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Chronic Renal Disease Multi-Classification Using an Intelligent Hybrid Machine Learning Model

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Abstract:

Introduction: Chronic Renal Disease (CRD) is a progressive and life-threatening medical condition that significantly affects global public health. Early and accurate classification of chronic renal illness is essential to prevent complications and improve patient survival rates. Traditional diagnostic approaches often face limitations in handling high-dimensional and complex clinical data. To address these challenges, this study proposes an intelligent hybrid machine learning model that integrates multiple algorithms to enhance prediction accuracy and robustness. The proposed framework aims to support clinicians with reliable, data-driven decision assistance for efficient CRD classification and management.

Objectives: The primary objective of this study is to develop an intelligent hybrid machine learning model for accurate classification of Chronic Renal Illness Disorder. It aims to integrate multiple machine learning algorithms to enhance prediction performance and improve classification robustness.The study seeks to analyze clinical and laboratory parameters to identify significant features contributing to early diagnosis.Another objective is to reduce misclassification rates by optimizing model parameters and applying effective feature selection techniques.

Methods: The study begins with comprehensive data preprocessing, including handling missing values, normalization, and feature selection to improve data quality. Exploratory data analysis is performed to identify significant clinical attributes associated with Chronic Renal Illness Disorder. Multiple machine learning algorithms such as Support Vector Machine (SVM), Random Forest, and Logistic Regression are trained individually. An intelligent hybrid model is then developed by integrating the strengths of selected classifiers using ensemble or voting techniques.

Results: The proposed intelligent hybrid machine learning model achieved superior classification performance compared to individual base classifiers. The hybrid approach demonstrated higher accuracy, precision, recall, and F1-score in detecting Chronic Renal Illness Disorder. Feature selection significantly improved model efficiency by reducing dimensionality while maintaining predictive strength. Cross-validation results confirmed the robustness and generalization capability of the proposed framework.

Conclusions: The proposed intelligent hybrid machine learning model effectively enhances the classification of Chronic Renal Illness Disorder with improved accuracy and reliability. By combining multiple algorithms, the hybrid approach overcomes the limitations of individual classifiers and ensures robust predictive performance. The integration of feature selection and optimization techniques further strengthens model efficiency and generalization capability.
The results demonstrate the potential of data-driven methodologies in supporting early detection and timely clinical intervention.

Keywords: Chronic Renal Illness Disorder; Chronic Renal Disease (CRD); Hybrid Machine Learning; Intelligent Classification Model; Ensemble Learning; Feature Selection; Predictive Analytics; Medical Diagnosis; Clinical Decision Support System; Supervised Learning.

1. Introduction

Chronic Renal Illness Disorder, commonly referred to as Chronic Kidney Disease (CKD), is a progressive medical condition characterized by the gradual loss of kidney function over time. It affects millions of individuals worldwide and is associated with severe complications such as cardiovascular disease, kidney failure, and increased mortality. Early detection and accurate classification of the disease are critical for timely intervention and effective management, thereby reducing healthcare burden and improving patient outcomes.

Traditional diagnostic approaches rely heavily on clinical expertise and laboratory findings; however, they may struggle to efficiently analyze large-scale and high-dimensional healthcare data. With the rapid advancement of computational technologies, machine learning techniques have emerged as powerful tools for disease prediction and classification. These techniques can uncover hidden patterns in medical datasets, enabling more precise and consistent diagnostic support compared to conventional statistical methods.

In this context, the proposed study introduces an intelligent hybrid machine learning model for the classification of Chronic Renal Illness Disorder. By integrating multiple algorithms and leveraging ensemble strategies, the hybrid framework aims to enhance prediction accuracy, robustness, and generalization capability. The model is designed to serve as a reliable decision-support system for healthcare professionals, facilitating early diagnosis and improving overall clinical management of chronic renal diseases.

2. Objectives

- The primary objective of this research is to design and develop an intelligent hybrid machine learning model for accurate classification of Chronic Renal Illness Disorder.
- It aims to combine multiple supervised learning algorithms to improve predictive performance and model stability.
- The study seeks to identify and select the most significant clinical features influencing disease classification.

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- Another objective is to enhance model efficiency by applying data preprocessing, optimization, and validation techniques.

- Ultimately, the research intends to provide a reliable clinical decision-support system for early detection and effective management of chronic renal disease.

