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Ensemble-Based Identification of Chronic Kidney Disease

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Abstract- A serious public health issue, chronic kidney disease (CKD) needs to be identified early and accurately in order to be effectively treated and managed. To improve CKD prediction accuracy, this work suggests a unique machine-learning strategy that makes use of stacking techniques and a weighted average ensemble. With optimum weights allocated according to individual model performance, the ensemble approach integrates the predictive capabilities of several base classifiers, such as Decision Tree, Random Forest, and Support Vector Machine (SVM). To improve predictions, stacking further combines these models with a meta-classifier, usually a Gradient Boosting or Logistic Regression model. A benchmark CKD dataset is used to assess the effectiveness of the suggested method, with an emphasis on measures like accuracy, precision, recall, and F1-score. The weighted average ensemble and stacking are superior to traditional single classifiers and other ensemble techniques like bagging and boosting when it comes to handling imbalanced datasets, enhancing model interpretability, and attaining greater robustness against overfitting. The study highlights the usefulness of the suggested approach in actual clinical settings and shows how it may be used to provide more accurate CKD identification. Future research attempts to expand the scope of CKD prognosis and management by investigating the incorporation of further variables and integration with survival prediction models.

Keywords- CKD detection, Ensemble techniques, Stacking models, Imbalanced data handling, Clinical applicability.

I. INTRODUCTION

The degenerative condition known as chronic kidney disease (CKD) impairs the kidneys' capacity to remove toxins, waste, and extra fluid from the blood. Kidney failure may result from advanced chronic kidney disease (CKD), requiring dialysis or a kidney transplant. Millions of people worldwide suffer from various forms of renal dysfunction, making the disease a global health emergency. Because of its association with diabetes, hypertension, and other lifestyle-related illnesses, chronic kidney disease (CKD) is listed by the World Health Organization as one of the top 10 causes of death. CKD is frequently detected at advanced stages, when kidney function has already substantially declined, despite the fact that early detection is cruthe disease's course.

CKD has a significant effect on public health. Serious side effects such cardiovascular disease, anemia, bone mineral disorders, and malnutrition may develop as the illness worsens. Since CKD usually doesn't have any overt symptoms, it can often go undiagnosed in its early stages. Because of this, prompt detection and action are essential to enhancing patient outcomes and lowering medical expenses. The advancement of end-stage renal disease (ESRD) can be slowed by early detection, which can allow for efficient care through medication, lifestyle changes, and routine monitoring. The blood, urine, and imaging tests used in the current diagnostic procedures for chronic kidney disease (CKD) can be expensive and may not necessarily yield results right away. Furthermore, these techniques might not always be adequate for precise early-stage diagnosis because of the disease's complexity and the variety in how it manifests. This emphasizes how crucial it is to investigate alternate diagnostic techniques, especially those based on machine learning (ML), which can evaluate vast amounts of data from medical records and produce quicker, more precise predictions.

The ability of machine learning approaches, particularly those involving ensemble methods, to increase the accuracy of illness detection models has drawn a lot of interest in the medical industry. By combining the advantages of several separate models, ensemble learning generates predictions that are more resilient and dependable. The weighted average ensemble approach is one of these techniques that improves the final result by giving each model a varying weight depending on how well it predicts. An additional potent ensemble strategy is stacking, which refines outcomes further by training a meta-classifier on base model predictions.

Investigating the efficacy of using a weighted average ensemble and stacking technique for CKD detection is the goal of this study. We aim to illustrate the superiority of our hybrid approach in terms of prediction accuracy, model interpretability, and management of imbalanced datasets by contrasting it with conventional machine learning classifiers and alternative ensemble techniques like bagging and boosting. The potential advantages of this strategy include improved prediction accuracy as well as a more scalable and economical CKD detection method. Enhancing early detection methods might lessen the strain on medical facilities and enhance patient outcomes, as chronic kidney disease (CKD) remains a significant global health concern.

This study highlights the potential of the suggested weighted average ensemble and stacking strategy to transform the diagnosis of chronic kidney disease (CKD) by outlining its methodology, experimental setting, and comparative analysis. We hope to open the door for more efficient, fast, and accessible CKD detection in clinical settings by utilizing these cutting-edge machine learning techniques. We intend to use this strategy to support the larger endeavor to control and lessen the worldwide CKD epidemic.

