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Improved Stacked Ensemble Technique in Enhancing the Classification of Diabetes Mellitus Patients

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Abstract: Diabetes mellitus is a global health challenge which is associated with various complications such as cardiovascular disease, vision impairment, and kidney failure. Therefore, early detection and accurate prediction of diabetes risk play a significant role in improving the management of the disease and minimising the long-term health complications. Individual machine learning methods that have been applied exhibit various limitations, such as overfitting, which negatively influence the performance due to reduced generalisation capability and high variance, making the model more sensitive to specific data features. The study aimed to solve this issue by applying a stacked ensemble learning technique in enhancing the classification performance of diabetes using the Pima Indian Diabetes Data. The study incorporated various base learners: Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), K-Nearest Neighbours (KNN), Gradient–Boosting Machine (GBM) and Logistic regression as a meta-learner. The base models were trained using a 10-fold cross-validation approach to ensure a robust model and minimise overfitting. The study showed that the stacked ensemble technique achieved an average AUC of 0.84 and a standard deviation of 0.05 across all folds, showing a stable predictive performance. To improve on interpretability SHapley Additive exPlanations (SHAP) analysed the contribution of individual features, such as Glucose and Body Mass Index (BMI), which were influential in predicting diabetes risk. Further, the SHAP analysed the contribution of base learners to meta-learner prediction and found Gradient Boosting and Random Forest exerted stronger influence on the stacked ensemble compared to others. Overall, the stacking ensemble provided a robust and reliable approach for an improved diabetes classification performance. Furthermore, the integration of explainable artificial intelligence, such as SHAP, improves model transparency and interpretability among healthcare professionals.

Keywords: Diabetes, Stacking Ensemble, Cross-validation, SHAP, Model Interpretability, Machine Learning, Meta-classifier

1. Introduction

Diabetes mellitus is a chronic disease caused by minimal insulin production that affects the ability of the human body to convert the energy gained from food, resulting in increased blood sugar. Over the years, diabetes and its related complications have become a global health concern since the number of affected individuals has continued to increase over time. World Health Organisation (WHO) statistics indicate that in 2022, about 830 million people lived with diabetes worldwide, and the prevalence continues to increase, especially in low and middle-income countries compared to high-income nations [1]. In Kenya, diabetes is a significant health challenge as the prevalence of the disease is 3.3% and the percentage continues to rise [2]. According to the WHO, diabetes is the 8th leading cause of death across the world, as it leads to other complications such as cardiovascular disease, diabetic foot, and others. Diabetes requires aggressive strategies that can help in the diagnosis, treatment, and approaches that can help in management. Therefore, the use of predictive modelling provides hope in attaining this demand, especially through the use of Artificial Intelligence and Machine Learning approaches. The predictive analysis that incorporates machine learning algorithms and statistical approaches on secondary and primary data is critical in enhancing knowledge and helping to predict the future. According to the study [3], the predictive analysis of healthcare data is critical in disease diagnosis since it enhances accuracy, improves patient quality of care, and optimises the resources to improve the patients' outcomes. Although diabetes can be predicted using common predictive modelling approaches, the machine learning approaches, especially ensemble techniques, are crucial in enhancing the performance and reliability of the model [4]. Further, the ensemble techniques help in capturing critical links and patterns in the dataset by providing accurate predictions, as they allow the combination of predictions from base models

The study aimed to bridge the gap in research through the application of a cross-validated stacked ensemble technique in diabetes classification in Kenya. The strategy involved the training of multiple heterogeneous base learner classifiers such as K-Nearest Neighbours, Logistic Regression, Random Forests (RF), Decision Tree, AdaBoost Classifier, and Gradient Boost Classifier, whose results were combined and provided an overall result by meta-classifier. The stratified k-fold classification validated the base and meta-level models, which improve the consistency and robustness. Further, the main goal is to improve accuracy in the diagnosis of diabetes and generalisation while ensuring there is no overfitting, which can contribute to reliable decision-making in the healthcare sector. Despite the stacked ensemble technique being powerful, it is complex in the model interpretation, which is a crucial challenge. Therefore, the project incorporated Shapley Additive exPlanation (SHAP) to help in the interpretation of the model by assessing the contribution of specific patterns in the diabetes data, which is critical in the diagnosis, increasing trustworthiness, and transparency of the predictions. The SHAP played a critical role in offering important insights into the driving factors that can contribute to diabetes risks.

