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A Hybrid Intelligent Framework to predict Health Risks among Women during Menopause using Ensemble Learning Techniques

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Abstract - **Ensemble Learning is an innovative learning technique that integrates multiple learning models to provide good results. It is the best and most efficient technique for solving different problems, mainly used for classification purposes to improve classification accuracy. This paper introduces an innovative framework to predict the level of risk among women during menopause using an ensemble technique. It has four phases, which mainly include a feature selection method, a feature importance method, and a new classifier with fuzzy rule-based decision making for predicting the level of risk among women during menopause. The Recursive Feature Elimination (RFE) method determines the most significant features, while the Random Forest Classifier identifies the most dominant features from all those relevant for classification. An ensemble classifier is a technique for integrating various classifiers that increases accuracy by combining multiple classification algorithms. This research suggests a multilayer stacking method and a stratified sampling method for an ensemble classification algorithm. The stratified sampling technique divides the original dataset into numerous samples. The base learners are well-known classifiers, namely Decision Tree, Naive Bayes, and K-Nearest Neighbor, and these classifiers build the ensemble model. The max voting technique integrates the learners' results. Finally, we have constructed various fuzzy-based if-then rules to predict the level of risk among women. The proposed ensemble- based framework improves accuracy compared to traditional approaches during feature selection and classification. Fuzzy rules for predicting the health risk level among women have successfully produced good results.**

Index Terms - Ensemble Learning, Risks prediction, Sampling Techniques, Menopause.

INTRODUCTION

In the current digital era, artificial intelligence-based applications play a role in business, medical, and scientific domains. One of the subsets of artificial intelligence techniques is the machine learning technique. Machine learning is a technique that combines a collection of scientific algorithms and statistical methods. In the medical world, disease prediction is a difficult task. It needs more clinical tests to predict the disease efficiently and correctly. Large amounts of healthcare information are available in the medical world, but they are not used to predict invisible information for successful decision-making. An effective automated system or model is needed to avoid the high cost of clinical testing. The tool or system associated with implicit instructions defined by the machine learning technique performs a specific task relying on patterns [1]. An interesting challenge in machine learning is managing more features in a dataset and building a model with good classification accuracy. The general quote in building a model is that combining several models is the best approach rather than using a single model [2]. Ensemble learning is one of the machine learning techniques that combines a variety of machine learning algorithms to solve problems.

Ensemble learning mainly solves classification problems because it enhances the overall classification performance by combining the advantages. Author Wolpert et al. [3] asserted that a single classifier cannot achieve optimum modelling for all pattern identification problems because each classifier has its domain of competence. Author Pagano et al. [4] also reported that combinations of multiple diverse classifiers can effectively enhance the overall classification accuracy of classification systems. The two most popular ensemble methods mainly used to classify a model are bagging and boosting. Bagging generates an ensemble using bootstrap samples from the training set by training individual classifiers. But the boosting technique is a general ensemble technique to build the best classifier from a collection of simple classifiers. The purpose of a series of model constructions in the boosting method is to correct the errors and improve the model accuracy.

This research paper aims to present a simple, computationally effective, and improved prediction model framework to find the level of health risk among women during menopause using ensemble learning techniques. The paper flow layout is as follows. Section 2 presents menopause concepts with the related works using machine learning techniques. The fundamentals of ensemble learning techniques is in Section 3. Section 4 discusses the phases of the proposed prediction model in depth. Section 5 outlines the experimental results of the proposed prediction model. Section 6 defines the conclusion of this work and the extension of research work in the future.

MENOPAUSE

This section covers menopause symptoms, health risks and its related works done by various researchers using machine learning techniques.