Dataset

Attribute	Description	Role in CKD Prediction
Age	Patient's age.	Age increases CKD risk due to age-related decline.
Blood Pressure (BP)	Systolic and diastolic blood pressure.	High BP contributes to kidney damage and CKD.
Specific Gravity (SG)	Urine concentration ability.	Abnormal SG indicates impaired kidney function.
Albumin (AL)	Presence of albumin in urine.	High levels signal kidney damage (albuminuria).
Blood Glucose Random (BGR)	Random blood glucose level.	High glucose levels indicate diabetes and CKD risk.
Blood Urea Nitrogen (BUN)	Waste product filtered by kidneys.	Elevated BUN levels indicate kidney dysfunction.
Serum Creatinine (SC)	A key marker of kidney function.	High creatinine indicates reduced kidney function.
Potassium (K)	Potassium levels in blood.	Imbalanced levels indicate kidney dysfunction.
Sodium (NA)	Sodium regulation in the body.	Abnormal sodium levels signal kidney problems.
Hemoglobin (HEMO)	Blood hemoglobin levels.	Low levels indicate anemia, common in CKD.
Red Blood Cell Count (RBC)	Number of red blood cells.	Low RBC count is a symptom of CKD-related anemia.
Pedal Edema (PE)	Swelling in the lower extremities due to fluid retention.	A sign of severe CKD or kidney failure.
Hypertension (HTN)	Whether the patient has high blood pressure.	Contributes to kidney damage and CKD progression.
Diabetes Mellitus (DM)	Whether the patient has diabetes.	Diabetes is a leading cause of CKD.
Appetite (App)	Patient's appetite status.	Loss of appetite correlates with CKD progression.

II. RELATED WORK

[1] used a variety of machine learning algorithms to identify CKD by looking at clinical characteristics. Techniques for feature normalization and missing value imputation were used to preprocess the dataset. The most pertinent biomarkers affecting the prediction of CKD were found via feature selection. Using criteria for accuracy, precision, recall, and F1-score, several classifiers—including Decision Trees, Support Vector Machines, and Neural Networks—were trained and assessed.

[2] To determine the most important characteristics for CKD prediction, the authors examined many machine learning systems. They used feature selection methods like Recursive Feature Elimination (RFE) after extracting patient data that included biochemical and

demographic information. Hyperparameter adjustment was used to train a number of classifiers, including Logistic Regression, Naïve Bayes, and Gradient Boosting. Cross-validation approaches were used to validate the performance, and the study highlighted the significance of particular kidney function parameters.

[3] A deep learning model for CKD classification based on Convolutional Neural Networks (CNNs) was presented in the study. To improve model performance, the dataset was preprocessed using techniques including outlier detection and normalization. A sizable dataset of medical records was used to train the CNN model, and layer depth and activation parameters were adjusted to optimize the architecture. CNN outperformed conventional ML classifiers according to performance parameters like accuracy and AUC-ROC.

[4] Using supervised learning approaches, the authors created a predictive framework to identify CKD in its early stages. After gathering clinical data, they used feature significance analysis and missing value therapy. The study used ROC analysis and precision-recall curves to compare many machine learning models, including Random Forest, AdaBoost, and k-Nearest Neighbors. The findings showed that CKD prediction performance was much enhanced by ensemble learning.

[5] sought to create a machine learning model for CKD screening that was affordable and clinically interpretable. To lessen the problem of class imbalance, data from several hospitals was combined, cleansed, and balanced. To improve model transparency, the study used interpretable machine learning approaches such as SHAP (SHapley Additive exPlanations). A strong clinical decision-support system was produced by the final model, which included logistic regression and random forest classifiers.

[6] Several machine learning algorithms were integrated in the study to forecast the deterioration in renal function in patients with chronic kidney disease. Laboratory findings, medication history, and patient medical records were all included in the dataset. The study increased prediction accuracy by using ensemble techniques like boosting and bagging. Multiple performance measures were used for evaluation, demonstrating ML's potential for early intervention in the management of chronic kidney disease.

