



African Journal of Biological Sciences



Machine Learning Classification Method Using Hybrid Model to Predict Chronic Kidney Disease

Priyanka Masih^{1*}, Sunita Kushwaha²

¹Research Scholar, MATS School of Information Technology, MATS UNIVERSITY, Raipur (C.G.), India,
Email: priyanka.masih123@gmail.com

²Assistant Professor, MATS School of Information Technology, MATS UNIVERSITY, Raipur (C.G.), India,
Email: sunita.skushwaha@gmail.com

*Corresponding author: Priyanka Masih
Email: priyanka.masih123@gmail.com

Article History

Volume 6, Issue Si4, 2024

Received: 15 May 2024

Accepted: 25 June 2024

doi:

10.48047/AFJBS.6.Si4.2024.3765-3779

Abstract

Chronic kidney disease (CKD) is a prevalent disease that presents a variety of challenges, including soaring costs for intervention, urgency, and more importantly, difficulty in early detection of the disease. It is a non-communicable disease that affects 10-15% of the global population. It depicts a medical condition that harms the kidneys and affects a person's overall health. Early and accurate detection of the stages of CKD is vital to minimize the impact of patients' health complications such as hypertension, anemia (low blood count), mineral bone disorder, poor nutritional health, acid base abnormalities, and neurological complications with timely intervention through appropriate medications. In the field of medical science, Machine Learning (ML) techniques have become valuable tools and play a significant role in disease prediction. The aim of this study was to develop and validate a predictive model for the diagnosis of chronic diseases. A dataset of chronic kidney disease with 400 samples was obtained from Kaggle. The current study used a prediction-based method that helps in detecting and diagnosing CKD patients, which enables a fast and accurate decision-making process at an early stage. Although various diagnostic methods are available, this study utilizes machine learning because of its high accuracy. In this study, we used a hybrid technique to build the proposed model. In our proposed model, we used the Pearson correlation for feature selection. In this step, the best models were selected based on critical literature analysis. In the second step, a combination of these models was used in the proposed hybrid model. The objective of this study was to evaluate the best machine learning classification techniques in terms of accuracy in predicting CKD. And also provides a solution for over fitting or imbalanced data and achieves the highest accuracy with better performance by using re-sampling method k-fold validation which evaluates the performance of Machine Learning. And for handling class imbalance in dataset using the SMOTE technique. Here eight machine learning classifiers, LR, RF, SVM, GBM, KNN, NB, ANN and K-Means Clustering, were used for analysis, and the stacking ensemble method was used to enhance the model performance. Logistic regression produced the best results, with an accuracy of 98.80% that's why we are using logistic regression as our Meta model. Finally, we achieved the highest accuracy of 100% using the stacking ensemble approach.

Keywords: Chronic Kidney Disease (CKD), Machine Learning, Random Forest (RF), Support Vector Machine (SVM), Logistic Regression, GBM, KNN, NB, ANN and K-Means Clustering, Hybrid Model, SMOTE, K-Fold cross validation.

Introduction

Chronic Kidney Disease (CKD) poses a significant risk to both physical well-being and the overall quality of life. It occurs when the kidneys are damaged and unable to perform the essential function of filtering blood. Consequently, excess fluid and waste from blood persist in the body, which may lead to a variety of health concerns. Early on, there were no obvious signs of the disease, making it a silent killer [2]. However, when the glomerular filtration rate (GFR) decreases, it is possible to treat the complications that arise, which can reduce the likelihood of developing cardiovascular disease and boost the chances of survival. Regular Laboratory tests can be used to diagnose and treat chronic kidney disease. For CKD prediction, a number of studies have been conducted utilizing various machine-learning models and determining their accuracy rates. Their goal is to save patients' lives while lowering treatment costs and human error hazards. For this using 8 different algorithm Logistic regression, random forest, SVM, GBM, KNN, NB, K-Means Clustering, ANN models were used as base models to predict and diagnose CKD. We studied how machine learning tools may help diagnose CKD early in developing nations based on their classification accuracy findings. Our proposed prediction model takes clinical symptoms as input and predicts the results using the stacking classifier with the logistic regression algorithm as a meta-classifier.

Machine learning is gaining significance in healthcare diagnosis because it enables intricate analysis, thereby minimizing human errors and enhancing the precision of predictions. Along with maintaining clinical symptoms, chronic kidney disease patients with CKD should include physical activities in daily life. They should exercise, drink water, and avoid junk food [5]. The core objective of this paper is to propose and implement a hybrid machine learning prediction model for chronic kidney disease, where due importance is given to accuracy. In this study, we analyzed the accuracy of the same data set with respect to different machine-learning algorithms and compared their accuracy scores to obtain a better model. Our focus remains on the solution of the over fitting problem using cross-validation and Balances the dataset using the SMOTE technique while achieving the highest accuracy to build the best hybrid model from the combination of available popular machine learning classifiers such as random forest, SVM, GBM, KNN, NB, K-Means Clustering, ANN models as base models.

Literature Review

This section covers research work related to algorithms and assesses some algorithms based on their accuracy. Different machine-learning techniques have been used for effective classification of chronic kidney disease from patients' data.

Bilal Khan and Rashid Naseem et al. [1] mainly focus on the empirical comparisons of seven ML algorithm. For this purpose, we select NB, LR, MLP, J48, SVM, NBTree, and CHIRP. Comparing overall accuracy metrics, precision, recall, F-measure CHIRP performance is 0.998 for all these three metrics and 99.75% for accuracy that show the better performance of CHIRP as contrasted with entire utilized techniques.

Md. Mehedi Hassan and Md. Mahedi Hassan et al. [2] did presented a predictive model using different machine learning algorithms, including NN, RF, SVM, RT, and BTM, to predict CKD earlier comparing overall accuracy metrics. Moreover, comparing overall accuracy metrics, NN has given

the best performance on the full dataset, and SVM has given the highest performance on the XGBoostdataset.