I. Menopause Symptoms and Health Risks

Menopause symptoms include irregular menstruation, vaginal dryness, hot flashes, chills, night sweats, sleep issues, mood swings, weight gain, and metabolic slowing. Menopause symptoms differ from one person to another [5]. The word can define all the changes a woman undergoes before or after a cycle has stopped, marking the end of the reproductive years. Menstruation ceases only if an egg is not released each month by the ovaries. This stage is the menopause stage. It is a midlife transition in a woman’s life, and it will happen only after the age of forty. It is a natural part of life and is not a disease or disorder. But some women face extreme menopause symptoms and may have encountered multiple risks in the postmenopausal stage [6]. The common symptoms during menopause are irregular menstruation, vaginal dryness, hot flashes, chills, night sweats, sleeping issues, mood swings, weight gain, and metabolic slowing. Menopause symptoms differ from one person to the next [7]. Heart disease, strokes, osteoporosis, cancer, depression, and other urinary incontinence may all occur during the menopause period, particularly if extreme symptoms and risk factors are present.

ENSEMBLE LEARNING - FUNDAMENTALS

Ensemble is the art of combining diverse set of learners (individual models) together to improvise on the stability and predictive power of the model. In this article, Models can be different from each other for a variety of reasons, starting from the population they are built upon to the modelling used for building the model. Ensemble learning integrates a variety of machine learning techniques to solve problems. Ensemble learning solves classification problems. The most popular methods mainly used to classify a model are bagging and boosting. Bagging generates an ensemble using bootstrap samples from the training set by training individual classifiers. But boosting is a general ensemble technique to build the best classifier from a collection of simple classifiers. A series of model constructions in the boosting method is to correct the errors and improve the model accuracy. Stacking is a very interesting way of combining models. In Gupta et al. (2021) study [8], a binary classifier based on a stacking ensemble is modelled with deep neural networks for the prediction of heart diseases, post-COVID-19 infection. This model is validated against other baseline techniques, such as decision trees, random forest, support vector machines, and artificial neural networks. Results show that the proposed technique outperforms other baseline techniques and achieves the highest accuracy. Besides stacking ensemble classifier, seven individual classifiers are established as the comparison. These classifiers include support vector machine (SVM), k-nearest neighbours (KNN), random forest (RF), gradient boosting decision tree (GBDT), decision tree (DT), logistic regression (LR) and multi-layer perceptron (MLP), where the hyper-parameters of each classifier are optimized using the grid search method. The prediction results show that the stacking ensemble classifier has a better performance than individual classifiers, and it shows a more powerful learning and generalization ability for small and imbalanced samples [9]. This study has introduced an ensemble machine learning model that combines predictions from multilayer perceptron (MLP), K-Nearest Neighbour (KNN), and Random Forest (RF) and predicts the outcome of the review as spam or real (non-spam), based on the majority vote of the contributing models [10].

Based on the concepts of ensemble learning with stacking concepts, this paper designed multilevel stacking ensemble classifier. At the first level of stacking, three base learners are integrated and the output of the first level prediction is the input of the second level learners. Again the output of the second level is the input of final predictor.

In the first level of stacking, This classifier used k-Nearest Neighbour (kNN), Decision Tree (DT), Nave Bayes (NB) Classifiers. In the second level, this model applied Random Forest (RF) and Logistic Regression (LR) classifiers. For final prediction, it has chosen Support Vector Machine (SVM) as a final predictor for classification.

PROPOSED FRAMEWORK

This section discusses the process and steps involved in developing the proposed classifier. The proposed classifier design is shown in Figure 1. The proposed classifier comprises several steps. The next subsections cover the dataset description, steps involved for implementation, and performance metrics. Finally, the experimental results sections compare the proposed classifier's performance with that of existing classifiers.

I. Dataset Description

For experimental analysis, we have used two datasets. The first dataset is available at https://doi.org/10.1371/journal.pone.0195658. PLOS provides this dataset. PLOS is a non-profit, open-access publisher. The dataset has details of Chinese women about their personal habits, health issues, parent health history, personal feelings about middle age, body height, weight, cholesterol level, BMI values, etc. [11]. The second dataset in this study is the SWAN (ICPSR 4368) Dataset. This dataset is a cross-sectional screener dataset downloaded from https://doi.org/10.3886/ICPSR04368.v5. The dataset has 16,142 women's personal details related to their health, feelings, and menopause symptoms. [12].

