performance in diabetes classification with intelligent recommendation for clinical management of each diabetes subtype. The proposed decision support system can play a significant role in addressing challenges associated with diabetes management in limited-resource settings.

Keywords: Type 2 Diabetes Mellitus, Ensemble Learning, Stacking Ensemble, XGBoost, Clinical Decision Support System

1. INTRODUCTION

Type 2 Diabetes Mellitus (T2DM) is a chronic metabolic disease characterized by insulin resistance, progressive beta cell dysfunction, and persistent hyperglycaemia that frequently results in profound cardiovascular, renal, neurological, and ophthalmic consequences if inadequately managed (Antar et al., 2023; Atun et al., 2022; Agyemang et al., 2023). The rising prevalence of diabetes has an overwhelming burden on health systems, as it continues to challenge treatment and management, with low- and middle-income countries facing limited capacities for specialized diagnostic services (Atun et al., 2022). Recent studies indicate that T2DM is not a homogenous disease but rather comprises distinct subgroups of patients with different underlying pathophysiology and therapeutic needs, including Mild Age-Related Diabetes (MARD), Mild Obesity-Related Diabetes (MOD), Severe Insulin-Deficient Diabetes (SIDD), and Severe Insulin-Resistant Diabetes (SIRD), each of which requires a different clinical intervention (Agyemang et al., 2023; Ordoñez-Guillen et al., 2023).

The unprecedented explosion of machine learning literature has triggered the development of innovative intelligent healthcare systems for advancing disease prediction, diagnosis, and management (Afsaneh et al., 2022; Ismail et al., 2022). Several studies have demonstrated the efficacy of machine learning algorithms, such as Decision Trees, Random Forests, the Support Vector Machine, Artificial Neural Networks, and hybrid

approaches, in forecasting and classifying T2DM based on the identified clinical indicators (Chang et al., 2022; Howlader et al., 2022; Shin et al., 2022; Dutta et al., 2022). The review articles reported that ensemble and hybrid machine learning approaches performed better than individual classification models because of their ability to combine the accuracy of various algorithms, thereby minimizing classification errors and enhancing generalization capacity (Fregoso-Aparicio et al., 2021; Petridis et al., 2024).

Although the machine learning paradigm has shown tremendous potential in diabetes prediction, most of the prior studies focused on accurately classifying between diabetic and non-diabetic patients rather than predicting clinically meaningful T2DM subtypes (Ordoñez-Guillen et al., 2023). In addition, very few studies have simultaneously emphasized predictive classification and incorporated recommendation strategies for clinical decision-support systems in disease management. Therefore, this study proposes a stacking ensemble framework that incorporates the predictive performance of the best-performing individual classifiers and develops a recommendation system for subtype-specific diabetes management. This framework promises to boost predictive accuracy in T2DM classification and offer treatment recommendations for patients with diabetes (Dutta et al., 2022; Petridis et al., 2024).

2. Research Method

The proposed system utilized an ensemble model for the classification of T2DM. The method used are data collection, ensemble model development, development of the management algorithm for T2DM and then the integration of the decision support framework as software for diagnosis of T2DM. Figure 1 presents the mind mapping diagram of the ensemble model for the classification of T2DM.