Ahmed Almulihiand Hager Saleh et al. [3] They proposed models were compared with five classical ML models, including LR, RF, K-NN, DT, NB, and hybrid models (i.e., CNN-LSTM and CNN-GRU). The proposed model had the highest ACC of 78.81%, PRE of 78.1%, REC of 78.81%, and F1 of 78.81. For the Cleveland dataset, the proposed model had the highest ACC of 97.17%, PRE of 97.42%, REC of 97.17%, and F1 of 97.15%. In addition, the proposed model achieved better results than the literature.

Pankaj Chittora and Sandeep Chaurasia et al. [4] In this perception, seven classifiers algorithm were applied viz. artificial neural network, C5.0, logistic regression, CHAID, linear support vector machine (LSVM), K-Nearest neighbors and random tree. For each classifier, the results were computed based on full features, selected features by CFS, selected features by Wrapper, selected features by LASSO regression, SMOTE with selected features by LASSO, SMOTE with full features. It was observed that LSVM achieved the highest accuracy of 98.86% in SMOTE with full features.

Hira Khalid and Ajab Khan et al. [5] In this article, they have used the Pearson correlation feature selection method and applied the same on machine learning classifier. GB, GNB, decision tree, and random forest are the base classifiers for the stacking algorithm, whereas these are implemented with the cross-validation on the basis of accuracy score. On the basis of these attributes, our proposed stacking model is able to predict whether the person is a CKD patient or not with 100% accuracy.

Adeba Debal and Tilahun Melak Sitoteet al. [6] they study three machine learning models RF, SV, DT, and two feature selection methods RFECV and UFS were used to build proposed models. Applying the models on the original dataset, we have got the highest accuracy with RF, SVM, and XGBoost. The accuracy was 99.8% for the binary class and 82.56% for five-class. DT produced lowest performance compared to RF. RF also produced the highest f1_score values. SVM and RF with RFECV produced the highest accuracy of 99.8%for binary class. XGBoost has 82.56% accuracy for five-class datasets, which is the highest.

Khaled Mohamad Almustafa et al. [7] They did different classifiers were applied for the classification of a CKD dataset. The algorithms were applied using random tree, K-nearest neighbor (K-NN), J48, stochastic gradient decent (SGD), decision table (DT) and naive Bayes classification algorithms, and a prediction model was proposed based on feature selections to efficiently predict CKD cases. It was revealed that the J48 and decision table classifiers outperform all other classifiers used for the classification of the chronic kidney disease dataset with accuracy of 99%, ROC equal to 0.999 and 0.992, MAE with 0.0225 and 0.1815, and RMSE with 0.0807 and 0.2507, respectively.

Zahid Ullah 1 and Mona Jamjoom et al. [8] did processed dataset was trained using different prediction models such as KNN, SVM, RF, and bagging. The models' performance was estimated to

show higher reliability and significance in terms of accuracy, sensitivity, F-measure, specificity, and AUC score. KNN outperformed the existing state-of-the-art methods used in the literature, showing the accuracy of the model to be used as a decision-making system for detecting and diagnosing CKD in the early stages.

Chamandeep Kaur and M. Sunil Kumar et al. [9] provide Random forests and decision trees are two examples of superior algorithms; both of these types of algorithms have a high level of accuracy and are influenced solely by the characteristics being considered. As a result, it might be worthwhile to conduct research into the application of a Random Forest model to manage missing values in datasets.

Namrata Singh et al. [11] performs a comparative analysis of rule-based classifiers in order to generate human interpretable rules for diagnosing CKD. Various rule-based approaches for comparison that have been used in the paper are JRip, CART, Conjunctive Rule, C4.5, NNge, OneR, Ridor, PART, and Decision Table-Naive Bayes (DTNB) hybrid classifier. The study concludes that among all the conventional classifiers cited, DTNB is the best rule-based classifier with highest area under ROC (0.999) along with lowest False Positive Rate (0.011).

Methodology

The proposed hybrid model was implemented in the R programming language using their essential libraries. We downloaded and preprocessed the chronic kidney disease 400 dataset from Kaggle. Missing values represented as "?" were replaced with NA, and the class variable was converted into a factor. Missing values were imputed using median imputation. We define logistic regression, random forest, SVM, GBM, KNN, NB, K-Means Clustering, ANN model as base models, and logistic regression as the meta-model. We used Synthetic Minority Over-sampling Technique (SMOTE) to handle Balances the dataset using the SMOTE technique and also used a 10-fold cross-validation to train and evaluate the stacking model. The caret stack function was used to perform the stacking. Finally, we printed a stacking model to evaluate its performance with the help of roc curve with threshold point.

Here we are using two techniques: –

1. SMOTE– perform Synthetic Minority Over-sampling Technique (SMOTE) to handle class imbalance. It is an oversampling method and has been widely used to deal with class imbalanced data. SMOTE increases the number of data instances by generating random synthetic data of minority class from its nearest neighbors using Euclidean distance. New instances become similar to the original data because they are generated on the basis of original features [18]. In this study, new training dataset is generated using SMOTE technique

2.k-fold cross validation – k-fold cross validation accuracy estimator to check the reliability of the methods [19]. Cross-validation is a data re-sampling method to assess the generalization ability of predictive models and to prevent over fitting. K-fold cross-validation is a fundamental technique in machine learning for evaluating model performance and ensuring reliable generalization to unseen data. It balances the trade-off between bias and variance in model assessment and is widely used in model selection, hyper parameter tuning, and performance estimation tasks.

The classifiers are discussed as under–

1. Logistic Regression (LR) – Logistic regression is a statistical method used to model the relationship between a binary dependent variable and one or more independent variables. It is widely used for classification tasks in which the outcome variable is categorical and has two possible outcomes, often labeled as 0 and 1. Logistic regression is a fundamental and widely used technique in statistics and machine learning for binary-classification tasks. It is efficient and interpretable and can handle both numerical and categorical independent variables.

2. Naïve Byes (NB) – The NB classifier is related to a group of probabilistic classifiers and is constructed based on the Naive Bayes (NB) theorem. It takes up vigorous independence between the component's/features and contains the most crucial part of how this classifier creates forecasts. It can be easily and appropriately used in the medical field to predict different diseases [10].