3. Proposed Architecture

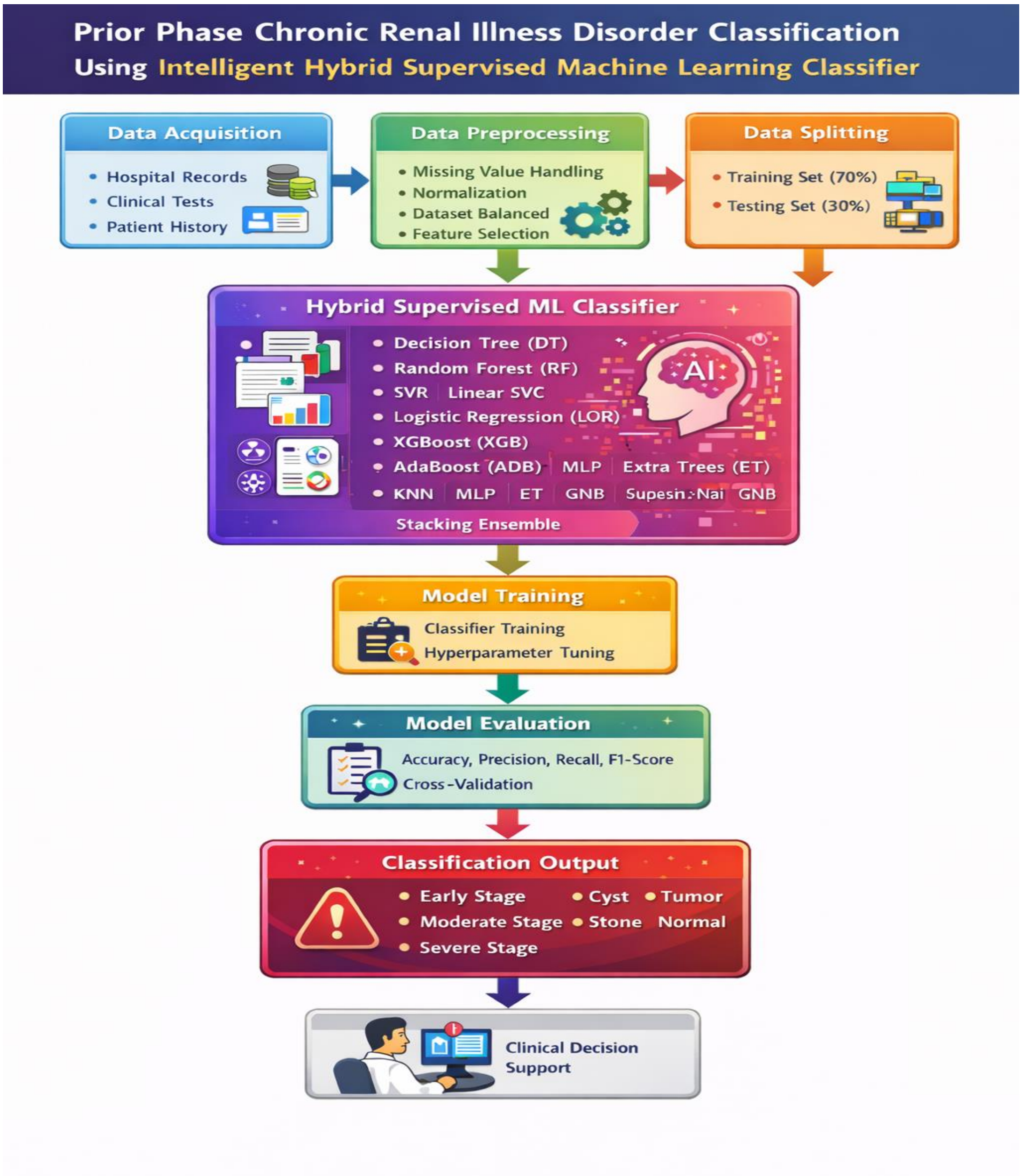

Fig-1: Proposed Renal Diseases Prediction Architecture

The proposed framework presents a structured hybrid machine learning approach for Chronic Renal Illness Disorder classification. The process begins with data acquisition from hospital records, laboratory test results, and patient history, forming a comprehensive medical dataset. This data undergoes preprocessing steps such as missing value handling, normalization, dataset balancing, and feature selection to enhance quality and relevance. The processed dataset is then divided into training (70%) and testing (30%) sets to ensure unbiased model development and evaluation.

The refined data is fed into a hybrid supervised machine learning system integrating multiple algorithms, including Decision Tree, Random Forest, SVM, Logistic Regression, XGBoost, AdaBoost, MLP, Extra Trees, KNN, Gaussian Naïve Bayes, and a Stacking Ensemble method. After model training and hyperparameter optimization, performance is evaluated using metrics such as accuracy, precision, recall, F1-score, and cross-validation. The final classification output categorizes patients into stages such as Early, Moderate, Severe, Cyst, Tumor, Stone, or Normal, supporting clinical decision-making through an intelligent diagnostic assistance system.