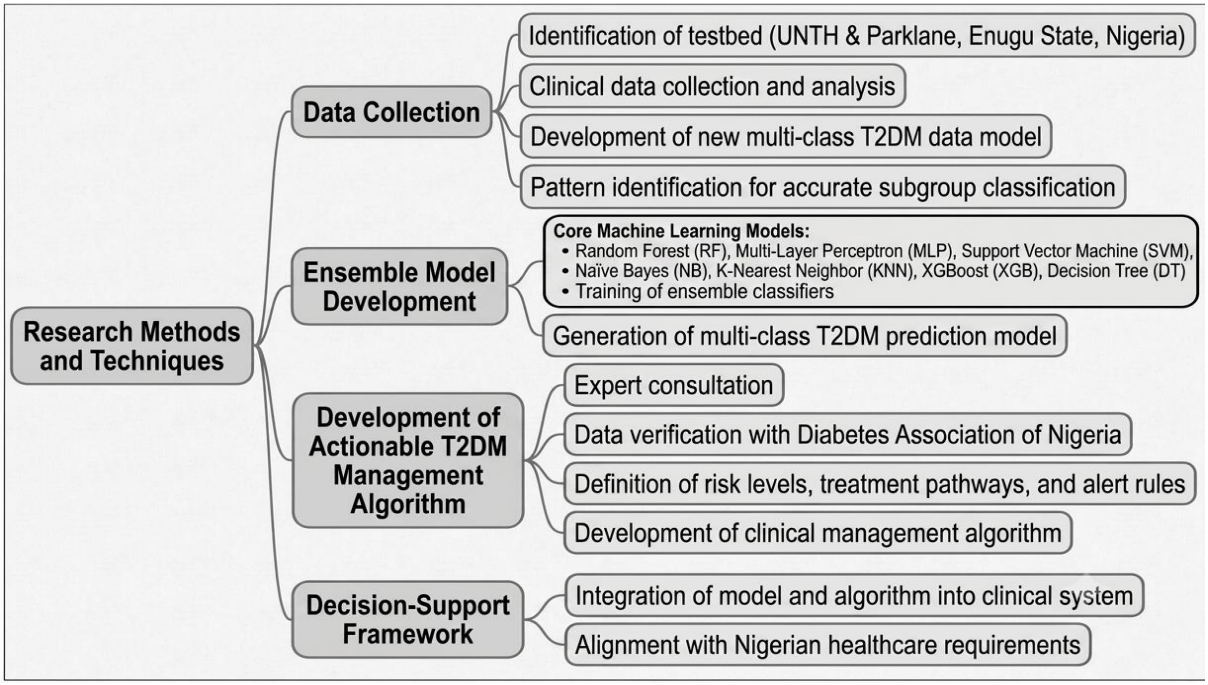


Figure 1: Mind mapping diagram of the ensemble model for the classification of T2DM

Figure 1 illustrates the end-to-end data flow of the research methodology, showing how raw clinical inputs are transformed into a functional ensemble-based decision-support framework for T2DM classification and management. The proposed system architecture for the ensemble-based T2DM classification and management framework is a multilayered, integrated platform that transforms raw clinical and diagnostic data into actionable patient insights. It begins with a data acquisition layer, which collects patient records from hospitals (UNTH and Parklane) and ensures structured inputs for analysis. The preprocessing and feature engineering layer applies cleaning, normalization, standardization, and class balancing, while a hybrid feature selection pipeline reduces dimensionality and highlights the most relevant variables. The ensemble learning layer constitutes RF, MLP,

SVM, NB, KNN, XGB, and DT are trained and fused via stack ensemble strategies to generate robust multi-class T2DM predictions.

2.1 Database Development

The database development was achieved through primary data collection. The data source is the University of Nigeria Teaching Hospital, Ituku, Ozala, Enugu, and Parklane Hospital, G.R.A, Enugu State. The participants in the datasets are men and women aged 19 to 85 years. The population size is 14200 for UNTH and 9100 participants from Parklane. The dataset used in this study was obtained by combining the clinical records from the independent healthcare data sources. Before the combination, the two datasets were cleaned (attribute mapping, data cleaning, removal of duplicate records, handling of missing values, and standardization of variable names and measurement units were performed), and the attributes were analysed to verify common variables relevant to clinical diagnoses of diabetes. Only attributes that were available in both datasets and considered clinically significant were retained for the merged dataset. The integration of these datasets was carried out to increase the number of patient records available for analysis while improving the diversity and generalizability of the proposed ensemble T2DM diagnosis. The total population sample size of participants is 23, 300 records of verified diabetes patients in the hospital from 2002 to 2024. For privacy, the actual identification numbers of all patients were changed, and any information that might compromise patients' privacy was not revealed. The resulting dataset contains demographic characteristics, anthropometric measurements, laboratory findings, metabolic indicators, lifestyle factors, and medical history variables that collectively provide sufficient information for accurate diabetes risk assessment and classification.

2.2 The Proposed Stacked ensemble learning model

The study trained 7 machine learning models, which are Random Forest, Multi-Layer Perceptron (MLP), Support Vector Machine (SVM), Naïve Bayes (NB), K-Nearest Neighbor (KNN), XGBoost (XGB), and Decision Tree (DT) (Okoye et al., 2026; Ebere et al., 2025; Ekene et al., 2026). The results were compared, and the best three were selected and applied to develop the ensemble model using the stacking technique. In this approach, rather than making the final prediction independently like existing ensemble model such as hard voting and soft voting, the outputs generated by these three classifiers are combined through a meta-learning process that learns how to optimally integrate their predictions. This approach exploits the complementary strengths of the selected classifiers, thereby reducing prediction errors and improving the overall classification performance.

For the base learner, let the three selected classifier by represented as M_1, M_2, M_3. The feature of a patient is represented as $x = [x_1, x_2, \ldots \ldots . . x_n]^T$. Each classifier independently predicts the probability of the four diabetes classes. For the first classifier, the prediction is represented in Equations 1 to 3;

$$P_1(x) = [p11, p12, p13, p14] \quad (1)$$

$$P_2(x) = [p21, p22, p23, p24] \quad (2)$$

$$P_3(x) = [p31, p32, p33, p34] \quad (3)$$

Where pi1 is the probability of the SIDD, pi2 is the probability of the SIRD, pi3 is the probability of MOD, and pi4 is the probability of MARD. Therefore, for the M_i classifier, each probability vector satisfies Equation 4.