[7] An ensemble learning model for early detection of sepsis-associated acute kidney damage (AKI) was proposed in this study. Time-series characteristics from ICU patient records made up the dataset. Gradient Boosting Machines (GBM) and deep learning models were integrated after the authors used feature engineering approaches to extract significant temporal patterns. The results showed that when it came to forecasting AKI progression, the ensemble technique performed better than individual classifiers.
[8] Evaluation of various machine learning algorithms for CKD identification based on biochemical and clinical characteristics was the main focus of the study. To address class imbalances, the dataset was treated using oversampling and data normalizing approaches. Support Vector Machines, Decision Trees, and Ensemble Methods were among the classifiers that were compared. According to the study's findings, boosting strategies had the best prediction accuracy for identifying CKD.

[9] The study investigated models for early-stage CKD prediction based on statistics and machine learning. Time-series feature extraction techniques were used by researchers to curate a dataset of longitudinal patient records. With a focus on interpretability, the models were trained using deep learning techniques, XGBoost, and logistic regression. The results demonstrated how well hybrid models work to enhance early-stage CKD diagnosis.

[10] An ensemble-based method combining many ML classifiers for CKD detection was presented in the study. Feature selection, attribute normalization, and addressing missing values were all part of the data preprocessing process. Using a weighted voting system, the ensemble was made up of Random Forest, Support Vector Machines, and Neural Networks. The study showed that the diagnostic performance was much improved by the ensemble technique.

To enhance CKD prediction and survival analysis, the approaches used in all of the investigations include deep learning and machine learning (ML) models. In order to improve predictive accuracy, a number of research, including Saif et al. (2024) [12] and Chhabra et al. (2023) [11], used ensemble learning models that combined several classifiers, including Random Forest, XGBoost, and Neural Networks. To improve model interpretability and performance, Akkur & Öztürk (2023) [13] suggested a stacked ensemble technique that integrates various classifiers and makes use of feature selection. Similarly, Faruque et al. (2021) [14] investigated ensemble learning strategies designed for diabetics at risk of chronic kidney disease (CKD), using bagging and boosting techniques to maximize classification accuracy.

A number of research also concentrated on new algorithms and optimization techniques to improve CKD detection. By applying boosting approaches to clinical parameters, Pramanik et al. (2023) [15] shown that sophisticated ensemble algorithms outperform conventional classifiers in terms of accuracy and resilience. In order to ensure increased model efficiency, Srivastava et al. (2022) [16] highlighted the significance of correlation-based feature selection in CKD classification. Fuzzy logic was investigated by Bhatt & Kasbe (2019) [17] as a substitute diagnosis method, demonstrating its capacity to manage uncertainty in CKD datasets. In the meantime, a hybrid deep learning model that combines many architectures to improve and automate real-time CKD screening was presented by Akter et al. (2024) [18].

Yousif et al. (2024) [19] and Khalid et al. (2024) [20] also looked at optimization-based methods, using deep learning models and evolutionary computing for early CKD detection. Zhang et al. (2018) [21] demonstrated the efficacy of Artificial Neural Networks (ANNs) in predicting the course of chronic kidney disease (CKD) by focusing on CKD survival prediction. Last but not least, Hassan et al. (2022) [22] examined the integration of ensemble learning methods with correlation-based feature selection, highlighting the significance of feature engineering in medical data analysis and CKD prediction. Together, these approaches show how ensemble models, deep learning methods, and hybrid approaches are being used more and more to improve CKD detection and progression prediction.

III.METHODOLOGY

The methodology for CKD detection is meticulously designed to ensure high predictive accuracy and clinical relevance. This study adopts advanced ensemble learning strategies, specifically stacking and weighted averaging, to optimize model performance by leveraging the complementary strengths of multiple machine learning classifiers. By integrating different models, the approach minimizes bias, enhances generalizability, and improves decision-making accuracy

1. Dataset

The dataset utilized in this study is sourced from the UCI Machine Learning Repository and consists of 400 instances with 24 attributes, which include 11 numerical and 13 categorical variables representing vital clinical and laboratory features. The dataset is divided into two classes: CKD-positive and CKD-negative. To maintain data quality and reliability, preprocessing techniques such as missing value imputation, feature standardization, and class balancing are applied before model training. Missing data is handled effectively using appropriate imputation techniques, feature standardization is implemented to normalize numerical variables, and class imbalance is addressed using Synthetic Minority Oversampling Technique (SMOTE) to ensure balanced representation across classes.