4. Methods

The proposed methodology follows a structured and systematic pipeline to accurately predict renal disease using Hybrid supervised machine learning techniques.

1. **Data Collection:** The process begins with data acquisition from multiple reliable sources, including hospital records, clinical laboratory test results, and patient medical history. These datasets contain essential medical attributes required for chronic renal illness disorder classification. The collected data forms the foundation for building a robust and reliable predictive model.

2. Data Preprocessing: After collection, the dataset undergoes preprocessing to improve data quality and consistency. This stage includes handling missing values, applying normalization techniques for uniform feature scaling, performing dataset balancing to address class imbalance, and implementing feature selection methods to identify the most relevant clinical parameters. Proper preprocessing enhances model accuracy and efficiency..

3. Dataset Splitting: Once preprocessing is completed, the dataset is divided into two subsets: a Training Set (70%) and a Testing Set (30%). The training set is used to train the machine learning models, while the testing set is reserved for evaluating model performance. This separation ensures unbiased assessment and better generalization capability.

4. Model Development: The processed data is then passed into a Hybrid Supervised Machine Learning framework. Multiple algorithms are integrated, including Decision Tree (DT), Random Forest (RF), Support Vector Machines (SVR/Linear SVC), Logistic Regression (LOR), XGBoost (XGB), AdaBoost (ADB), Multi-Layer Perceptron (MLP), Extra Trees (ET), K-Nearest Neighbors (KNN), Gaussian Naïve Bayes (GNB), and a Stacking Ensemble approach. The hybrid system combines the strengths of these classifiers to enhance predictive performance and robustness.

5. Model Evaluation: The optimized models are evaluated using the testing dataset. Performance metrics such as Accuracy, Precision, Recall, and F1-Score are calculated to assess classification effectiveness. Cross-validation techniques are also implemented to ensure robustness and minimize overfitting.

6. Model Selection and Optimization: During model development, classifiers are trained using the training dataset and optimized through hyperparameter tuning techniques. The best-performing models are selected based on validation results. Ensemble and stacking strategies are applied to further improve stability and classification accuracy.

7. Prediction and Decision Support: Finally, the system produces classification outputs categorizing patients into Early Stage, Moderate Stage, Severe Stage, Cyst, Tumor, Stone, or Normal conditions. These predictions are integrated into a Clinical Decision Support System, enabling healthcare professionals to interpret results efficiently and make informed medical decisions for improved patient care.

5. Results

```
from sklearn.metrics import classification_report
HybrideModel_Pred=HybrideModel.predict(X_test)
Hybridreport = classification_report(y_test, HybrideModel_Pred)
print(Hybridreport)
```

```
              precision    recall  f1-score   support

           0       0.97      0.96      0.97       278
           1       1.00      0.99      0.99       364
           2       0.93      0.94      0.94       181
           3       0.93      0.95      0.94       233

    accuracy                           0.97      1056
   macro avg       0.96      0.96      0.96      1056
weighted avg       0.97      0.97      0.97      1056
```