2. Literature Review

Diabetes has become one of the leading causes of disabilities and death globally, as it is one of the major contributors to problems such as cardiovascular disease, kidney failure, amputations, and vision issues. According to the International Diabetes Federation (IDF), about 537 million people were affected by the disease in 2021, and the figures are expected to rise in the next 10 years [5]. The development of technology for the past few decades has made the world data-centric, which has prompted the use of ML algorithms in practical and experimental applications in the healthcare sector. A study by [6] indicated that ML models are useful in the prediction and diagnosis of various healthcare challenges, whether non-infectious or infectious diseases.

Various studies have used ML algorithms to predict various diseases to enhance the diagnosis and the predictions. Based on the study [7] applied deep learning to predict paediatric diabetes using primary data from Mansoura University Children's Hospital Diabetes (MUCHD), which led to high performance and an accuracy of 99.8% in the diagnosis. The use of various metrics such as the F-score, sensitivity, and precision increased the reliability of the study results. Further, a study [8] applied various machine learning algorithms, such as ANN, LR, and SVM algorithms, to predict diabetes on a Pima Diabetes dataset, which showed an accuracy of 88.6% on ANN, 78.8571% for LR, and 78.2857% on SVM. A study by Liu et al (2018) used medical notes to predict various chronic diseases using machine learning models such as CNN and recurrent neural networks with Long and Short-term Memory, which showed that such models outperform models that incorporate structured data and also enhance the performance.

Further, study by [9] implemented a stacked ensemble by combining RF, ANN, and NB algorithms on data of adoption of chlorine dispensers from 27,457 households, where the stacked ensemble technique outperformed individual classifiers and attained an accuracy of 69.1%, which reinforced the practical application of stacked ensemble in real-world settings. Das et al. (2025) applied various ensemble techniques, such as Random Forests, XGBoost, LightGBM, KNN, and CatBoost, to predict diabetes, whereby they applied the Behavioural Risk Factor Surveillance System dataset that led to an accuracy of 96.40%. Further, [10] aimed to predict the early risk of diabetes using various ML classification algorithms. The study showed that Random Forests had the largest accuracy of 98.0778%, F-score of 0.9790 and ROC score of 0.9979.

In addition, a study conducted in Saudi Arabia by [11] used a type 2 diabetes mellitus dataset of 3000 patients from various hospitals using various ML algorithms such as LR, RF, DT, SVM, and Ensemble Majority. The study used cross-validation with 10 repetitions, and the results indicated that SVM outperformed all other algorithms by attaining 82.1% accuracy. However, on the second dataset, after cross validation indicated that RF had an accuracy of 88.27%. A comparative study conducted by [12] aimed to apply simple ML methods such as SVM, DT, ANN, LR, and Naïve Bayes to help diabetes prevention, indicating that LR achieved the highest accuracy of 77%. Further, [13] aimed to predict diabetes at an early stage using various classifiers such as KNN, NB, XGBoost, DT, and RF. The authors evaluated the accuracy of the algorithm using the precision, whereby XGBoost showed to have a precision accuracy of 77% outperforming other models, indicating its capability in accurately predicting diabetes outcomes, which is crucial in early prevention and clinical decision-making about the treatment and management of the disease

Various studies have applied SHAP to help in the interpretability of healthcare problems, thus providing valuable insights into diabetes prediction. A study by [14] applied the SHAP analysis to elaborate on the contribution of various features in the diabetes dataset with variables such as age, blood pressure, BMI, and high cholesterol. The study showed that high cholesterol was identified as a critical influential feature in diabetes prediction. Further, a study by [15] aimed to enhance the interpretability of diabetes risks using SHAP analysis and found that General Health, Age, BMI, and High blood pressure are the critical features for both the Original and Recursive Feature Elimination (RFE) datasets. The use of SHAP analysis enhanced the transparency and application of predictive models in a clinical setup, assisting in the early identification and prevention of diabetes in healthcare.

According to study [16] the SHAP framework to explain the models prediction and indicated that age, polyuria, and polydipsia are the crucial predictors of diabetes risk. The SHAP framework and decision trees help in providing predictive abilities and transparency in model interpretability. Study by [17] integrated SHAP on ensemble learning models to enhance efficiency and accuracy in predictions, and feature selection enhanced the model performance and helped in giving efficient and reliable clinical applications. The study by [18] used SHAP to extract the importance of features while fitting Random Forest (RF), Extra Tree (ET), Adaboost and XGBoost models. The study concluded that glucose is the specific feature that leads most to diabetes prediction, while BMI and age have a significant impact.