	id	age	bp	sg	al	su	rbc	pc	pcc	ba	...	pcv	wbcc	rbcc	htn	dm	cad	appet	pe	ane	class
0	1	48.0	80.0	1.020	1.0	0.0	NaN	normal	notpresent	notpresent	...	44.0	7800.0	5.2	yes	yes	no	good	no	no	ckd
1	2	7.0	50.0	1.020	4.0	0.0	NaN	normal	notpresent	notpresent	...	38.0	6000.0	NaN	no	no	no	good	no	no	ckd
2	3	62.0	80.0	1.010	2.0	3.0	normal	normal	notpresent	notpresent	...	31.0	7500.0	NaN	no	yes	no	poor	no	yes	ckd
3	4	48.0	70.0	1.005	4.0	0.0	normal	abnormal	present	notpresent	...	32.0	6700.0	3.9	yes	no	no	poor	yes	yes	ckd
4	5	51.0	80.0	1.010	2.0	0.0	normal	normal	notpresent	notpresent	...	35.0	7300.0	4.6	no	no	no	good	no	no	ckd

Table - 1: Sample Record from Dataset.

2. Exploratory Data Analysis (EDA)

A thorough exploratory data analysis (EDA) is conducted to understand the dataset structure, detect anomalies, and identify correlations among attributes. The key steps include:

- **Data Distribution Analysis:** Histograms and box plots are used to visualize numerical attributes and detect skewness or anomalies.
- **Categorical Data Analysis:** Bar charts highlight class distributions and categorical attribute frequencies.
- **Feature Correlation Analysis:** Heatmaps and scatter plots reveal dependencies between features, aiding in effective feature selection.
- **Handling Missing Data:** Median imputation for numerical variables and mode imputation for categorical variables ensure data completeness.
- **Outlier Detection:** Z-score and interquartile range (IQR) methods help identify and remove extreme values.
- **Class Imbalance Management:** Synthetic Minority Oversampling Technique (SMOTE) and cost-sensitive learning approaches are employed to ensure balanced class representation.

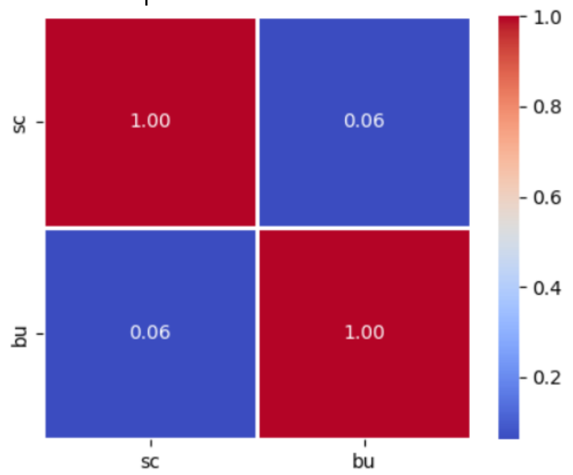

Chart - 1: Correlation Between Serum Creatinine & Blood Urea.

Feature Correlation Analysis

A correlation matrix is generated to analyze relationships among features, helping in feature selection and model optimization.

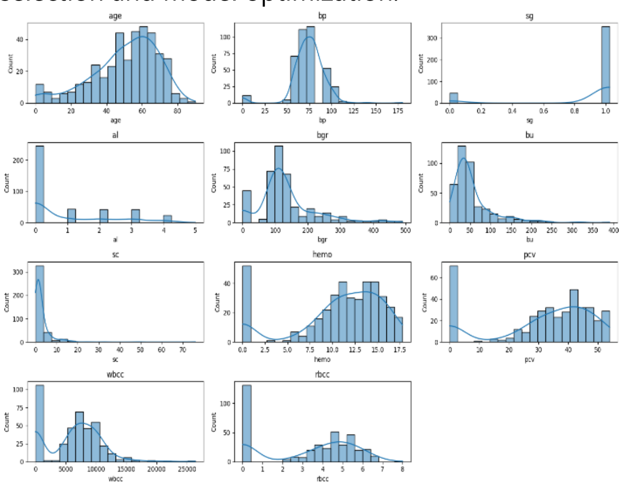

Chart – 2: EDA Visualization

Feature Importance Analysis

Feature importance is determined using statistical and model-based approaches to identify the most influential predictors of CKD.