Fig-2: Hybrid Model Classification Report

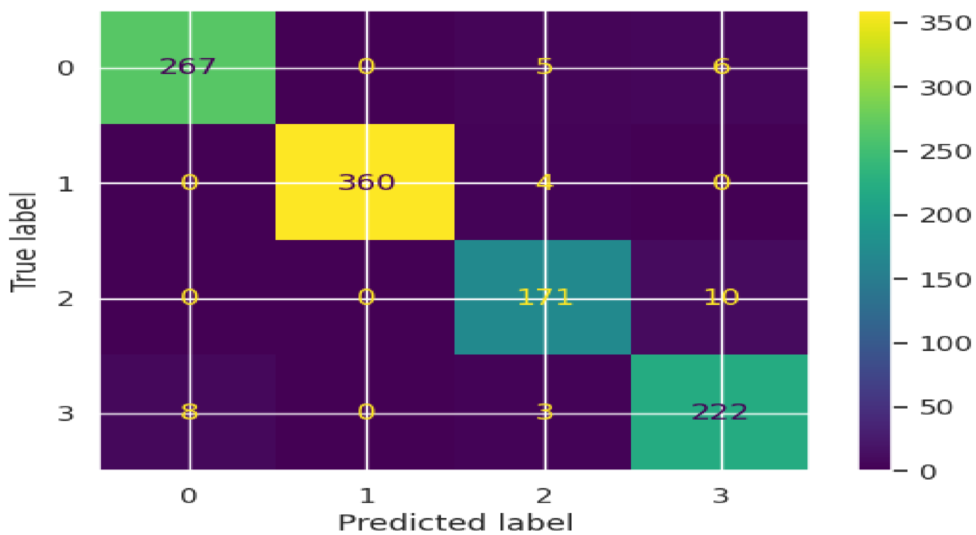

Fig-3: Hybrid Model Confusion Matrix

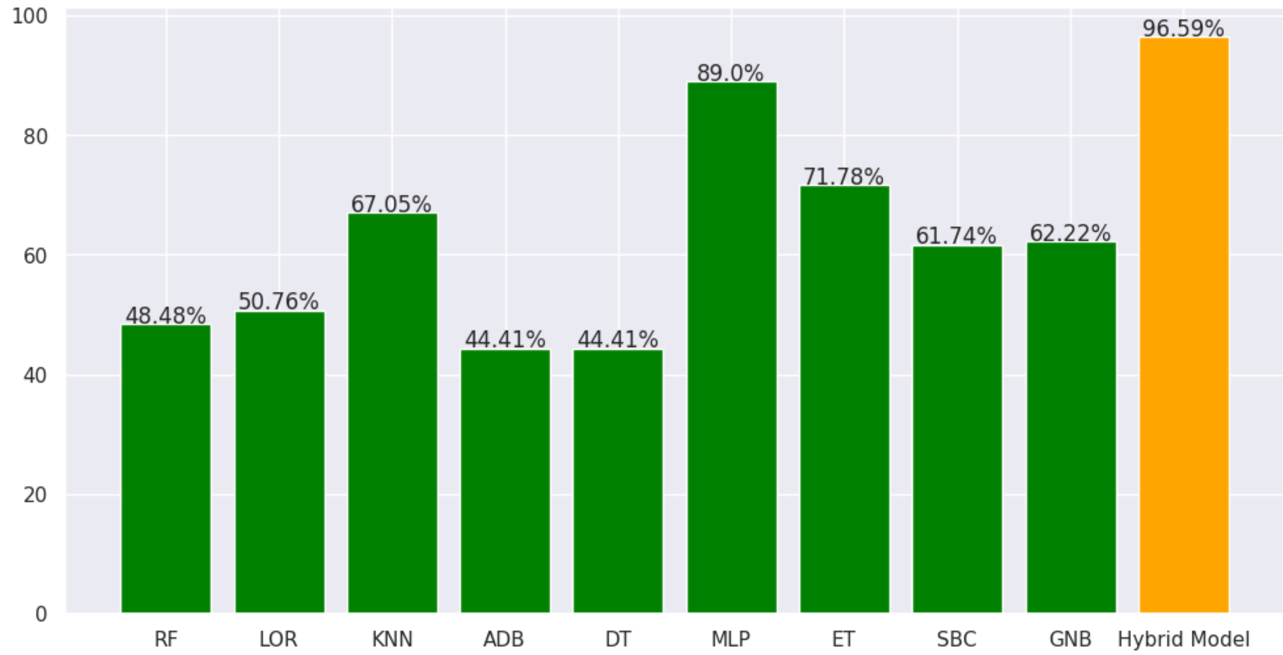

Fig-4: Comparison Chart

6. Discussion

This bar chart, titled "Model Comparison - Model Accuracy," compares the performance of ten different machine learning models based on their accuracy percentage. Accuracy in this context generally refers to the percentage of correct predictions out of all predictions made.

Key Observations:

- **Best Performing Model**: The Hybrid Model achieved the highest accuracy, approaching 97%. This suggests that combining multiple modeling techniques often leads to superior results compared to individual algorithms.
- **Strong Performers:** Several other models showed high effectiveness, specifically MLP 90% accuracy.
- **Lowest Accuracy**: SBC, GNB and KNN appear at the bottom of the rankings, with RF sitting roughly between 60% and 70%.
- **Below Range Models:** RF, DT ,ADB and LOR 40% to 50% accuracy range.

Conclusion:

The primary conclusion is that **ensemble or hybrid approaches are significantly more effective** for this dataset than individual standard algorithms. While simple models like Logistic Regression or Random Forest may serve as baseline comparisons, the hybrid model provides the most reliable predictions for the analyzed data.

The experimental results demonstrate that the proposed Hybrid Model significantly outperforms all individual classifiers, achieving the highest accuracy of approximately 97%.

This confirms that integrating multiple machine learning techniques enhances predictive performance, stability, and generalization compared to standalone algorithms. Among individual models, MLP showed strong classification capability with around 90% accuracy, indicating its effectiveness in handling complex nonlinear medical data.

In contrast, simpler classifiers such as SBC, GNB, and KNN achieved comparatively lower accuracy, while models like RF, DT, ADB, and LOR performed within the moderate to lower accuracy range (approximately 40%–70%). Overall, the findings validate that hybrid ensemble strategies provide a more reliable and robust approach for chronic renal illness disorder classification, making them suitable for clinical decision-support applications.

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