3. Random Forest – random selection of characteristics is utilized for each split, and therefore, it is similar to a decision tree in operation. The term forest refers to a collection of random trees. This classifier uses an input feature set to classify the input for each individual tree in the forest. The random tree output was chosen from the most popular votes [2].

4. A Support Vector Machine (SVM) – is a predictive ML method that is used to find the hyper plane that amplifies the separation between classes. A hyper plane sorts the values and separates positive values from negative values with a maximum margin. In this method, instances are represented as points in the space. The points near the maximum margin are support vectors [10].

5. The Gradient Boosting Machine (GBM) – is a machine learning technique used for both regression and classification tasks. It is an ensemble learning method that builds a strong predictive model by combining the predictions of multiple weak models, typically, decision trees. GBM is known for its high predictive accuracy and is widely used in various applications.

6. KNN (k-Nearest Neighbors) –KNN is a simple type of supervised algorithm. This method can be used for both classification and regression problems. However, they are primarily used for classification problems. KNN does not use a particular training stage and uses all the data for training; therefore, it is a lazy learning algorithm, and it does not consider anything about the underlying data. Therefore, it is a nonparametric learning algorithm. KNN stores the entire dataset because it has no model, so no learning is required [4].

7. Artificial neural networks (ANNs) – are promising tools in clinical medicine and are inspired by biological neural networks. They consist of interconnected nodes organized into layers to process data and learn patterns. ANNs excel at recognizing complex patterns, making accurate predictions, and adapting to the change. ANNs' architecture includes input, hidden, and output layers with weighted connections adjusted during training. However, ANNs often require large amounts of high-quality and diverse training data for optimal performance and generalization. They can lack interpretability, act as black boxes, and make decision processes unclear [10].

8. K-Means Clustering (for unsupervised learning) – Data clustering was applied to the dataset to identify unique groups of data within the collection. K-means clustering was used on the dataset to achieve this objective. The optimum number of clusters, found to be three, was determined using the elbow approach [2].

9. Hybrid model – A hybrid model using the stacking technique combines predictions from multiple base models with a Meta model to improve the predictive performance. Stacking, also known as stacked generalization, is an ensemble learning technique where the predictions of base models are used as features to train a higher-level model, the meta-model, which makes the final predictions. Stacking is to control the complementary strengths of different base models by combining their predictions in a way that maximizes predictive performance. This technique often leads to better generalization and robustness compared to individual models. Overall, a hybrid model using stacking technique offers a powerful framework for building predictive models by integrating diverse algorithms and leveraging their collective predictive power. The stacking technique involves using multiple independent machine learning models as input to process the original data. After that, the Meta classifier is used to predict the input along with the output of each machine learning model and individual algorithm's weights are estimated. Algorithms that are performing best are selected, and others having low performance are removed. In this technique, multiple classifiers as base model are combined and then, by using different machine learning algorithms, are trained on the same dataset through the use of a meta-classifier to make Stacking Model [3].

The meta-model using the chronic kidney disease dataset, follow these steps:

- 1) Load the necessary libraries.
- 2) Load and preprocess the chronic kidney disease dataset.
- 3) Use SMOTE technique to handle imbalance class.
- 4) After handling data using K-Fold cross validation
- 4) Define the base models: Logistic regression, Random Forest, SVM, GBM, k-NN, Naive Bayes, ANN, and K-Means Clustering.
- 5) Define the meta-model Logistic regression.
- 5) Define the stacking procedure.
- 6) Train the stacking model.
- 7) Evaluate the stacking model.

In this study, we have considered the CKD dataset, and this dataset is split into two parts 75% of data is used for training purposes and 25% data for test purpose. We implemented eight machine learning algorithms that are Logistic regression, Random Forest, SVM, GBM, k-NN, Naive Bayes, ANN, and K-Means Clustering. We applied stacking classifiers to build the Hybrid model that combines these eight algorithms. We analyzed the accuracy of the same dataset with respect to different machine learning algorithms and compared their accuracy score to get the best model. We implemented a stacking classifier technique to build a new model with improved accuracy.