$$\sum_{j=1}^{4} p_{ij} = 1 \quad (4)$$

The outputs of the three base learners are concatenated to construct the input vector of the stacking model in Equation 5,

$$Z = [P_1(x), P_2(x), P_3(x)] \quad (5)$$

The vector Z is referred to as the meta-feature vector, since it contains prediction information generated by the three selected classifiers rather than the original patient attributes. The stacking ensemble employs a meta-classifier $g(.)$ to learn the optimal relationship among the outputs of the three base learners. The final prediction output is therefore presented as Equation 6.

$$\hat{y} = g(Z) \quad (6)$$

Where g(.) is the meta-classifier and $\hat{y}$ is the predicted diabetes subtypes. The classifier type is XGB and the multi class prediction becomes Equation 7.

$$P(y = c|Z) = \frac{\exp(W_c Z + b_c)}{\sum_{j=1}^{4} \exp(W_j Z + b_j)} \quad (7)$$

Where $c \in \{SIDD, SIRD, MOD, MARD\}$. Therefore, the final stacked ensemble model is represented as Equation 8.

$$\hat{y} = g[M_1(x), M_2(x), M_3(x)] \quad (8)$$

Where x is the patient feature vectors, $M_1(x)$, $M_2(x)$, $M_3(x)$ are the probability outputs of the three best models, g(.) is the meta-classifier, and $\hat{y}$ is the final diabetes subtypes predicted by the stacking ensemble.

2.3 Design of the Decision Support Recommendation System

The clinical management algorithm was designed to bridge the gap between automated diabetes subtype classification and clinical decision-making. The algorithm integrates the output of the stacking ensemble classifier with predefined clinical management rules to generate patient-specific recommendations. After receiving the patient's clinical measurements, the algorithm first validates and preprocesses the input data before forwarding it to the trained stacking ensemble model for subtype prediction. Based on the predicted class, the algorithm automatically selects the corresponding management pathway and generates appropriate clinical recommendations for healthcare professionals. The final diagnosis, prediction confidence, and management recommendation are then displayed to the user and stored in the patient database for future reference. The data was obtained through expert consultation from the UNTH and Parklane Teaching Hospital. Three self-volunteered domain experts provided several actionable recommendations. These recommendations were cross-examined by an independent expert from UNTH. The common recommendation was then used for our design requirements. Table 1 presents the recommendation for each class, while the decision logic is in Table 2.

Table 1: Clinical Management Recommendations for Each Diabetes Subtype

Predicted Class	Clinical Characteristics	Recommended Clinical Management
NORMAL	Blood glucose and metabolic parameters are within the normal range.	Continue healthy lifestyle practices, maintain a balanced diet, engage in regular physical exercise, undergo routine diabetes screening, and attend periodic medical check-ups.
MARD (Mild Age-Related Diabetes)	Diabetes primarily associated with increasing age and relatively mild metabolic abnormalities.	Encourage lifestyle modification, schedule regular blood glucose monitoring, provide dietary counselling, promote moderate physical activity, and conduct periodic clinical follow-up to monitor disease progression.
MOD (Mild Obesity-Related Diabetes)	Diabetes associated with obesity and elevated body mass index (BMI).	Recommend structured weight management programmes, nutritional counselling, increased physical activity, obesity management, routine glycaemic monitoring, and regular assessment of cardiovascular risk factors.

SIDD (Severe Insulin-Deficient Diabetes)	Marked insulin deficiency with poor glycaemic control and increased risk of complications.	Recommend immediate specialist evaluation, comprehensive assessment of insulin deficiency, intensive blood glucose monitoring, consideration of insulin-based therapy under physician supervision, and frequent follow-up visits.
SIRD (Severe Insulin-Resistant Diabetes)	Severe insulin resistance with increased risk of metabolic and cardiovascular complications.	Recommend interventions aimed at improving insulin sensitivity, intensive lifestyle modification, weight reduction, cardiovascular risk assessment, regular monitoring of renal and metabolic function, and specialist endocrine consultation where necessary.

Table 2: Decision Logic Used by the Algorithm

Predicted Diabetes Class	System Action
NORMAL	Display preventive healthcare recommendations and schedule routine follow-up.
MARD	Display age-related diabetes management recommendations and periodic monitoring plan.
MOD	Display obesity management recommendations and lifestyle intervention plan.
SIDD	Display insulin deficiency management recommendations and urgent specialist referral advice.
SIRD	Display insulin resistance management recommendations and cardiovascular risk monitoring plan.

This decision logic in Table 2 integrates naturally into your algorithm, where the stacking ensemble predicts the diabetes subtype, and the clinical management algorithm maps the predicted class to the corresponding management recommendation before displaying and storing the result. It also keeps the recommendations within the scope of a clinical decision support system rather than prescribing treatment independently.