3. Materials and Methods

3.1. Study Design and Data Variables

The study involved an experimental research design to align with the study‘s objective of assessing the effectiveness of the stacked ensemble learning approach in classifying diabetes patients. The research involved training multiple base learners, such as DT, SVM, KNN, and RF, which was followed by a meta learner that combined the predictions in the stacked ensemble technique. The secondary diabetes for the study was obtained from UCI Machine Learning and it was originally from National Institute of Diabetes and Digestive and Kidney Disease with the objective of determining whether a patient has diabetes or not based on various features. The dataset comprised of 768 observations of medical information of Pima Indians patients.

3.2. Data Pre-processing

Real-time dataset contains noise, missing or gaps in values, which may not comply with the format, thus making it unsuitable while training the machine learning models. Therefore, preprocessing was critical since it helped in improving the effectiveness and accuracy while training the machine learning models. According to [19], data preprocessing is critical before feeding any machine learning models by ensuring that there is class balancing, identification of the outliers, and removal of the missing values. In this case, equation 1 was used to to remove the missing values.

$$\sigma^2_{\text{obs}} = \frac{1}{n_{\text{obs}}} \sum_{i=1}^{n_{\text{obs}}} (X_i - \bar{X}_{\text{obs}})^2 \tag{1}$$

Where $\bar{X}_{\text{obs}}$ represents the mean of the observed values and n_{obs} is the number of the observed values.The approach was critical when the missing values are completely random.

3.3. Model Training

80% of the data was used to train the ML algorithms to ensure that they learn the patterns and the relationship. On the other hand, the 20% was used in the validation to allow an unbiased assessment of the model performance of the unseen data. 80% of the dataset was divided into k equal-sized folds (k=10), and for each k iterations, one of the folds acted as the validation set while the k-1 folds were used to train the base classifiers.

3.4. Stacked Ensemble Technique with Cross-Validation

The stacking ensemble technique was employed in the study to integrate the prediction of multiple base learners such as the support vector machine (SVM), random forest (RF), decision tree (DT), K-Nearest Neighbors (KNN) and Gradient Boosting Machine (GBM). These predictions served as input features for a meta-classifier, Logistic Regression (LR), which generated the final prediction (Figure 1).

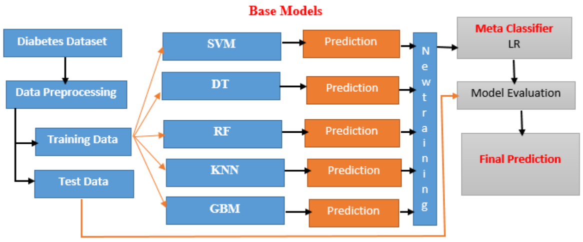

Figure 1. *Stacked Flowchart.*

3.5. The Development of Base-learners

3.5.1. K-Nearest Neighbor (K-NN)

KNN was used in the study as base learner and was used due to its instant based nature which is critical in capturing the local neighborhoods The proximity between different data points measured using Euclidean equation *Euclidean Distance*

$$d(j,k) = \sqrt{\sum_{i=1}^{n} (j_i - k_i)^2} \tag{2}$$

3.5.2. Decision Tree

Decision trees was used in the study to split the data into partitions and selecting features that will minimize impurity through the use of entropy.

$$\text{Entropy}(S) = -\sum_{i=1}^{c} P_i \log_2 P_i \tag{3}$$

3.5.3. Random Forest

Random forests was used as it applies the bootstraps aggregation of different decisions trees which enhanced the generalization and the robustness. Gini index is critical in RF as it helps in identifying the splitting point and reliable feature while dividing the data.

$$\text{Gini}(A_i) = 1 - \sum_{i=1}^{n} p_i^2 \tag{4}$$

3.5.4. Support Vector Machine (SVM)

SVM was used in the study as increases the separation of classes and minimises the prediction error. SVM classifiers such as *maximum margin* classifiers, which minimised the generalisation error by increasing the margin between two disjoint half-planes. Finding the optimal hyperplane leads to the *soft margin optimization problem*

$$\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{l} \xi_i \tag{5}$$

3.5.5. Gradient Boosting Model

The Gradient Boosting model was used in the study to help in building a strong model through a combination of weak learners, usually decision trees and correcting errors of previous trees. The gradient boosting approach provides an estimation $\hat{f}(x)$ in the form of a weighted sum of functions $h(x)$, called weak or base learners, from a class of models $\mathcal{H}$, which reduces the expected value of the loss function $L(y, f(x))$ which is expressed below.