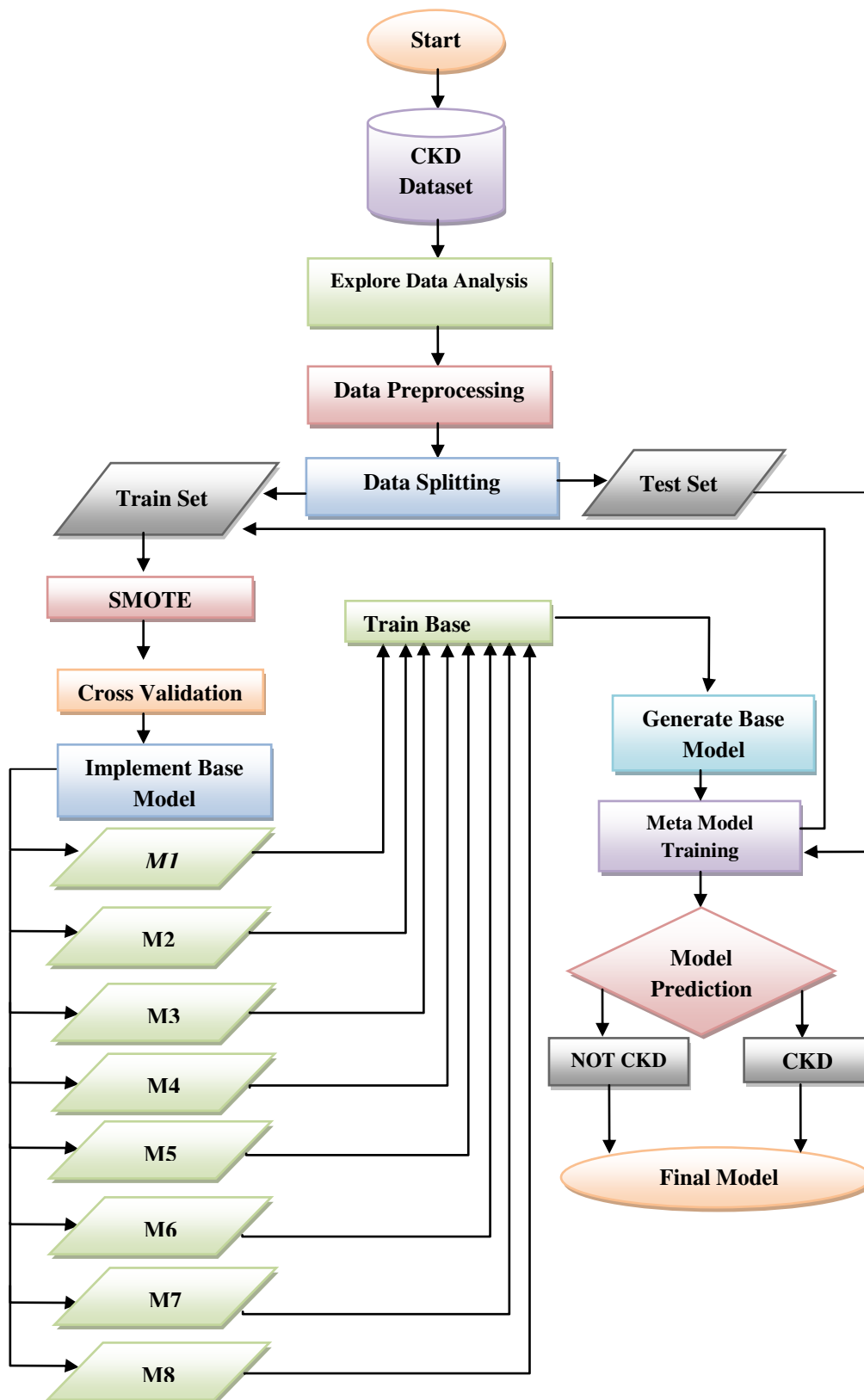


Figure 2: Flowchart of the proposed model

10. Stacking Technique Stacking improves the model’s performance, decreases the generalization error, and enables a wide use for the model. Stacking combines several machine learning models through a meta classifier. The stacking model consists of two main layers. The first layer is composed of different machine learning models called base classifiers. The base classifiers

proceed with the output prediction process on the input data with various classification performances. Stacking combines all the output predictions to form new inputs to the second layer. The second layer is called the Meta classifier, where the new inputs are the input for the Meta classifier to obtain the final prediction [20].

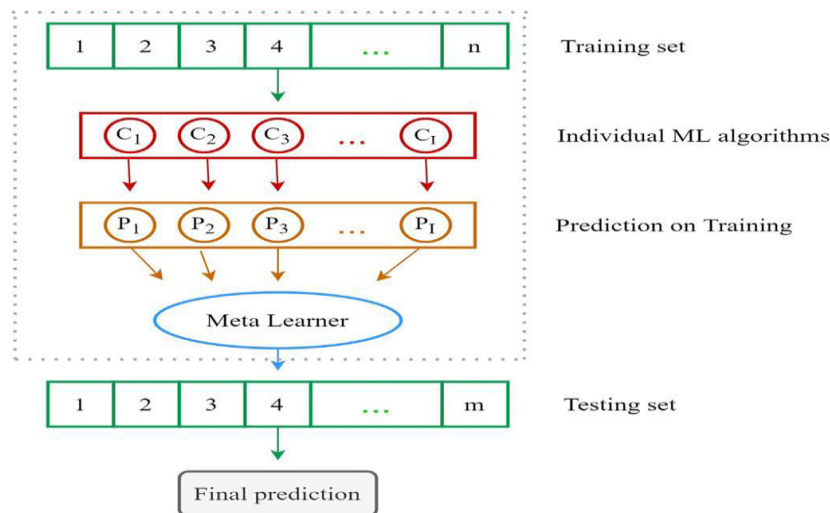


Figure 1: Process of stacking ensemble

Dataset

We are using total 400 data from CKD Dataset heretotal 16 attributes were 15 independent attributes and 1 dependent attribute Classification classes:(ckd=250, notckd=150) from the Kaggle dataset of chronic kidneydisease as input features In the Chronic Kidney Disease (CKD) dataset, the independent attributes (features) that are commonly used for predicting the presence or absence of CKD include a variety of demographic, clinical, and laboratory measurements. Here are some of the main independent attributes often used for algorithm result calculation:

1. **Age:** The age of the patient.
2. **Blood Pressure (bp):** Systolic and diastolic blood pressure measurements.
3. **Specific Gravity (sg):** Specific gravity of the urine, which indicates level of aluminum in the patient urine.
4. **Albumin (al):** Level of albumin in the blood.
5. **Sugar (su):** Level of sugar in the blood.
6. **Blood glucose random (bgr):** Level of blood glucose or sugar level glucose tolerance.
7. **Blood urea (bu):** Level of blood in urea.
8. **Serum Sodium (sod):** Level of serum sodium in the blood
9. **Serum Creatinine(sc):** Level of serum creatinine in the blood, which is an important marker of kidney function.
10. **Potassium(pot):** Level of potassium in blood
11. **Hemoglobin (hemo):** Hemoglobin levels in the blood.
12. **Packed cell volume(pcv):** Level of dehydration
13. **White Blood Cell Count (WBC) (wc):** Number of white blood cells in the blood.
14. **Red Blood Cell Count (RBC) (rc):** Number of red blood cells in the blood.

These are some of the common attributes used in predicting CKD accurately.

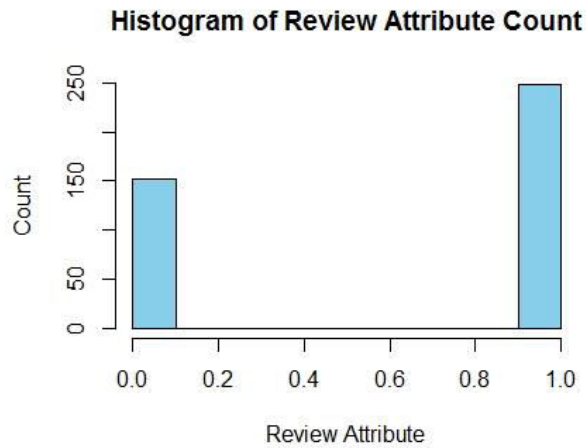


Figure 3: Histogram Plot count CKD and Not-CKD

The histogram shows graphical representation of review attribute using with two classes showing there counts where, CKD with 250 and Not-CKD 150. It shows the shape of the data distribution. It has two components X-axis represent range of values in dataset and Y-axis count of data points.