2.4 Program development

The program development process began with the implementation of the database structure for storing patient demographic information, clinical records, diagnosis history, and generated reports. This was followed by the development of the graphical user interface, which provides healthcare professionals with an intuitive platform for patient registration, health record management, diabetes diagnosis, and report generation. The intelligent diagnosis module was subsequently integrated into the application by loading the trained stacking ensemble model, which receives patient clinical parameters, performs prediction, and returns the appropriate diabetes subtype together with the associated confidence score and clinical recommendation. Extensive functional testing was carried out throughout the development process to verify that each module operated correctly both independently and as part of the integrated system. The trained models were serialized using Joblib and integrated into the application for real-time prediction. The combination of Python, Google Colab, and these supporting libraries provided a robust, scalable, and efficient environment for developing and deploying the proposed intelligent Diabetes Management System.

3. System Results

The ensemble learning model was developed using the stacking approach. In this work, the three-model probability are the input which was then applied to train the meta-learning in this case the XGB. The justification for the XGB the meta-learning was the best in the individual classifiers and also good because it already has prior knowledge of T2DM vectors as the base model. The results of the training were measured with precision, recall, f1-score and accuracy; the result is posited in Table 3.

Table 3: Classification Performance of the Proposed Stacking Ensemble Model

Class	Precision	Recall	F1-Score	Support
MARD	0.99	1.00	0.99	698
MOD	0.96	0.95	0.95	862
NORMAL	1.00	1.00	1.00	1270
SIDD	1.00	1.00	1.00	764
SIRD	0.96	0.97	0.96	1066
Accuracy	**98.18%**			**4660**

Table 3 presents the classification performance of the proposed stacking ensemble model for the five diabetes classes. The model achieved an overall classification accuracy of 98.18%, correctly classifying the majority of the 4,660 test samples, which demonstrates its ability to generalize effectively across different patient categories. The NORMAL and SIDD classes recorded perfect performance, with precision, recall, and F1-score of 1.00, indicating that every normal patient and Severe Insulin-Deficient Diabetes patient in the testing dataset was correctly identified without any misclassification. Similarly, the MARD class achieved an excellent performance, with 0.99 precision, 1.00 recall, and 0.99 F1-score, showing that almost all Mild Age-Related Diabetes cases were correctly detected while maintaining very few false-positive predictions. The SIRD class also produced strong results, recording 0.96 precision, 0.97 recall, and 0.96 F1-score, suggesting that the model was highly effective in identifying Severe Insulin-Resistant Diabetes patients despite the clinical similarities that often exist between SIRD and other diabetes subtypes. Among all the classes, MOD recorded the lowest performance, with 0.96 precision, 0.95 recall, and 0.95 F1-score. Although this is slightly lower than the other classes, the results are still very high and indicate that only a few MOD cases were confused with closely related diabetes categories due to similarities in their clinical characteristics. Figure 2 compared the different model with the ensemble model considering accuracy.

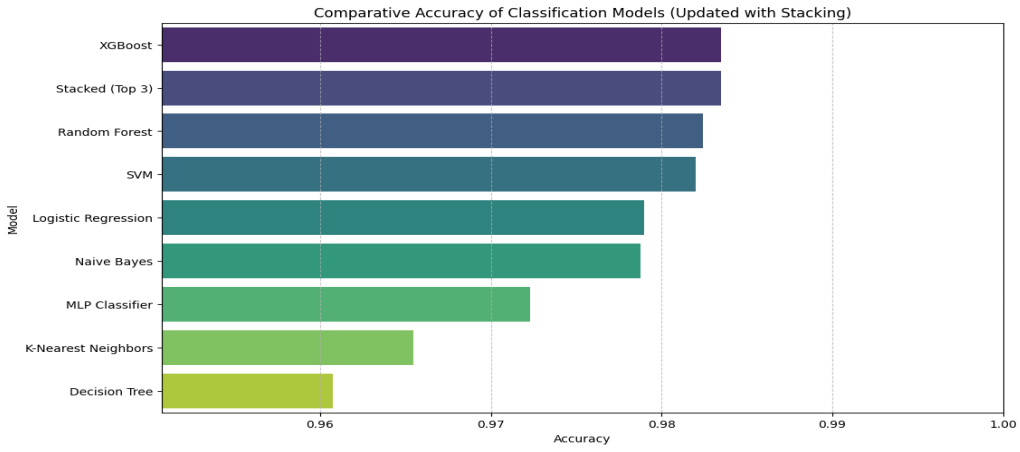


Figure 2: Comparative analysis of the classifiers and also the stacked ensemble models

Figure 2 compares the classification accuracy of the individual machine learning models with the proposed stacking ensemble model. The results show that XGBoost achieved the highest individual model accuracy of approximately 98.4%, closely followed by the Stacking (Top 3) model with an accuracy of about 98.2%. Random Forest and SVM also produced strong performances, recording accuracies above 98.0%, indicating their effectiveness in distinguishing between the different diabetes subtypes. In contrast, Logistic Regression and Naïve Bayes achieved moderate accuracies of approximately 97.9%, while the MLP Classifier recorded about 97.2%. The K-NN and Decision Tree models produced the lowest accuracies of approximately 96.5% and 96.1%, respectively, suggesting that these algorithms were less effective in capturing the complex relationships among the clinical features. Although the stacking ensemble did not slightly exceed the performance of XGBoost, it achieved a comparable accuracy while offering a more balanced and robust classification by combining the strengths of the top-performing base learners. Figure 3 presents the comparative ROC curve analysis.

