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Evaluation of Boosted Random Forest and Multi-Objective Artificial Neural Network for the Diagnostic Severity of Chronic Kidney Disease (CKD) Patients

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Introduction: Kidney illnesses diminish kidney function and the growing number of individuals suffering from chronic kidney disease (CKD) demands accurate prediction techniques. Early diagnosis allows patients to receive prompt therapy, therefore slowing the course of the disease.
Objective: The purpose of this study was to determine whether integrating Machine Learning (ML) with deep learning techniques is feasible, such as Boosted Random Forest-Multi-Objective Artificial Neural Network (BRF-MOANN), to diagnose and assess the severity of CKD in patients.
Method: A study at Apollo Hospital in India analyzed a CKD dataset involving 250 people with disease and 150 without the disease. Data pretreatment and reduction methods were used to optimize the dataset for model construction. A wrapper algorithm was implemented, enhancing feature selection and producing a more efficient and predictive model. Adopting BRF-MOANN in clinical practice could advance CKD diagnosis and therapy, improving disease management and patient quality of life.
Result: Furthermore, the integrated multi-objective optimization system generated personalized treatment suggestions that improved patient outcomes. The research findings, which included

numerous performance criteria such as precision (98,84 %), recall (98,64 %), F1-score (99,28 %) and accuracy (99,04 %), show that the BRF-MOANN model is more successful than conventional techniques in detecting the severity of CKD.
Conclusion: The findings show that BRF-MOANN outperforms traditional methods to provide a more comprehensive and precise diagnosis of CKD severity.

Keywords: Kidney Illnesses, Chronic Kidney Disease (CKD), Diagnostic Severity, Boosted Random Forest-Multi-Objective Artificial Neural Network (BRF-MOANN).

1. Introduction

Chronic kidney disease (CKD) is identified by albuminuria or renal function degradation, such as a glomerular filtration removal (GFR) ratio below 60 ml/sec per 1,75 m2, lasting three months or more.[1] Researchers spend considerable time determining if a patient has renal disease. Owing to the low incidence of renal function loss, the illness is disregarded until severe symptoms occur. [2] Atherosclerosis, tumors, cysts and deformities can result from CKD, a chronic disease marked by structural abnormalities in renal function. One typical clinical manifestation is renal fibrosis, which impairs kidney function and can cause symptoms in children such as growth retardation, hypertension and edema. [3] The Kidney Disease Improving Global Outcomes (KDIGO) defines CKD patients by albuminuria and GFR. Albuminuria crosses the renal barrier, while GFR assesses excretion. GFR and albumin classify CKD because they reflect long-term progression. GFR (total) is calculated by adding GFR (single nephrons) to the total number of nephrons. Nephron loss is CKD. CKD treatment requires risk factor identification and albuminuria can help diagnose and predict CKD. [4] CKD worsens over time and requires quick diagnosis and treatment. [5] The project aims to develop CKD prediction tools using analysis, feature rating and class balance. ML algorithms are trained and evaluated using performance measures. The study [6] uses seven ML methods to classify renal patient datasets as CKD or not: Neural network architectures include SVM, J48, NB Tree, Multi-layer Perceptrons, Naive-Bayes and CHIRP. The article [7] predicts CKD using ML classifiers and repository data. Seven classification methods were used: random trees, logistic regression, logistic regression with C5,0, Chi-square artificial association detectors neural networks with reinforcement learning and linear support vector algorithms with L1 and L2 penalties.

The study [8] develops effective diagnosis, treatment and preventative methods. The research proposes soft-max, categorical cross-entropy and an advanced deep cognitive network customized classification and forecasting framework. According to the model, advanced deep learning can improve clinical decision-making and early disease prediction. The paper [9] uses data mining and ML. CKD is a big concern and 8 ML classifiers quantify its severity. PCA is utilized for feature extraction and Random Forest (RF) has the most remarkable accuracy. The study [10] was to identify cases of CKD and non-CKD classification by analyzing the CKD dataset and comparing the effectiveness of several ML algorithms, particularly Rcode, in predicting chronic diseases [11] for reliable prediction using ML, Decision-Tree (DT) classification, Logistic-Regression (LR) and K-Nearest-Neighbor (KNN) models were created. LR categorization was the most accurate.