Result

In this paper, we have selected machine learning because in terms of accuracy, it performs better as compared to other available approaches. We are using 8 machine learning classifiers. These different machine learning classifiers were used as a combination for the chronic kidney disease predictions. This is also overcomes the over fitting problem and results in higher accuracy. In order to improve accuracy and to come up with a novel approach as compared to the existing work, we have implemented the proposed hybrid model with the best combination of Logistic regression, Random Forest, SVM, GBM, KNN, Naive Bayes, ANN, and K-Means Clustering. The results described in Figure 4 show that diagnosis of chronic kidney disease is effective using the Logistic regression with combination as a stacking technique in the hybrid model.

Table 1: Comparison of Machine Learning Classification Models

Comparison of Machine Learning Classification Models without SMOTE	
Models	Percentage
Hybrid Model	100%
Random forest	97.90%
SVM	97.40%
GBM	97.90%
KNN	98%
Naïve Bayes	96.80%
ANN	87.20%
K-Means Clustering	61.70%

Random forest 97.90%, SVM 97.40%, GBM 97.90%, KNN 98%, Naive Bayes 96.80%, ANN 87.20% and K-Means Clustering 61.70% and our Hybrid Model gives highest accuracy with 100%. And at the same time, it has reduced the chances of over-fitting.

Table 2: Comparison of Machine Learning Classification Models with SMOTE

Comparison of Machine Learning Classification Models with SMOTE	
Models	Percentage
Hybrid Model	100%
Random forest	98.90%
SVM	98.5%
GBM	98.20%
KNN	98.7%
Naïve Bayes	98.6%
ANN	88.05%
K-Means Clustering	63.50%

Classification Models with SMOTE results Random Forest98.90%, SVM 98.5%, GBM 98.20%, KNN 98.7%, Naive Bayes 98.6%, ANN 88.05% and K-Means Clustering 63.50% and our Hybrid Model gives highest accuracy with 100%. And at the same time, it has reduced the chances of over fitting and with SMOTE handle imbalance class to improve the performance of models.

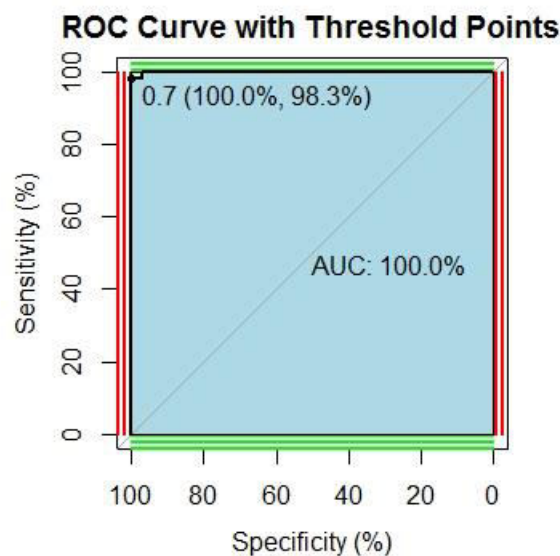


Figure 4: ROC Curve with 0.7 threshold point without SMOTE

Here, Hybrid Model without SMOTE provide result of ROC Curve it gives sensitivity 100% and Specificity 98.3% were AUC=100% with threshold point0.7.

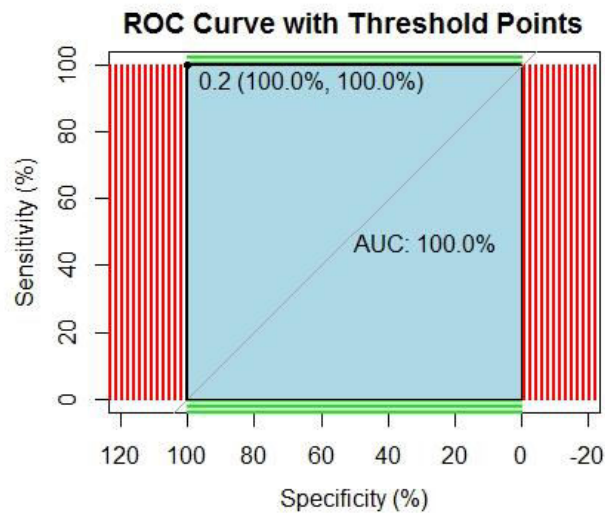


Figure 5: ROC Curve with 0.2 threshold point with SMOTE

Here, Hybrid Model with SMOTE provide result of ROC Curve it gives sensitivity 100% and Specificity 100% were AUC=100% with threshold point 0.2.

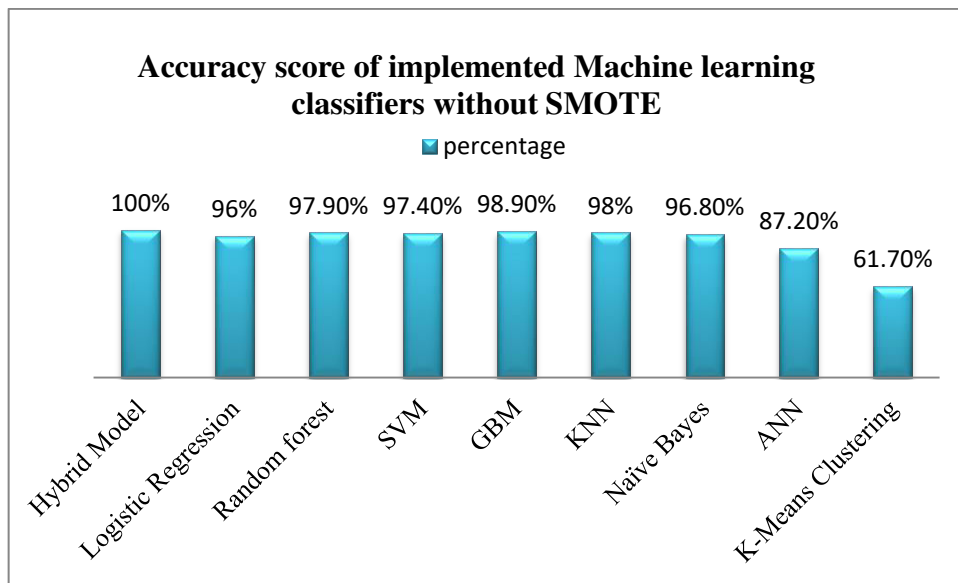


Figure 6: Accuracy score of implemented Machine learning classifiers without SMOTE