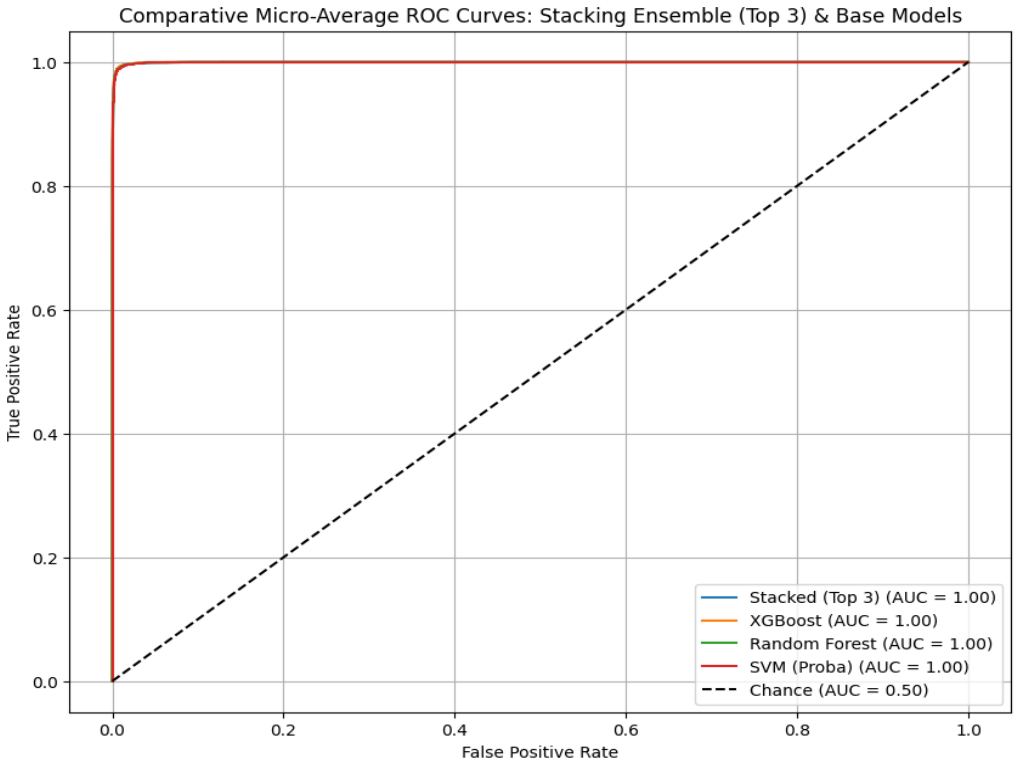


Figure 3: Comparative ROC curve

Figure 3 presents the comparative micro-average ROC curves of the proposed stacking ensemble model and the three best-performing base models, namely XGBoost, Random Forest, and SVM. The ROC curves for all four models are concentrated near the upper-left corner of the graph and remain far above the diagonal reference line, which represents random classification (AUC = 0.50). This indicates that each model possesses an excellent ability to distinguish between the five diabetes classes while maintaining a very high true positive rate and an extremely low false positive rate. The micro-average Area Under the Curve (AUC) for all models is reported as 1.00, demonstrating near-perfect discrimination across the entire multi-class classification problem.

3.1 Practical validation of the software

This section presents the result of the software testing. The results began with the user authentication section which are the user registration part and then the login part. After successful registration, the user information is securely stored in the system database, allowing the individual to log into the application using the newly created credentials. The registration module ensures proper management of authorized users while preventing duplicate accounts through validation checks. This module provides a secure mechanism for managing clinicians, administrators, and other healthcare professionals who interact with the diabetes management system. Figure 4 is the dashboard.