The available CKD dataset used in the study shows its reliability. [12] HOMA-IR assessed insulin resistance. The RF method had the best Receiver Operation Characteristics (ROC) value inequality. The body weight index affected I.R. more. ML was first utilized to predict I.R. in CKD patients and the RF approach has the best ROC.

The following phase of the investigation is organized as follows: The research's technique is described in phase 3; the findings and a discussion are presented in phase 4; and the final phase concludes.

2. Methodology

The collected data must be used well to forecast, analyze and manage diseases. Categorization models handle value-based problems. Research leverages the CKD dataset to construct an ML framework for information discovery. Figure 1 depicts the suggested methodology.

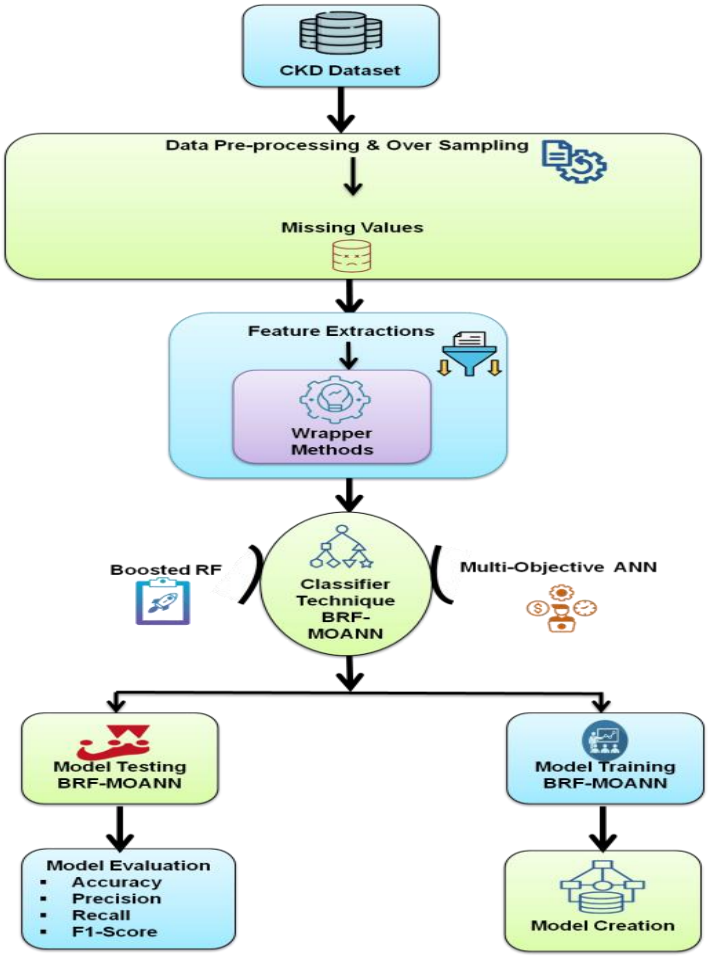

Figure 1. Work Flow Model [Source: Author]

Data Collection

Apollo Hospital in India [13] provided the two-month CKD dataset. Irvine CKD datasets have 250 CKD patients and 150 controls. Patients vary from 2 to 90 years old, with 62,5 % and 37,5 % prevalence.

Data Preprocessing

Working with contradictory datasets can improve productivity. ML apps require data preprocessing to ensure data accuracy and reliability. To investigate the dataset and comprehend its features to prepare it for simulation. Preprocessing information is the term used to describe this procedure.

Missing Values

Practical data sets, especially medical ones, need more data. Almost every patient record and attribute needs values. In the CKD dataset 4, 96 % of variables have missing values and 10% of parameters have at least one missing value in 60,75 % of cases. The absent data percentage for the variables ranges from 0,29 % to 37,9 % is shown in Table 1.

Table 1. Sodium Level Arbitrary Box Chart (Source: Author)

Data Types	Missing Data's	Valid Number
Age	9	398
Blood Pressure-BP	12	387
Albumin-Al	46	359
Sugar-Su	48	357
Blood Urea-BU	17	391
Blood Glucose-BGr	48	358
Sodium-Na	89	313
Potassium-K	92	318
Hemoglobin-hemo	86	395
RBC counts	120	269
WBC counts	131	298

The CKD dataset has been imputed using single imputation methods, but missing values are partially random, according to Little's test, missing values are completely at random. Multiple imputations (MI) are used in this study for substituting missing values m instances. Using MI, seven reproduced databases based on logistic and linear regression for continuous and categorical variables are produced. The dataset that has the closest standard errors and means is selected.