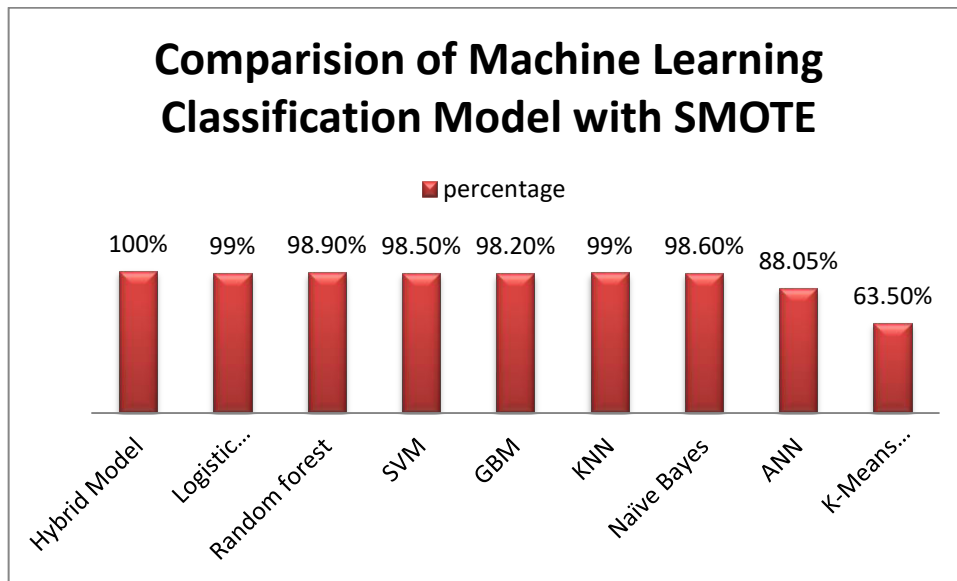


Figure 7: Accuracy score of implemented Machine learning classifiers with SMOTE

Table 3: Comparison of the feature selection results without SMOTE

Model Name	Accuracy	Precision	Recall	F1-Score	AUC
Hybrid Model	100%	100%	100%	100%	100%
Logistic Regression	96%	100%	97.60%	99.80%	98.80%
Random Forest	97.90%	100%	97.20%	96.50%	98.60%
SVM	97.40%	96%	97.20%	98.50%	98.60%
GBM	97.90%	98.60%	93.20%	96.30%	94.30%
k-NN	98%	99%	89%	94%	90%
Naive Bayes	96.80%	94.50%	97.20%	95.80%	96.80%
ANN	87.20%	80%	88.80%	84.20%	87.50%
K-Means Clustering	61.70%	78.90%	86.00%	80.20%	50%

Table 4: Comparison of the feature selection results with SMOTE

Model Name	Accuracy	Precision	Recall	F1-Score	AUC
Hybrid Model	100%	100%	100%	100%	100%
Logistic Regression	99%	100%	98.3%	99.90%	98.90%
Random Forest	98.90%	100%	97.80%	96.90%	98.60%
SVM	98.5%	97.3%	98.60%	98.50%	98.60%
GBM	98.20%	98.70%	94.20%	96.30%	94.9%
k-NN	98.7%	99.3%	89.4%	95.3%	91.5%
Naive Bayes	98.6%	95.60%	98.20%	96.20%	97.90%
ANN	88.05%	82.5%	89.50%	85.60%	88.5%
K-Means Clustering	63.50%	79.3%	87.02%	82.40%	52.3%