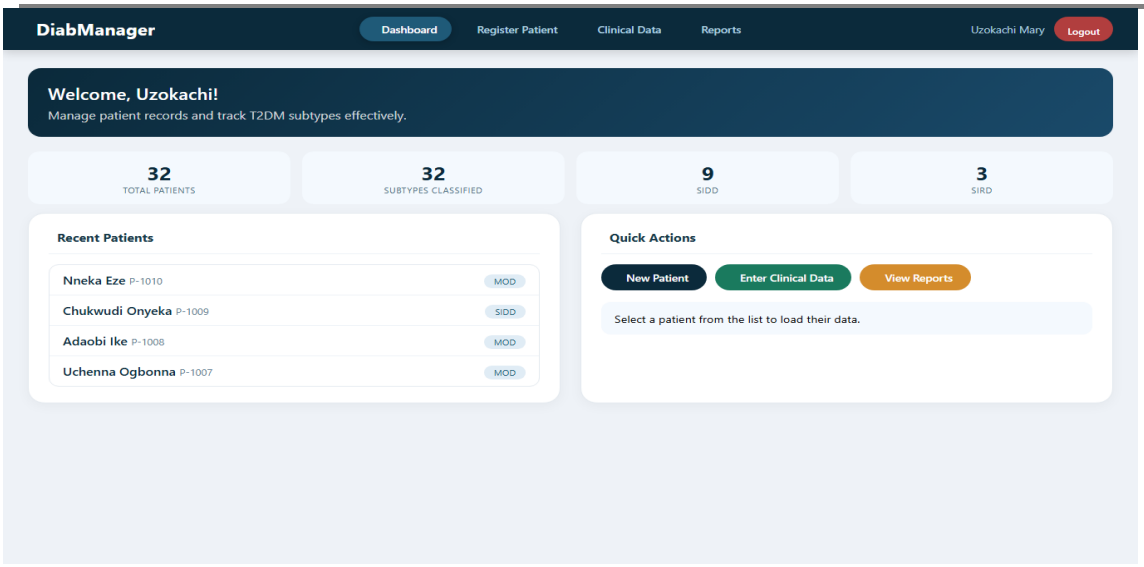


Figure 4: The central dashboard system

Figure 4 shows the central dashboard of the proposed diabetes management system. The dashboard is designed to improve usability by organizing all major operations into a single interface. Healthcare personnel can easily monitor system activities, navigate between modules, and review recent patient records without unnecessary complexity. Figure 5 presents the patient registration result.

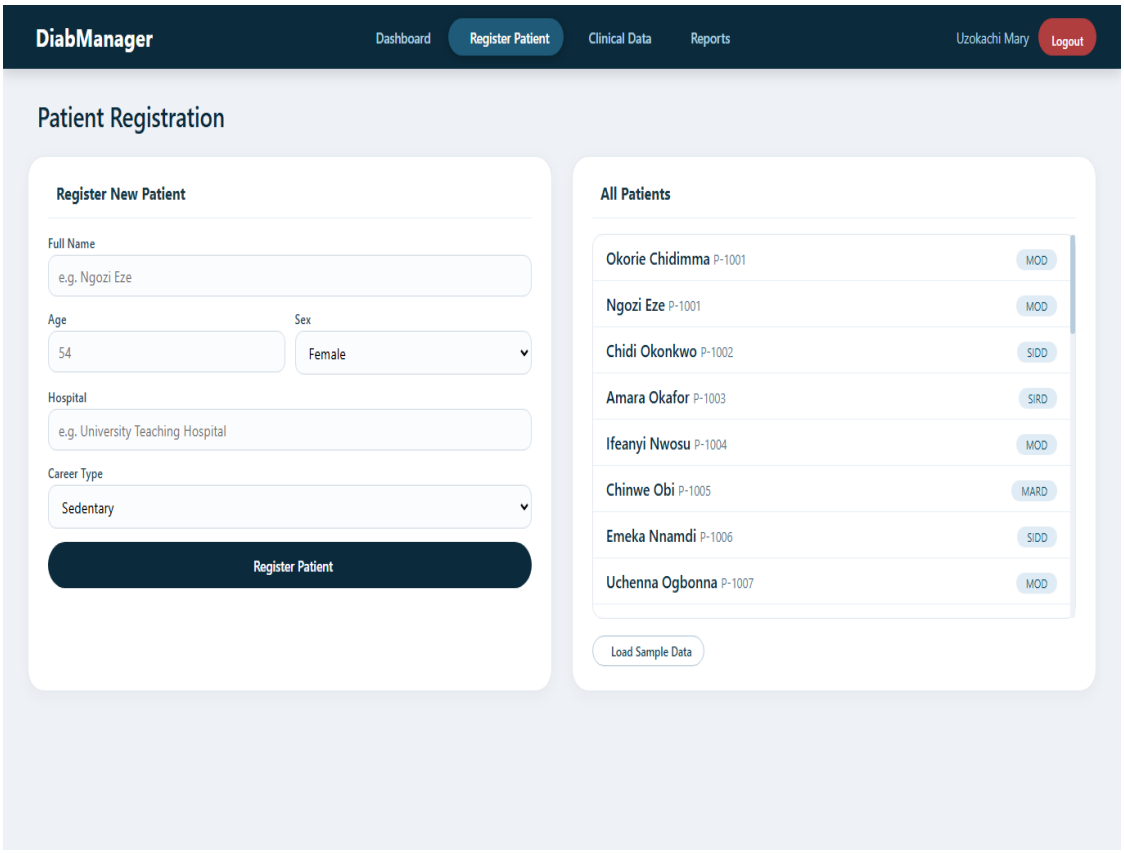


Figure 5: The patient registration result

Figure 5 presents the patient registration interface after patient information has been successfully entered into the system. The page displays demographic and clinical information including the patient's personal details and medical history, confirming that the registration process has been completed successfully. The interface also provides options for editing, updating, or deleting patient records whenever necessary.