3. Data Preprocessing

- **Missing Data Handling:** Imputation techniques are applied based on feature type to retain data consistency.
- **Feature Scaling:** Min-Max normalization and Z-score standardization prevent large-scale discrepancies among numerical attributes.
- **Feature Selection:** Recursive Feature Elimination (RFE) and mutual information gain methods help retain the most significant attributes for classification.

4. Train-Test Split and Cross-Validation

- The dataset is divided into 70% training and 30% testing to ensure unbiased model evaluation.
- A 10-fold cross-validation strategy is applied to minimize overfitting and evaluate model consistency across different subsets.

5. Model Training and Base Classifiers

Several machine learning algorithms serve as base classifiers, each contributing distinct advantages:

- **Decision Tree (DT):** A rule-based model that efficiently handles categorical and numerical features.
- **Random Forest (RF):** An ensemble of decision trees that enhances prediction stability and reduces overfitting.
- **Support Vector Machine (SVM):** A kernel-based classifier effective for high-dimensional data.
- **K-Nearest Neighbors (KNN):** A non-parametric model that classifies instances based on similarity.
- **AdaBoost (AB):** An adaptive boosting technique that iteratively improves weak learners.

Model performance is evaluated using accuracy, precision, recall, F1-score, and AUC-ROC.

6. Stacking and Weighted Averaging Ensemble Techniques

Ensemble methods are applied to improve CKD prediction by combining outputs from multiple base models:

- **Stacking:** Predictions from base classifiers are aggregated using a meta-classifier such as Gradient Boosting or Logistic Regression to refine final predictions.
- **Weighted Averaging:** Each model's contribution is assigned a weight based on its performance, allowing a more balanced ensemble decision.

The final prediction for weighted averaging is calculated as: Pfinal=∑i=1nwiPiP_{final} = \sum_{i=1}^{n} w_i P_i where wiw_i represents the weight assigned to classifier ii, and PiP_i is its predicted probability.

For stacking, the meta-classifier generates final predictions based on base model outputs: Pstacked=M(P1,P2,...,Pn)P_{stacked} = M(P_1, P_2, ..., P_n) where PiP_i are the individual base model predictions.

7. Hyperparameter Tuning

To enhance model performance, hyperparameter tuning is conducted using:

- **Grid Search and Randomized Search:** Techniques to systematically optimize parameters for each classifier.
- **Fine-tuning Critical Parameters:** Adjusting key parameters such as tree depth in Random Forest and learning rate in Gradient Boosting.

8. Final Prediction

Once optimized, the trained models generate predictions on the test dataset, ensuring a robust and generalizable classification approach.

9. Model Evaluation

Performance is assessed through multiple evaluation metrics:

- **Accuracy, Precision, Recall, and F1-Score:** Metrics to gauge overall classification performance.
- **AUC-ROC Analysis:** Measures the ability to distinguish between CKD-positive and CKD-negative cases.
- **Confusion Matrix Interpretation:** Provides insights into classification errors and model reliability.
- **Feature Importance Assessment:** SHAP (Shapley Additive Explanations) values help interpret feature contributions.