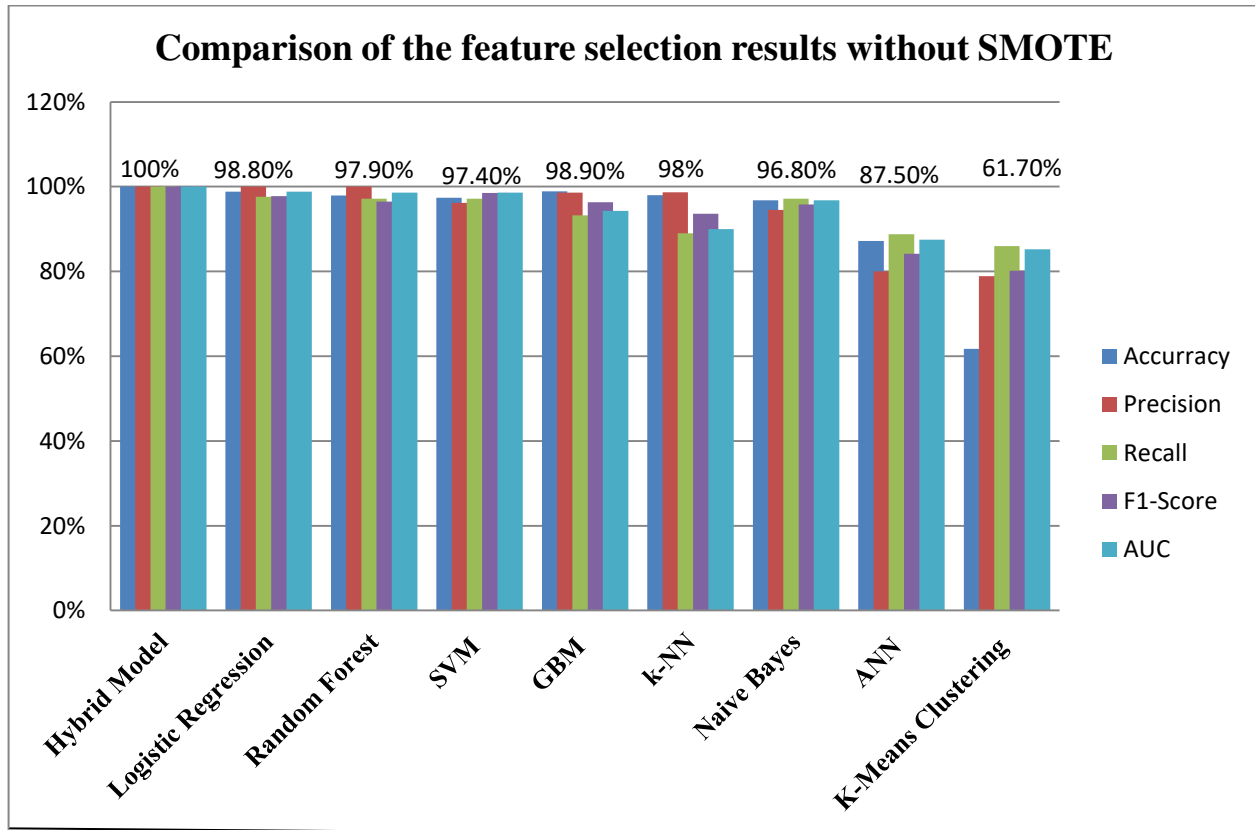


Figure 8: Comparison of the feature selection results without SMOTE

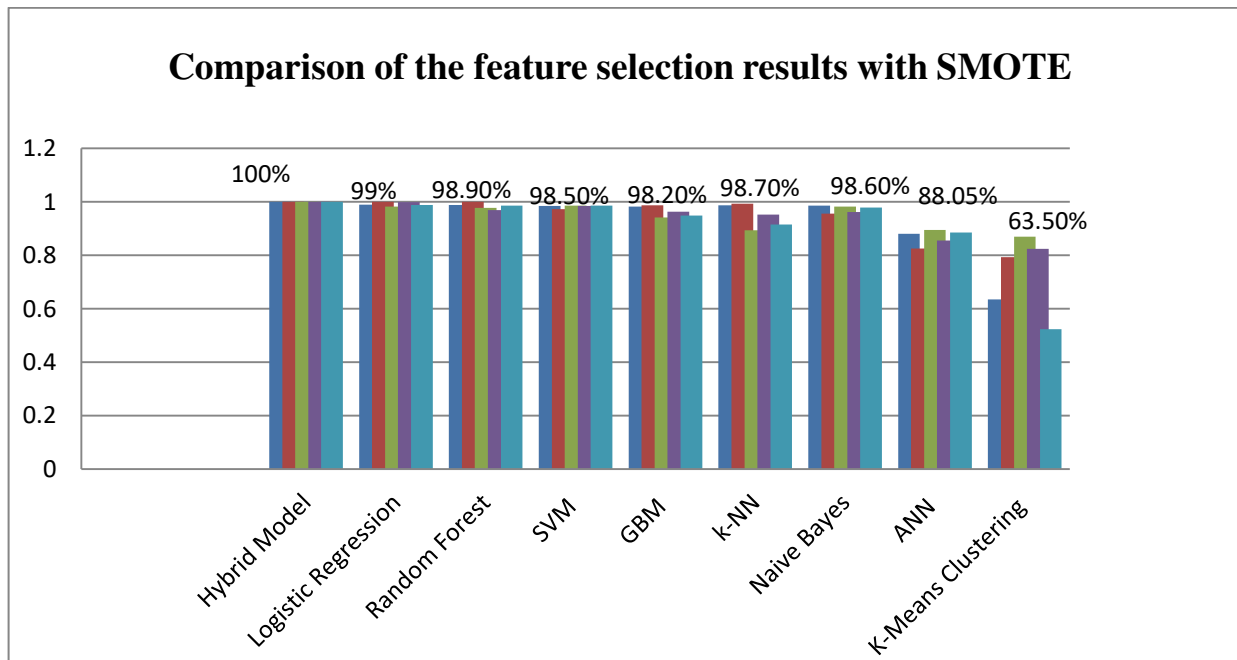


Figure 9: Comparison of the feature selection results with SMOTE

Comparative Evaluation of Our Proposed Model

To conduct our study, we used eight different models to evaluate our model’s accuracy to that of existing CKD prediction systems. Table 4 highlights our model’s overall performance in

comparison to other models. The performance of all models on the without SMOTE and with SMOTE dataset is shown in Table 3 from the below Table 4, it is noticed that our applied Hybrid model have provided the best Performance in terms of accuracy, sensitivity, specificity. Experimenting with all characteristics yielded the highest accuracy (100%) with the Hybrid model, while lower accuracy of 61.70% with K-Means Clustering. Each row of the table represents an algorithm that was utilized in our investigations, as well as related studies and the findings that were presented. When compared to other studies, the results of our proposed models seem to be pretty good.

Conclusion

Early prediction is very crucial for both experts and patients to prevent and slow down the progress of chronic kidney disease. In this paper, we mainly focus on the experimental comparisons of eight ML algorithm. For this purpose, we select Random Forest, SVM (Support Vector Machine), GBM (Gradient Boosting Machine), k-NN (k-Nearest Neighbors) Naive Bayes, ANN (Artificial Neural Network), K-Means Clustering. Here these algorithms are implemented with the 10 cross-validation on the basis of accuracy score and using SMOTE. In this study, we evaluated these algorithms on the same dataset. Here we have used dataset of CKD from Kaggle that contains 16 attributes and 400 instances. On the basis of these attributes, our proposed Hybrid stacking model is able to predict whether the person is a CKD patient or not. The stacking algorithm is implemented with the best machine learning classifiers with 100% accuracy. Cross-validation enhances the performance of the stacking model. As we have worked on the chronic kidney disease data of the binary group, the stacking algorithm performs better with these combinations of algorithms. In this paper using Hybrid stacking method in future bagging ensemble method were using to enhance the model's performance.