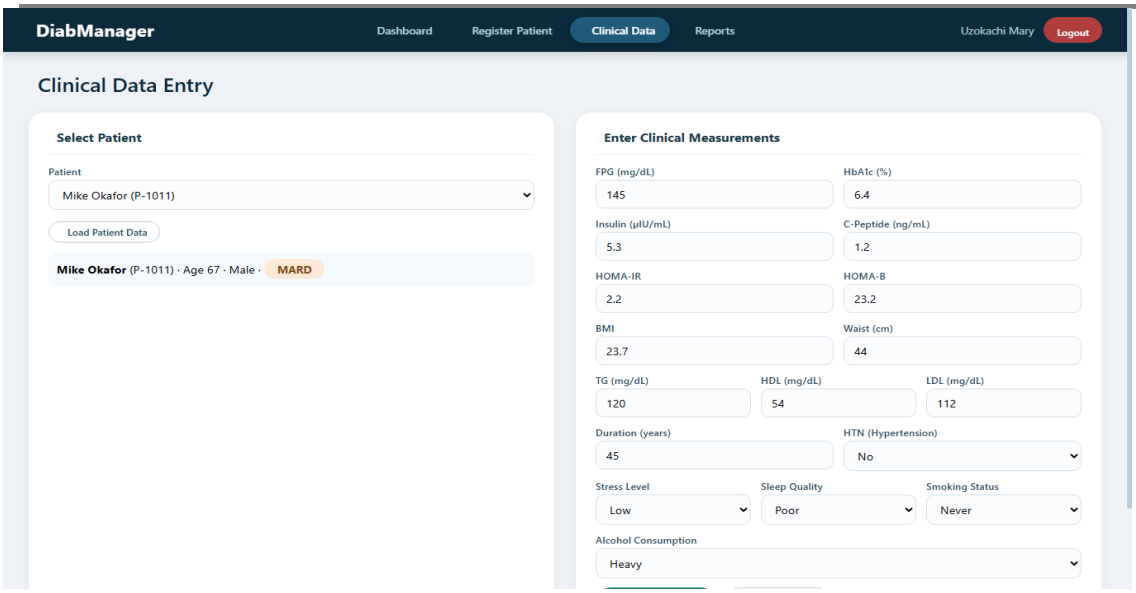


Figure 6: Result of clinical data

Figure 6 illustrates the clinical data entry section of the proposed system. This interface allows healthcare professionals to enter the patient's clinical measurements required for diabetes subtype classification. The input fields include important laboratory and physiological parameters such as fasting plasma glucose (FPG), HbA1c, insulin level, C-peptide, HOMA-IR, HOMA-B, body mass index (BMI), waist circumference, triglycerides, HDL, LDL, hypertension status, smoking status, alcohol consumption, stress level, sleep quality, and duration of diabetes. Figure 7 is the classified result.

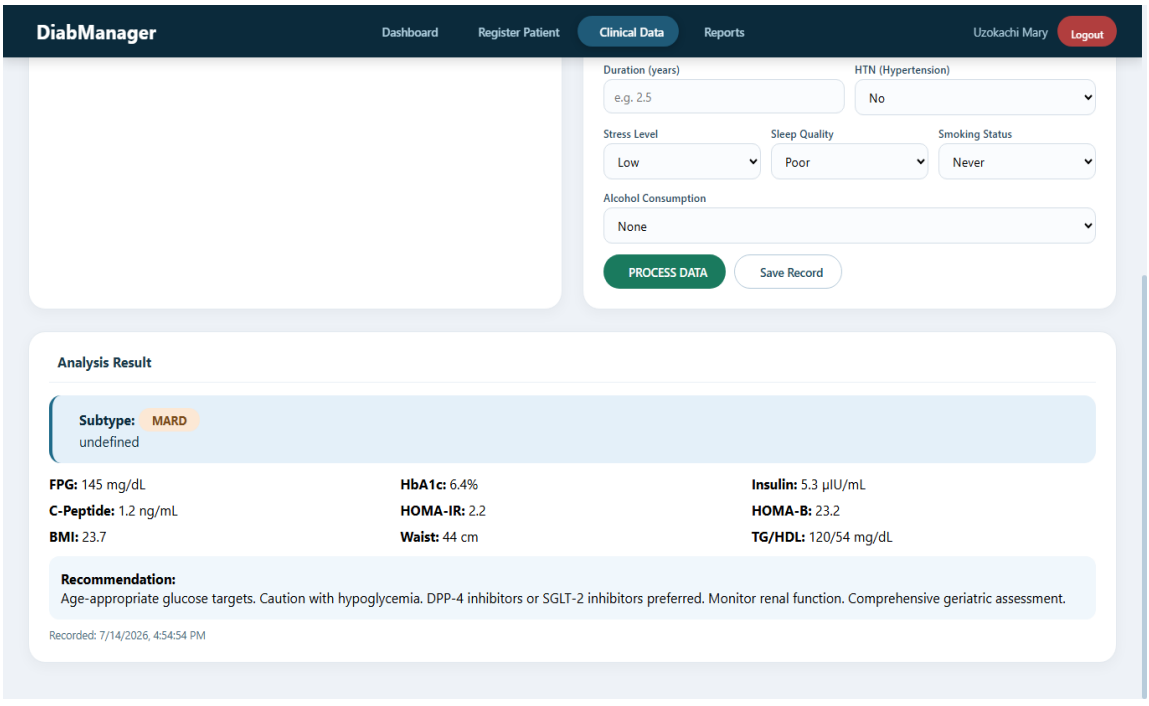


Figure 7: Result of the diagnostic section when the data is processed with the ensemble classifier