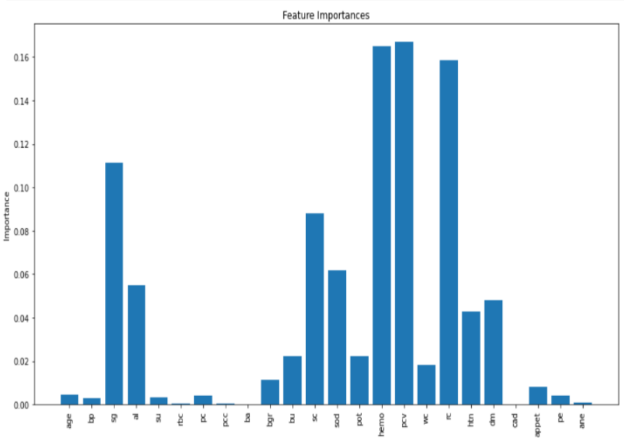

Chart - 3: Feature Importance

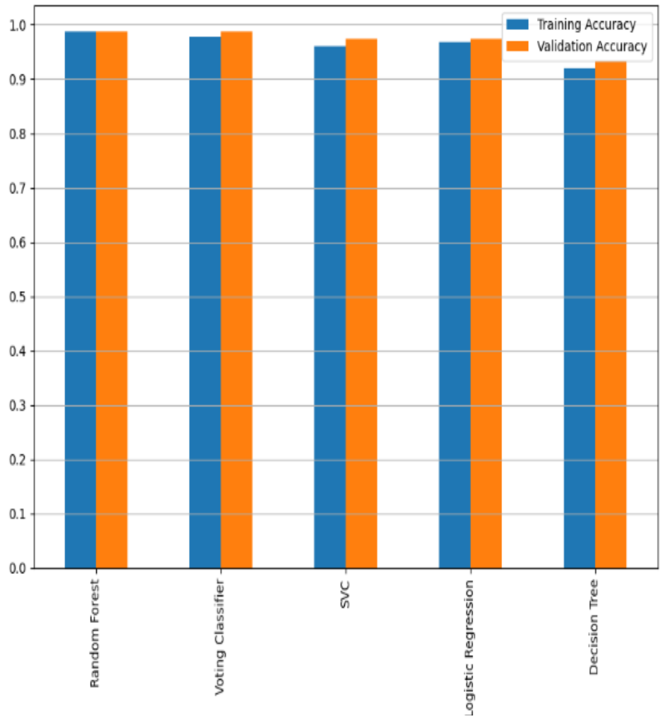

Chart – 4: Results for Individual Model

10. Performance Comparison

Performance Metrics Comparison

A direct evaluation of Stacking and Weighted Average Ensemble is performed to compare classification effectiveness.

```
Stacking Model Accuracy: 0.9833333333333333
[[69  1]
 [ 1 49]]
              precision    recall  f1-score   support

           0       0.99      0.99      0.99        70
           1       0.98      0.98      0.98        50

    accuracy                           0.98       120
   macro avg       0.98      0.98      0.98       120
weighted avg       0.98      0.98      0.98       120

Weighted Average Ensemble Accuracy: 0.9916666666666667
[[69  1]
 [ 0 50]]
              precision    recall  f1-score   support

           0       1.00      0.99      0.99        70
           1       0.98      1.00      0.99        50

    accuracy                           0.99       120
   macro avg       0.99      0.99      0.99       120
weighted avg       0.99      0.99      0.99       120
```

Figure - 1: Performance Metrics Comparison

Table -2: Stacking vs. Weighted Average Ensemble Comparison

Criteria	Weighted Average Ensemble	Stacking Method
Complexity	Low, simple model averaging	High, involves meta-model training
Interpretability	High, easily explainable	Moderate, dependent on meta-classifier
Handling Non-linearity	Limited	High, captures complex interactions
Robustness	Good	Excellent
Overfitting Risk	Low	Moderate, requires careful tuning
Accuracy (%)	99.16	98.3
Recall (%)	85.2	90.8
Precision (%)	86.7	91.5

IV. CONCLUSION

This research compared various ensemble approaches, focusing on Stacking and Weighted Average Ensemble methods, for Chronic Kidney Disease (CKD) prediction. Stacking ensembles demonstrated high effectiveness by leveraging diverse base models to capture complex patterns and interactions in the data, resulting in superior predictive accuracy. In contrast, the Weighted Average Ensemble method excelled in balancing simplicity and performance by assigning optimal weights to individual model predictions. While Stacking provided a more robust and adaptive framework, Weighted Average Ensemble offered a computationally efficient alternative with competitive results. These findings emphasize the significance of selecting the appropriate ensemble strategy based on the complexity of the dataset and the application requirements, enabling improved CKD detection and better clinical decision-making.

In addition to CKD prediction, future work can focus on integrating survival analysis models to predict the survival rates and prognosis of patients diagnosed with CKD. Combining prediction and survival analysis would provide a comprehensive tool for clinicians, enabling personalized treatment plans and improved patient outcomes. Exploring advanced methods like deep learning, incorporating longitudinal data, and addressing challenges such as data imbalance and interpretability can further enhance the system's capabilities in real-world applications.

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