References

1. Bilal Khan 1, Rashid Naseem 2, Fazal Muhammad 3, Ghulam Abbas 4 , (Senior Member, IEEE), And Sunghwan Kim 5 , "An empirical evaluation of machine learning techniques for chronic kidney disease prophecy", IEEE Access, vol. 8, pp. 55012-55022, 2020.
2. Md. Mehedi Hassan and Md. Mahedi Hassan, "A Comparative Study, Prediction and Development of Chronic Kidney Disease Using Machine Learning on Patients Clinical Records", 22 February 2023
3. Ahmed Almulihi 1, Hager Saleh, Ali Mohamed Hussien 3, Sherif Mostafa 2, Shaker El-Sappagh 4,5, Khaled Alnowaiser 6, Abdelmgeid A. Ali 7 and Moatamad Refaat Hassan 3, "Ensemble Learning Based on Hybrid Deep Learning Model for Heart Disease Early Prediction", 18 December 2022
4. Pankaj Chittora 1, Sandeep Chaurasia 1, (Senior Member, IEEE), Prasun Chakrabarti 2,3, (Senior Member, IEEE), Gaurav Kumawat 1, Tulika Chakrabarti 4, Zbigniew Leonowicz 5, (Senior Member, IEEE), Micha. Jasi.Ski 5, (Member, IEEE), Ukasz Jasi.Ski 5, Radomir Gono 6, (Senior Member, IEEE), El.Bieta Jasi.Ska 7, And Vadim Bolshev 8 " Prediction of Chronic Kidney Disease - A Machine Learning Perspective", February 1, 2021.
5. Hira Khalid, 1 Ajab Khan , 1 Muhammad Zahid Khan , 2 Gulzar Mehmood , 3 and Muhammad Shuaib Qureshi "Machine Learning Hybrid Model for the Prediction of Chronic Kidney Disease", Hindawi Computational Intelligence and Neuroscience, Volume 2023

6. Dibaba Adeba Debal1 and Tilahun Melak Sitote2, "chronic kidney disease prediction using machine learning techniques", (2022) 9:109
7. Khaled Mohamad Almustafa, " Prediction of chronic kidney disease using different classification algorithms", 2 June 2021
8. Zahid Ullah 1 and Mona Jamjoom2 "Early Detection and Diagnosis of Chronic Kidney Disease Based on Selected Predominant Features", Hindawi Journal of Healthcare Engineering, Volume 2023
9. Chamandeep Kaur 1, M. Sunil Kumar 2, Afsana Anjum 1, M. B. Binda 3, Maheswara Reddy Mallu 4, and Mohammed Saleh Al Ansari 5, "Chronic Kidney Disease Prediction Using Machine Learning", Journal of Advances in Information Technology, Vol. 14, No. 2, 2023
10. S. Pouriyeh, S. Vahid, G. Sannino, G. De Pietro, H. Arabnia, and J. Gutierrez, "A comprehensive investigation and comparison of Machine Learning Techniques in the domain of heart disease," in Proceedings of the 2017 IEEE Symposium on Computers and Communications (ISCC), Heraklion, Greece, July 2017.
11. Namrata Singh And Pradeep Singh, " Rule Based Approach For Prediction Of Chronic Kidney Disease: A Comparative Study", Vol. 10(2), 867–874 (2017)
12. P. Ghosh, F. M. Javed Mehedi Shamrat, S. Shultana, S. Afrin, A. A. Anjum, and A. A. Khan, "Optimization of prediction method of chronic kidney disease using machine learning algorithm," in Proceedings of the 2020 15th International Joint Symposium on Artificial Intelligence and Natural Language Processing (iSAI–NLP), Bangkok, Thailand, November 2020.
13. U. H. Amin, J. Li, Z. Ali, M. H. Memon, M. Abbas, and S. Nazir, "Recognition of the Parkinson's disease using a hybrid feature selection approach," J. Intell. Fuzzy Syst., vol. 39, no. 1, pp. 1–21, Jul. 2020.
14. S. Khan, M. Z. Khan, P. Khan, G. Mehmood, A. Khan, and M. Fayaz, "An ant-hocnet routing protocol based on optimized fuzzy logic for swarm of UAVs in FANET," Wireless Communications and Mobile Computing, vol. 2022, Article ID 6783777, 12 pages, 2022.
15. M. Z. U. Haq, M. Z. Khan, H. U. Rehman et al., "An adaptive topology management scheme to maintain network connectivity in Wireless Sensor Networks," Sensors, vol. 22, no. 8, p. 2855, 2022.
16. M. Kavitha, G. Gnaneswar, R. Dinesh, Y. R. Sai, and R. S. Suraj, "Heart disease prediction using hybrid machine learning model," in Proceedings of the 2021 6th International Conference on Inventive Computation Technologies (ICICT), Coimbatore, India, January 2021.
17. David H. Wolpert, "Stacked Generalization", Elsevier, Volume 5, Issue 2, 1992, Pages 241–259
18. Ishaq, A.; Sadiq, S.; Umer, M.; Ullah, S.; Mirjalili, S.; Rupapara, V.; Nappi, M. Improving the prediction of heart failure patients' survival using SMOTE and effective data mining techniques. IEEE Access 2021, 9, 39707–39716.
19. K. Pal and B. V. Patel, "Data Classification with k-fold Cross Validation and Holdout Accuracy Estimation Methods with 5 Different Machine Learning Techniques," *2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC)*, Erode, India, 2020, pp. 83–87, doi: 10.1109/ICCMC48092.2020.ICCMC-00016.
20. Navid Kardani, Annan Zhou, Majidreza Nazem, Shui-Long Shen, Improved prediction of slope stability using a hybrid stacking ensemble method based on finite element analysis and field data, Journal of Rock Mechanics and Geotechnical Engineering, Volume 13, Issue 1, 2021, Pages 188–201, ISSN 1674–7755,