II. Preprocessing and Feature Selection

Preprocessing is a common requirement for standardization techniques of datasets for many machine learning models. Its main functionality is for the removal of noisy data, the removal of NaN (Not a Number) values by replacing mean and mode values, and the removal of NaN columns (empty columns). During preprocessing, the PLOS dataset has a total of more than 150 features. The remaining 108 features are received as input after preprocessing. Although the SWAN dataset contains over 100 features, only 90 are selected after preprocessing.

- ***Selecting features with Recursive Features Elimination (RFE):*** RFE (Recursive Feature Elimination) is an optimization- based wrapper method. The aim is to find the best features available in a dataset. It builds a model repeatedly determining the optimal subset of features until all of them have been analyzed. Then it arranges all of the features in order of elimination.

  Algorithm 1 Recursive Feature Elimination (RFE)

```
Require: TrainedFeatures
Ensure: BestFeatures
RF = TrainedFeatures, n = 40
while RF ≥ 0 and n > 1 do
   SF = subsetfeaturesof DecisionTreeClassifier()
   LF = RF SF
   RF = RF LF
   if RF < 40 then
   n ←1
   end if
end while
BF = RF
return BF
```

The two important configuration settings are to be considered while using RFE. The first configuration is an available number of features. The second configuration is an algorithm used to help in feature selection. RFE works for a subset of features by searching the training dataset. The search starts with all the features and successfully removing them until the target number is reached [13].This is achieved by fitting the model with the given machine learning algorithm, ranking features by relevance, eliminating the least important features. This process is repeatedly fitting the model until just a small number of features remain [13]. This concept is described in RFE pseudo-code. The decision tree classifier is used as a learning algorithm to fitting the model. Only forty features are selected from the datasets as a result of Recursive Feature Elimination algorithm.

- ***Feature importance:*** Feature importance is a technique that assign a score to all input features based on predicting the target variable. The score is defined as how the input features play a role for predicting the target variable. The scores are useful and can be used in better understanding of the data, the model and reducing the number of features. Feature importance gives better interpretability of data. Feature importance scores help to identify the best subset of features and training a robust model. The types of scoring the features are correlation scores, scores calculated by linear models, decision trees, and permutation importance scores. The Random Forest algorithm for feature importance is implemented to identify the most important features in the dataset. After being fit the model, the model provides the relative importance scores for each input feature. Out$_{en}$ features are the input of the random forest algorithm to find the top most important features for classification. This reduced feature set is called as optimal trained dataset. The overall design framework is shown in the Figure 1.

III. Multilevel stacking Ensemble Classifier

The medical field has various techniques to diagnose health risks and diseases. Individual classification algorithms must prove and develop perfect models capable of predicting health risks. Hence, by introducing the ensemble learning methods, higher performance could be achieved, leading to the accurate prediction of health risks among women during menopause.

Ensemble learning is a learning technique mainly considered for classification purposes. The main goal is to integrate multiple classifiers. An ensemble classifier is a combination of more than one prediction model. Its prediction is better than the traditional classification algorithm. Generally, two types of ensemble framework are available. They are dependent frameworks and independent frameworks. In a dependent framework, each classifier is sequentially trained. In an independent framework, each classifier is trained in a parallel manner.