Figure 7 presents the diagnostic processing interface after the patient's clinical data has been submitted to the proposed stacking ensemble classifier. During this stage, the system automatically preprocesses the input data before passing it through the trained machine learning models that constitute the stacking ensemble. The classifier evaluates the patient's clinical features simultaneously and combines the outputs of the base learners through the meta-classifier to generate the final prediction. The integration of the stacking ensemble model therefore provides a reliable framework for intelligent diabetes subtype classification.

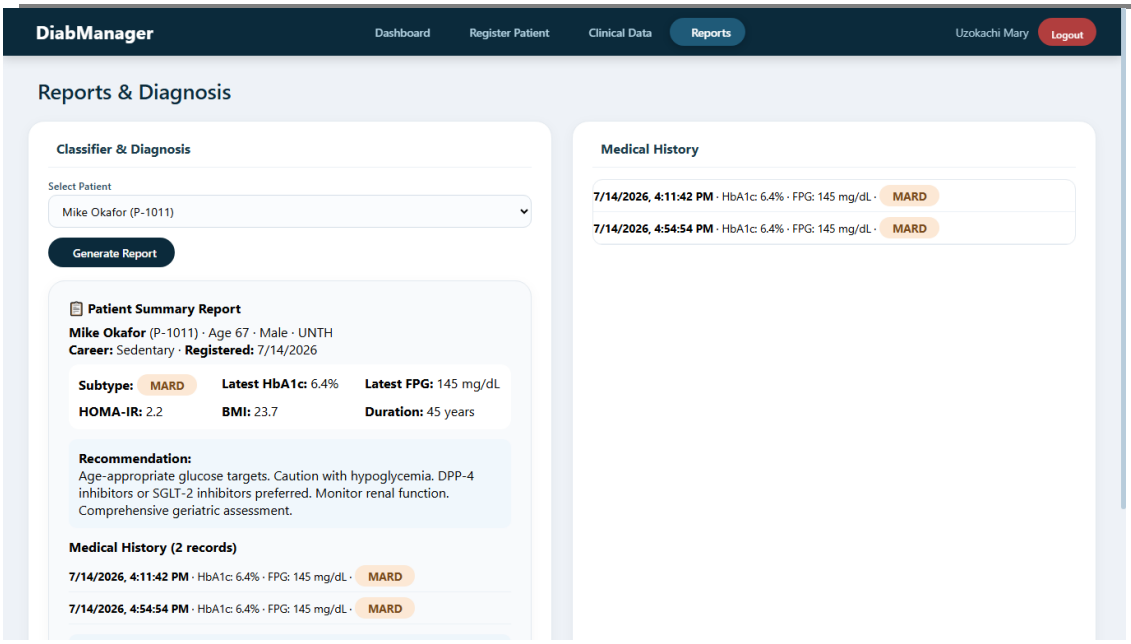


Figure 8: Result of the diagnosis

Figure 8 shows the final diagnosis generated by the proposed diabetes management system after the ensemble classification process has been completed. The interface displays the predicted diabetes subtype, such as Normal, MARD, MOD, SIDD, or SIRD, together with the associated prediction confidence and relevant clinical interpretation. This enables healthcare professionals to quickly identify the patient's diabetes category and make informed treatment decisions.

4. CONCLUSION

This study presents an ensemble-based decision support framework for the classification and management of Type 2 Diabetes Mellitus using clinical information collected from two healthcare institutions in Enugu State, Nigeria. The proposed framework used seven machine learning algorithms and a stacking ensemble approach wherein the outputs of the best classifiers were combined using an XGBoost meta-classifier. Besides disease classification, a clinical recommendation module was included to provide management recommendations for Normal, MARD, MOD, SIDD, and SIRD patients.

The experimental results showed that the proposed stacking ensemble achieved a classification accuracy of 98.18% and excellent precision, recall, and F1-score for all diabetes categories. The results further showed that the stacking approach harnessed the power of the best classifiers and reduced classification errors. In addition, the developed software successfully integrated intelligent diagnosis, patient management, and clinical recommendation in a single platform. From the results, it can be concluded that ensemble machine learning can provide a reliable and practical framework for supporting diabetes diagnosis and management, thereby improving clinical decision-making and precision healthcare.

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