Feature Extraction Using Wrapper Method

Essential identification using mixed filtration wrap embedded decision making. The method uses greedy search and forward selection to find a subset of attributes. This method adds characteristics to a void model until it stops improving performance. The same ML must be used to find subgroups. A simple technique separates the range of values presented to multiple discrete portions in the One-R approach, which interprets the numerical aspects as a continuum. The gain ratio, unlike the y-means computation, is split by knowledge of the pulled-down data as in (Equation 1):

$$GR = \frac{JG}{G(fr)} \quad (1)$$

According to Eq. (1), component Y must be predicted hence, knowledge received must be normalized by isolating feature fr energy and repeating the process to reverse. Series gain ratios should decrease constantly and to be normalization-oriented [0, 1]. Gain ratio (G.R.) = 0 shows no correlation between z and fr\z. However, gain ratio = 1 indicates that the feature's information is employed to forecast Z. While the I.G. uses more, the G.R. uses less in (Equation 2):

$$IG(fr, z) = G(fr) - G(fr\backslash z) \quad (2)$$

Entropy (G) is an index of an uncontrolled variable's ambiguity. The entropies of Fr and entropy of consecutive measurement as a result, Z is represented by the numbers G (Fr) and G(fr\z)as in (Equation 3):

$$G(fr) = -\sum_j O(fr_j)\log_2\left(O(fr_j)\right) \quad (3)$$

The highest data advantage is 1. Critical functions gain lots of data. I.G. is calculated independently for each attribute and the most excellent k values indicate which features are necessary. This philter-based First Search (F.S.) algorithm does not delete unnecessary characteristics in (Equation 4):

$$G(fr|z) = -\sum_j O(z_j)\sum_j O\,(fr_j|z_i)\log_2\left(O(fr_j||z_i)\right) \quad (4)$$

3. Classifier Techniques

This research proposes supervised classification learning techniques for CKD detection utilizing training data. These algorithms learn from experience and forecast data without scripting. Many criteria are used to compare the results, showing that ML is helpful in CKD diagnosis.

Boosted Random Forest

Random forest is Breiman's DT-based ML technique. In RF ensemble, DT learns poorly and enforces tree variety unilaterally. Faster, overfit-resistant RF handles skewed data. Learning through multiple choice trees creates distinct individuals. Small change bagging produces several DTs from bootstrapped retraining data. Filtering aspect variables reduces variety and biases. Unexpected stimuli can be predicted after training in (Equation 5):

$$e = \frac{1}{C}\sum_{C-1}^{C} e_a\,(w)$$

(5)

Where C is the ideal tree count. Moreover, the prediction's uncertainty, or σ, can be expressed as follows in (Equation 6):

$$\sigma = \sqrt{\frac{\sum_{c-1}^{C}(e_a(w)-e)^2}{C-1}} \quad (6)$$

Multi-Objective Artificial Neural Network

In this study, multi-objective ANNs use the weighted sum approach, multi-task learning, Pareto-based methodologies and surrogate-based optimization, with all neurons in a single hidden layer (Figure 2).

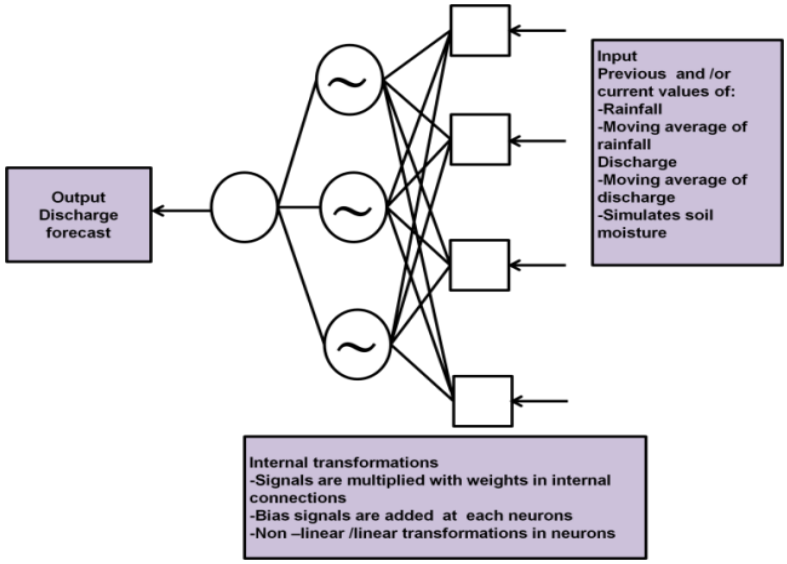

Figure 2. Multi-Objective ANN (Source: Multi-objective performance comparison of an artificial neural network and a conceptual rainfall—run (tandfonline.com))