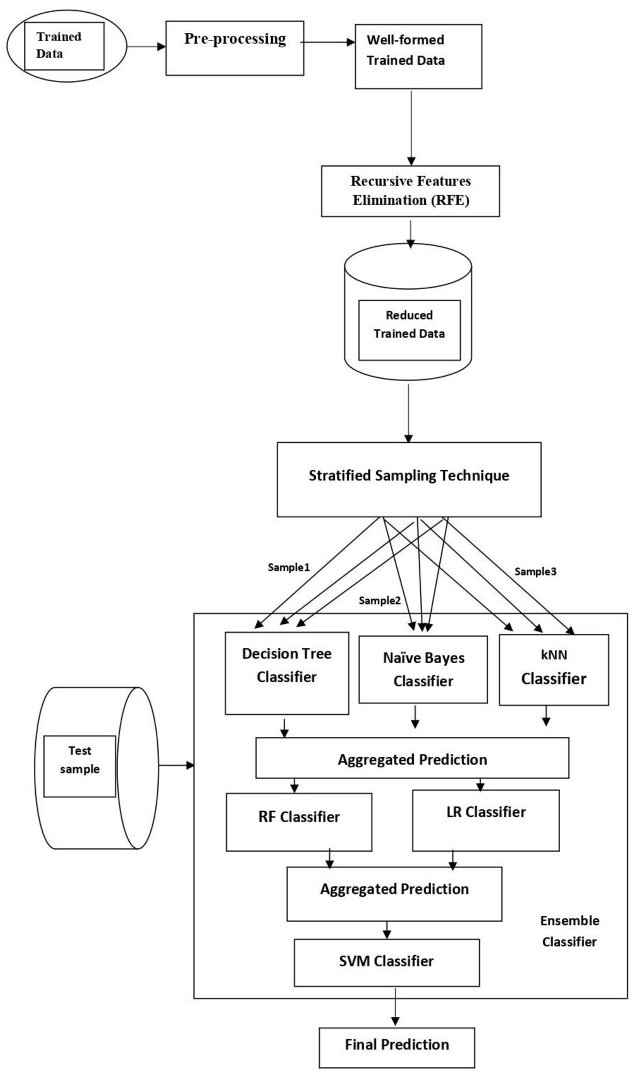

Figure. 1. The proposed Prediction Model Framework Design

The ensemble classifier creates the prediction model using a sample as input. Sampling is the process of selecting a subset of samples from a larger dataset. The advantages of a good sample should be the same as those of the original dataset. The sample is made using sampling techniques. Overfitting can be avoided through sampling in model building [14]. Sampling is also important for improving the accuracy of the ensemble classifier. Simple random sampling, systematic sampling, and stratified sampling are all common sampling techniques [14].

A quality sample is helpful to build an accurate prediction ensemble model instead of using the whole dataset. In ensemble learning, sampling techniques try to provide a sample with several features. They are:

1) It provides greater accuracy.
2) It provides sample with much reliability.
3) Sample with proper class distribution like that in original dataset.

Stratified random sampling is a sampling method. The sample is taken from each group using a simple random sampling technique. A “strata” is the term given to each group. It increases the homogeneity within strata and increases the heterogeneity between strata [14]. The training data set is first divided into groups depending on the values of the base classes. After that, a stratified sampling method is used to sample the groups. Finally, these samples are used as the ensemble classifier’s training dataset. Compared to the simple random sampling technique with stratified sampling, stratified can generate fewer biases (unfairness) in a sample because the sample contains an equal proportion of classes in the original dataset.

Algorithm 2 *Proposed Classifier Algorithm (Stacked-ESTMC)*
Require: Optimal Trained Data D
Ensure: Final Prediction

1. Read the trained dataset D.
2. Apply the sampling technique on given dataset to extract samples.
3. Split the dataset into the number of samples based on the number of classifiers plus one (n+1) for the final test.
4. Split the samples into train and test sample sets.
5. Give each sample as an input of the base classifiers or level 0 to train the model.
6. Find each sample prediction using the multilevel stacking approach and store it in its output variable.
   $Prediction_{sample} = Stackingclassifier\ (sample_{input})$
7. Repeat the previous step for each sample in the Dataset.
8. Find final prediction by aggregating the results of all samples predictions using max voting technique.
   $Prediction_{final} = maxvoting\ (Prediction_1, \ldots, rediction_N)$
9. Set this new model as a final classification model.
10. Apply this new classifier model on test sample data to make final predictions.