$$\hat{f} = \arg\min_{f \in \mathcal{F}} \mathbb{E}_{x,y}[\Psi(y, f(x))] \tag{6}$$

3.6. Meta Classifier (Logistic Regression)

The logistic regression helped in combinin the prediction of base learners and modelling the chance of the outcome while considering individual features, which modelled using the logarithm of chance.

$$\log\left(\frac{\pi}{1-\pi}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k \tag{7}$$

3.7. Model Interpretability Using SHAP

The SHAP approach was used in identifying the features' contribution in model prediction where SHAP values played a critical role in ascertaining the influence of each attribute on the diabetes prediction.

$$\text{SHAP}_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!\ (|N| - |S| - 1)!}{|N|!} [f(S \cup \{i\}) - f(S)] \tag{8}$$

4. Results and Discussion

4.1. Performance of Individual Classifiers

The study results indicated that Random Forest had the highest accuracy of (0.7708 ± 0.0445), closely followed by Decision Tree (0.7707 ± 0.0597). Gradient Boosting (0.7629 ± 0.0576) and Support Vector Machine (0.7617 ± 0.0414) exhibited competitive performance, while K-Nearest Neighbours recorded the least mean accuracy (0.7434 ± 0.0631)

Table 1. *Comparison of Base Learner Performance.*

Model	Accuracy (Mean ± SD)	AUC (Mean ± SD)
Random Forest	0.7708 ± 0.0445	0.838 ± 0.047
Decision Tree	0.7707 ± 0.0597	0.813 ± 0.075
Gradient Boosting	0.7629 ± 0.0576	0.832 ± 0.059
Support Vector Machine	0.7617 ± 0.0414	0.815 ± 0.032
K-Nearest Neighbours	0.7434 ± 0.0631	0.794 ± 0.065

The analysis of the Receiver Operating Characteristics (ROC) offered critical insights into the discriminatory capabilities of the base models. Random Forest achieved an AUC of 0.838 ± 0.047, Gradient Boosting recorded 0.832 ± 0.059, Support Vector Machine achieved 0.815 ± 0.032, Decision Tree 0.813 ± 0.075, and KNN 0.794 ± 0.065. The results indicated that ensemble methods outperformed the single tree and instance-based classifiers in the discrimination of non diabetic and diabetic patients.

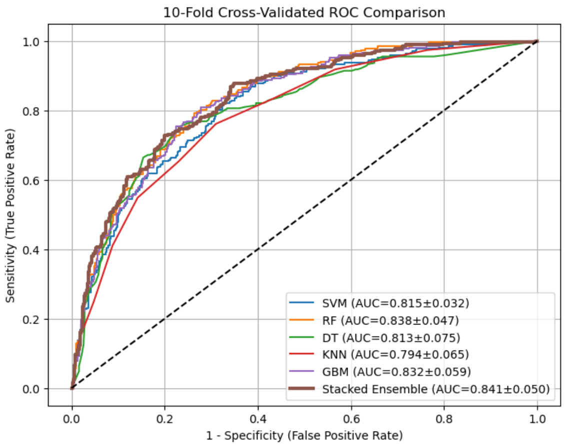

Figure 2. *ROC Comparison.*

4.2. *Performance of Stacked Ensemble*

The stacked ensemble model showed an overall accuracy of 0.7617, F1-score of 0.6288, precision of 0.6889, recall (sensitivity) of 0.5784, and AUC-ROC of 0.8263. After 10-fold cross-validation, the stacked ensemble model attained an average AUC of 0.841 ± 0.050. Results aligns with [20] showed superior performance using a stacked ensemble with LR as the meta-learner combining with oversampling and achieved an accuracy of 91.5% which demonstrated the performance of the stacked ensemble technique. [9] implemented a stacked ensemble by combining RF, ANN, and NB algorithms on data of adoption of chlorine where the stacked ensemble technique outperformed individual classifiers and attained an accuracy of 69.1%, which reinforced the practical application of stacked ensemble in real-world settings.