The ANN receives time series values $\mathrm{Wt}, \mathrm{Wt}-1, \ldots, \mathrm{Wt}-\mathrm{m}$, where Wt represents a temporal input variable and m represents a time interval. The hidden layer transfer function and (equations 7) define the logistic coefficient.

$$\mathrm{e}(\mathrm{w}) = \frac{1}{1+\exp(-\mathrm{w})} \tag{7}$$

By examining the combination of nonlinear averaged mutual information (AMI) and linear correlation scores between the discharge time series and several different time series, it was possible to assess the value of specific factors as input for an ANN. Following Shannon's hypothesis regarding entropy, AMI is calculated as follows in (Equation 8):

$$\mathrm{J}(\mathrm{w};\mathrm{z}) = \mathrm{G}(\mathrm{w}) - \mathrm{G}(\mathrm{w}|\mathrm{z}) \tag{8}$$

The uncertainty of $\mathrm{G}(\mathrm{w}|\mathrm{z})$ is measured by its restricted entropy, which indicates its information given that z can be determined. The combined and minimum distributions of probability coefficients w and z can be used to calculate the AMI similarly but cheaper in (Equation 9):

$$\mathrm{J}(\mathrm{w};\mathrm{z}) = \sum_{\mathrm{z}\in\mathrm{z}}\sum_{\mathrm{w}\in\mathrm{w}} \mathrm{o}(\mathrm{w},\mathrm{z})\log_2\left(\frac{\mathrm{o}(\mathrm{w},\mathrm{z})}{\mathrm{o}(\mathrm{w})\mathrm{o}(\mathrm{z})}\right) \tag{9}$$

Analyzed resource selection based on AMI growth and excluded the vaporization parameter due to fewer data points. Three submerged neurons were ideal after transistors

increased. Automated optimization, Levenberg-Marquardt, conjugating gradients, traditional back-propagation and genetic algorithms were used.

4. Analysis of Results

Each classifier's output has been evaluated using many metrics and verified against the diagnostic severity of CKD utilizing a multi-objective ANN and boosted RF. Experiments use Python 3,3 and Jupiter Notebook. Lots of Sciket-learn's free Python ML libraries have been used. This study evaluates accuracy using the F1-measure, sensitivity and precision. The outcome of the procedure is depicted in Table 2.

Table 2. Result for BRF-MOANN (Source: Author)

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
KNN	64,39	59,01	92	73,09
Random Tree	83,34	92,99	86	84,39
SVM	96,05	94,08	91,094	96,43
Gaussian Naïve Bayes	93,75	96,08	95,48	83,46
BRF-MOANN	99,04	98,84	98,64	99,28

True positives are outputs that are appropriately categorized. Development output must be negative or true negative to be adequately identified. False positives are unexpected positive results. False negatives occur when output is negative and the projected development is wrong. The most straightforward measure to understand is accuracy, calculated as the ratio of total correct predictions to total guesses. It is described in mathematics as in (Equation 10):

$$\text{Accuracy} = \frac{\text{TN+TP}}{\text{TP+TN+FP+FN}} \tag{10}$$

Precision evaluates the model's ability to find relevant instances in retrieved instances. The ratio of correct optimistic forecasts to all optimistic predictions is measured. Figure 3 and Table 2 show accuracy (a) and precision (b) results of the existing and proposed approaches. This is its mathematical description in (Equation 11):