IV. Fuzzy Rule for Decision Making

Fuzzy rule is a conditional statement. The form of fuzzy rules is given by IF THEN statements. If x is A then y is B (where A and B are linguistic values defined by fuzzy sets on universes of discourse X and Y). x is A is called the antecedent or premise, y is B is called the consequence or conclusion. In rule definition, non-numeric values are often used to facilitate the expression of rules and facts. Fuzzy Expression is a core concept in fuzzy rules. Variables in classical math take numerical values. In fuzzy logic, the linguistic variables are non-numeric and are described with expressions. Expressions map continuous variable like numerical temperature to its linguistic counterpart. For example, temperature can be described as cold, warm or hot. There is no strict boundary between cold and warm - this is why these expressions are fuzzy. To create new expression, we use function that takes numerical value of continuous variable and returns truth value. Truth value ranges between 0 and 1 - it's a degree of membership of continuous value to that linguistic variable. For defining expression, we have used Trapezoidal membership function as a membership function. Trapezoidal membership function is defined by four parameters: a, b, c and d. Span b to c represents the highest membership value that element can take. And if x is between (a, b) or (c, d), then it will have membership value between 0 and 1.We can apply the triangle MF if elements is in between a to b or c to d. There are two special forms of trapezoidal function based on openness of function. They are known as R function (Open right) and L function (Left open). The following Figure 2 and Figure 3 shows the trapezoidal membership function notation and equation respectively:

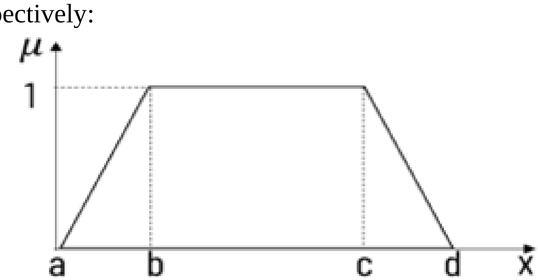

Figure. 2. Trapezoidal Membership Function

Expressions can be reused/mixed using logical operators: AND, OR, and NOT. Although expressions define linguistic variables, they aren't strictly bound to any variable. They are rather the adjectives we use to describe something and their meaning depends strictly on context. Both person and data could be big but this particular adjective has slightly different meaning in each case. Fuzzy expressions are mainly created by the various features in a dataset along with membership function. Fuzzy rule object bounds variable with expressions. Fuzzy Rules can also be evaluated to see how true they are for given input. In the fuzzification process, we mapped our crisp inputs into fuzzy degrees of membership as an fuzzy expressions. Now we take those fuzzy degrees of membership and perform some fuzzy logic operations to map from the domain of the antecedent to the domain of the consequent. In simpler terms, we have turned hard numbers into abstract "judgements" about our input, and now we need to know what to do with those "judgements" based on our fuzzy rules. We have defined more than fifty fuzzy rule using different fuzzy expressions.

$$\mu_{trapezoidal}(x;a,b,c,d) = \begin{cases} 0, & x \le a \\ \frac{x-a}{b-a}, & a \le x \le b \\ 1, & b \le x \le c \\ \frac{d-x}{d-c}, & c \le x \le d \\ 0, & d \le x \end{cases}$$

$$= \max\left(\min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right)$$

Figure. 3. Trapezoidal Membership Function Equation

Then by applying AND, OR, and NOT operators we have defined or combined various fuzzy rules to create a set of finite rules. These finite rules are mainly used to identify the level of risk among women.

V. Final Prediction

The last phase of this hybrid framework is to predict the level of severity among women during menopause. The algorithm 3 describe the framework functionalities for prediction.