Table 2. *Performance Metrics of the Stacked Ensemble Model.*

Metric	Value
Accuracy	0.7617
Precision	0.6889
Recall (Sensitivity)	0.5784
F1-score	0.6288
AUC-ROC	0.8263
Cross-validated AUC	0.841 ± 0.050

4.3. *Model Interpretability Through SHAP*

The SHAP analysis indicated that glucose is the influential predictor, followed by BMI, Diabetes Pedigree Function, and Age. The study results align with the findings from [18], who concluded that glucose contributed significantly to the diabetes prediction while BMI and age also had a substantial influence.

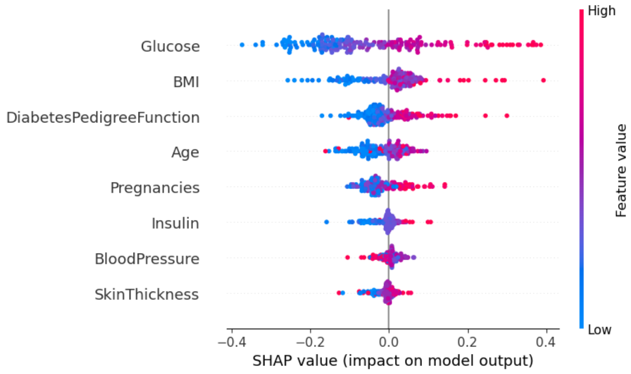

Figure 3. *SHAP on Varibles.*

Gradient Boosting SHAP value had the widest spread, which ranged from -0.55 to +1.05. The results indicated that GB contributed heavily to the meta learner's final prediction.

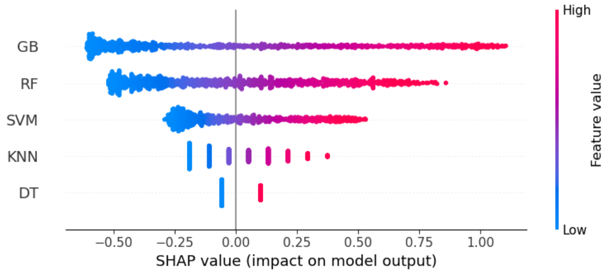

Figure 4. *SHAP on Algorithms.*

5. Conclusion and Recommendations

5.1. *Conclusion*

The findings indicated that individual classifiers, such as Random Forest and Decision trees, attained a competitive performance. However, the stacked ensemble technique produced consistent and improved discriminatory ability with an average of 0.841 under 10-fold cross-validation. Further, the incorporation of the SHAP interpretability was critical in strengthening the transparency in the prediction by identifying glucose, BMI, Diabetes Pedigree Function, and Age as the crucial features which aligns with crucial clinical knowledge.

5.2. *Recommendations*

Based on the study results, it will be critical for the use of the stacked ensemble technique in developing clinical decision support in the early screening of diabetes. Healthcare data scientists should prioritise the use of validation approaches to ensure reliability in performance estimation to prevent over-optimistic results. Further, the integration of explainable artificial intelligence, while integrating SHAP, can enhance transparency and adoption of the models in the healthcare sector. The policymakers and healthcare institutions may leverage the explainable ensemble models to improve preventative screening approaches.

Future studies can expound on this work by validating the stacked model with larger and more diverse clinical datasets to improve the generalisability and statistical power. More studies may try to explore the incorporation of advanced boosting models, such as XGBoost and deep learning architectures, for comparative analysis. Further, studies that integrate biomarkers such as lifestyle indicators and HbA1c may help in enhancing the predictive accuracy. Also, intergration of SMOTE on stacked approach can play critical role in addressing the class imbalances which can improve the its performance.

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Abbreviations

WHO	World Health Organisation
RF	Random Forest
DT	Decision Trees
SVM	Support Vector Machine
AUC	Area Under the Curve
SHAP	SHapley Additive exPlanations
ROC	Receiver Operating Characteristic
JKUAT	Jomo Kenyatta University of Agriculture
SMOTE	Synthetic Minority Over-sampling Technique
KNN	K-Nearest Neighbor

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Authors Contributions

Samuel Mwangi: Conceptualization, Formal Analysis, Investigation, Software, Methodology, Resources, Validation, Visualization, Writing - original draft, Writing - review & editing

Herbert Imboga: Supervision, Methodology, Writing – review & editing

Wilson Kamami: Supervision, Writing – review & editing

Susan Mwelu: Supervision, Methodology, Writing – review & editing

Conflicts of Interest

There is no conflicts of interest among authors.

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