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{11}$$

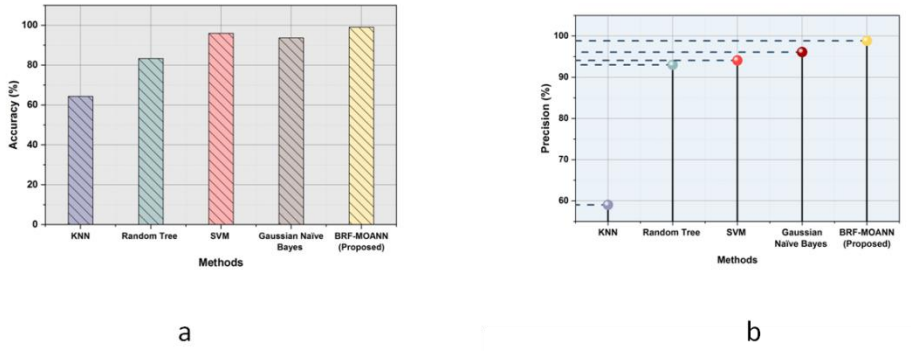

Figure 3. Comparison of (a) Accuracy and (b) precision (Source: Author)

Recall, or sensitivity, measures a model's ability to recognize the relevant events and the percentage of correct optimistic forecasts of the good events. This is its mathematical description in (Equation 12):

$$\text{Recall} = \frac{\text{TP}}{\text{FN+TP}} \tag{12}$$

The harmonious average of recall and accuracy yields the F1-score, which balances both requirements. It's useful when classes are unequal and want to balance accuracy along with recall. Table 2 and Figure 4 show the comparison of the recall (C) and F1-Score (D) of the existing and proposed approaches in (Equation 13):

$$\text{F1 score} = \frac{2 * (\text{precision} * \text{recall})}{(\text{precision+recall})} \tag{13}$$

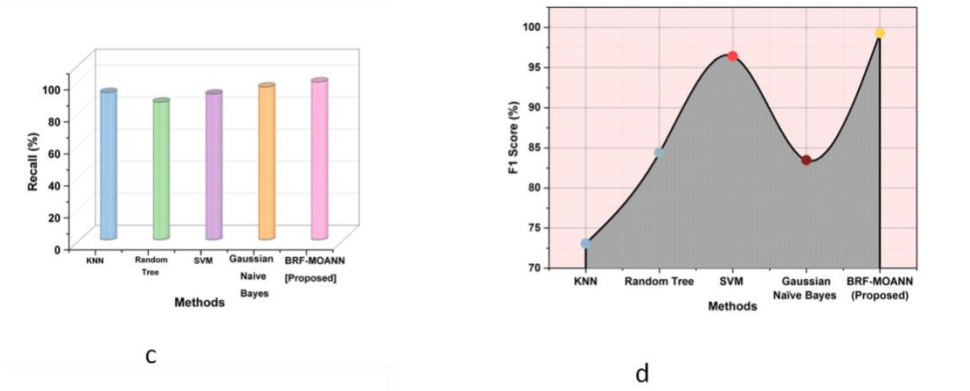

Figure 4. Comparison of (c) Recall and (d) F1 score (Source: Author)

5. Discussion

CKD prediction was evaluated using analytical methods and performance measures like recall (sensitivity), f1-score, confusion matrix, accuracy and precision. The 320 training data points and 80 testing data points were split into 80 % training and 20 % testing. RF and Multi-objective ANN models were the most accurate in both data sets due to their high sensitivity and specificity. Compared to the other ML techniques, the KNN algorithm [(14)] is susceptible to noise, outliers and huge datasets, with reduced accuracy. SVM [(15)] performance depends on parameters, computational complexity and massive dataset handling issues. SVMs are sensitive to noisy data and complex decision boundaries [(16)]. GNB [(17)] has a poor f1-score because it assumes feature independence, which would not be acceptable for real-world datasets. The evaluation matrixes of boosted RF and multi-objective ANN are high.

6. Conclusion

In addition to removing toxic substances, kidneys maintain blood pressure, electrolyte balance and acid-base equilibrium. Kidney failure causes modest to severe illnesses and

other organ malfunctions. ML programs can predict CKD as ML diagnosis methods become increasingly popular in medicine. We found that the RF method and multi-objective ANN (accuracy 99, 04 %) outperformed others. The primary purpose of this investigation is to determine the diagnostic severity of prolonged renal failure by the application of multi-objective ANN and ML algorithms for improved RF. We plan to compare the results to another dataset to validate our findings with larger datasets. We plan to utilize the correct data to predict the probability that a person with the condition would be less common if there was a family history of renal impairment, high blood pressure, diabetes, or other CKD risk factors.

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