The final prediction steps mainly focus on predicting the woman health risk and the level of risk during menopause.

Algorithm 3 Proposed Prediction Algorithm
Require: Optimal Trained Data D
Ensure: Level of Health
Begin

1) Read the pre-processed trained Dataset D.
2) Apply ensemble based feature selection and feature importance technique to find the most significant features in the Dataset D.
3) Apply proposed classifier to classify the Dataset.
4) Create fuzzy expressions using linguistic variables of the most significant features in the Dataset using Trapezoidal membership function.
5) Generate different fuzzy rules using fuzzy expressions.
6) Generate the most finite fuzzy rules using the logical operators AND, OR and NOT for prediction.
7) Apply test data to the proposed classifiers and find final prediction for the test data.
8) Check if the final prediction value returns as two from the classifier, then check the level of risk using finite fuzzy rules.
9) Display the level of risk based on the results produced by the finite fuzzy rules.

10) If the final prediction value returns as one from the classifier, then display the prediction as no risk or normal

End

RESULTS AND DISCUSSION

The dataset is split into four samples using a stratified sampling technique to solve the overfitting problem. The fourth sample is a test sample of the classifier. Every three samples are the input of base classifiers, and the aggregated result of the base classifiers at the first level is the input of the advanced learners at level 2. The prediction of level 2 is the input of SVM, the Meta classifier of the model. The final prediction is the aggregated prediction of all samples as the final result of the proposed classifier.

Various performance metrics determine the performance of the proposed classifier, including accuracy, precision, recall, and F1-Score. Table I and II show the performance of the proposed classifier based on the samples. The proposed classifier performs well with good accuracy of more than 99.9 percentage accuracy.

TABLE I – PERFORMANCE ANALYSIS OF THE PROPOSED CLASSIFIER – PLOS DATASET

Samples	PLOS Dataset			
	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Sample1	99.73	98.23	99.23	99.75
Sample2	99.56	99.09	97.96	99.57
Sample 3	99.91	99.12	99.72	99.91
Proposed Classifier	99.93	99.99	99.87	99.93

TABLE II - PERFORMANCE ANALYSIS OF THE PROPOSED CLASSIFIER - SWAN DATASET

Samples	SWAN Dataset			
	Accuracy (%)	Precision (%)	Recall (%)	F1 Score(%)
Sample1	99.91	99.91	99.89	99.91
Sample2	99.95	99.89	99.89	99.91
Sample 3	99.93	99.87	99.99	99.93
Proposed Classifier	99.99	99.99	99.99	99.99

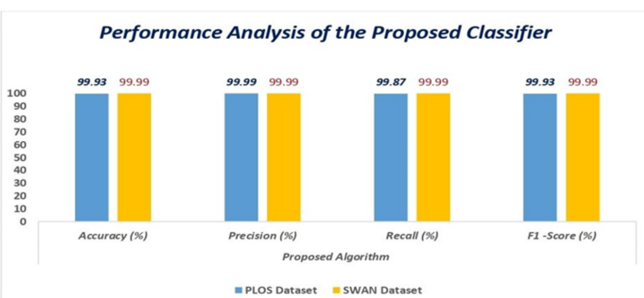

Figure. 4. Performance Analysis of the proposed classifier with existing classifiers

I. Comparison of the proposed classifier with existing traditional classifiers

TABLE III - PERFORMANCE ANALYSIS OF VARIOUS CLASSIFIERS – PLOS DATASET

Classifiers	Classifiers Performance Metrics (in %)			
	Accuracy	Precision	Recall	F1 Score
Naïve Bayes	81.02	79,32	89.41	84.06
k-Nearest Neighbour	98.45	98.61	96.61	98.61
Decision Tree	98.69	98.53	98.77	98.7
Random Forest	98.82	99.11	98.82	98.87
Logistic Regression	99.62	99.66	99.66	99.66
Support Vector Machine	99.64	99.62	99.74	99.68
Proposed Classifier	99.93	99.99	99.87	99.93

TABLE IV - PERFORMANCE ANALYSIS OF VARIOUS CLASSIFIERS - SWAN DATASET

Classifiers	Classifiers Performance Metrics (in %)			
	Accuracy	Precision	Recall	F1 Score
Naïve Bayes	88.84	93.58	91.13	92.34
k-Nearest Neighbour	99.85	99.69	99.83	99.89
Decision Tree	99.81	99.89	99.81	99.81
Random Forest	99.83	99.81	99.82	99.83
Logistic Regression	99.85	99.83	99.83	99.86
Support Vector Machine	99.95	99.94	99.93	99.95
Proposed Classifier	99.99	99.99	99.99	99.99

TABLE V -FINAL PREDICTION FRAMEWORK RESULTS - LEVEL OF RISK

Rules	Prediction results		
	Classifier Prediction	Fuzzy Rule	Risk Level
No Rule	1	NO	Normal / Healthy
Rule 1	2	HIGH	High Level Risk
Rule 2	2	MEDIUM	Medium Level Risk
Rule 3	2	LOW	Low Level Risk

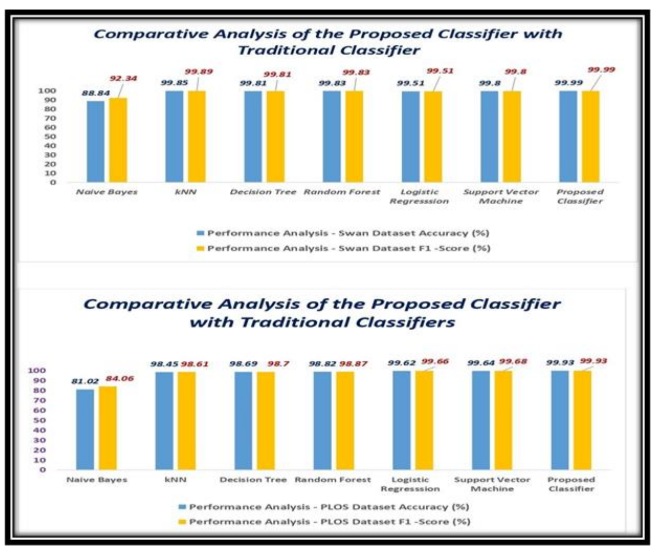

Figure. 5. Performance Analysis of the proposed classifier with existing classifiers

The proposed classifiers use various base and advanced classifiers. A comparison between the traditional classifiers and the proposed one shows how the performance of the proposed classifier differs from other classifiers. Table III and IV shows the various classifiers used for building the stacking method based classifiers with final result of this proposed classifier. The result shows that the best accuracy and F1-score of the proposed classifier.

Figure 5 shows the performance comparison of various classifiers with the proposed classifier. Table V shows the final prediction results based on fuzzy rules. The proposed classifiers' results are the value of the condition of fuzzy decision- making. If the classifier result is no risk, then the "No" fuzzy rule generates the output "Normal/Healthy" as a final prediction of the proposed model. Likewise, if the classifier result is yes, then rules 1, 2, and 3 will be the results of the proposed model.

CONCLUSION

This novel classifier integrates various learners with a multilevel stacking method for predicting the health risks among women during menopause. The Max-voting algorithm in Bootstrap Aggregation aggregates the predictions of each base classifier. Likewise, at the second level, the result of the first level prediction is the input of the second level classifiers. The second level integrated result is the input of the final level Meta classifier Support Vector Machine (SVM) for getting the final prediction. The final result of the proposed classifier is well. The proposed classifier produces better predictions than other machine learning classifiers. In addition, the proposed classifier can predict and provide early warning of health risks in women who are experiencing menopause. The prediction model produces more similar and accurate results during the execution process. The professionals can use this model for the level of risk prediction during menopause among women.

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