Result-Based Re-computation for Chronic Kidney Disease Prediction Using SVM Classification

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Abstract. A crucial area of operation for cognitive intelligence systems is medical therapy. Across a wide range of health datasets, machine learning algorithms produce rapid disease prediction with excellent accuracy. A supervised machine learning approach for classification and regression applications is the Support Vector Machine (SVM). Error-Tolerant is the most difficult part of the SVM implementation. When utilizing an SVM in people's safety applications, where a change in the classification result is impermissible, this is an actual problem. In this proposed system, ResultBasedRe-computation (RBR) is used as a productive approach to protect SVMs from errors.RBR is a useful method for protecting SVMs against kernel function faults. The constraints that affect the SVM result are re-computed for effective fault tolerance based on the observation from the classification. Other machine learning classifier's results were also compared and it was found that the RBR system with SVM gave the highest accuracy.

Keywords: Chronic Kidney · Support Vector Machine Classification · Machine Learning · RBR

1 Introduction

The two bean shaped kidneys each measure around the size of a first. One on each side of the chine, they are only found below the rib cage. The kidneys filter 120–150 quarts of blood per day to product 1–2 quarts of undine. The discharge of waste materials and surplus fluid from the body through the urine is the kidney's most important function. Urine is produced through a highly complex process of excretion and re-absorption. To guarantee a stable equilibrium of bodily chemicals, this process is crucial. Wastes are concentrated in the body when a person has 8CKD. The kidney's primary job is to filter excess water and waste from the blood in order to produce urine. The global all-age mortality ration from CKD increased by 41.5 between 1990 and 2017 [1]. According to cross-sectional studies, China had a prevalence of chronic renal disease of about 10.8, which equates to about 119.5 million patients [2]. CKD is influenced by age and gender in

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addition to these serious disorders. According to studies, hospitalization cases are rising 6.23 percent year, but the world mortality rate is staying the same. CKD is progressing quickly. Instead of performing numerous expensive tests, the doctor may use a machine learning system to predict this.

In a easy amount of occasion, we will be able to diagnose of Condition of CKD inpatients if we only input the computer a few of the case's gathered information. This allows us to save a lot of time and spare the patient any discomfort during the numerous exams.[5] Machine learning algorithms like K-NN, Naïve Bayes classifier, support vector machine, Random Forest classifier, a and others can be used to build any model. Our investigation goal is examined, CKD data can predict CKD risk using SVM algorithm.The support vector machine is a admired machine learning technique due to its excellent performance, versatility, and efficient. In most cases, it can be used on terabytes of data and still be much faster and less expensive than working with deep neural networks. Due to their decision boundary method, which optimizes the distance between all classes' nearest data points, SVMs differ from other classification algorithms. SVM classifier is prone to errors, hence applying it to medical applications results in varied consequences. Result Based Re-computation is employed to safeguard SVM against classification errors in order to prevent such unfavorable situations. Many machine learning classifiers' outputs were examined, and it was discovered that RBR WITH SVM provided the best accuracy performance.

2 Literature Survey

Numerous researchers work on the prediction of CKD using a variety of classification algorithms. And those researchers receive the predicted output of their model. Diabetes and high blood pressure, sometimes known as hypertension, are the two main causes of chronic kidney disease. The way that [23] characteristics chronic renal disease is unaffected by the age of the patient. The scenario is comparable to that of blood pressure reading, the definition of hypertension, and its prevalence. Age related increases in blood pressure are common, although senior hypertension is linked to detrimental effects. [4] used 113 blood and 5 demographic factors to predict the progression status of CKD based on the level of proteinuria.

[10] proposed using a cost-benefit analysis of only five features.

Hemoglobin, albumin, specific gravity, diabetes mellitus, and hypertension out of all 24 attributes can be used to generate a highly accurate, economical detection classifier [19]. The three main risk factors for chronic kidney disease are hypertension, obesity, and diabetes (CKD). Only five features—specific gravity, albumin, diabetes mellitus, hypertension, and hemoglobin—out of all 24 attributes can be used to generate a highly accurate, economical detection classifier [19]. The three main risk factors for chronic kidney disease are hypertension, obesity, and diabetes (CKD). Using past patient data and diagnosis records, data mining and analytics approaches can be utilized to forecast CKD [3] analyzed the potential of several machine learning technique for the early diagnosis of chronic kidney disease.

Disease, and the findings show that the fact of machine learning is positive and feasible approach for the early prediction of CKD. [16] discussed how analytics and data mining can be used to forecast CKD. Furthermore, [22] suggested that the use of simple machine learning techniques may boost doctor's trust in computer aided CKD risk classifications in developing nations, improving the result's reusability [8].

The purpose of feature selection is to extract the most important features. The trained data used a 10-fold CV Random Forest and ANN. A Random Forest algorithm is used to achieve accuracy. Various authors investigated and evaluated their proposed model with varying numbers of classifiers. The authors of [7] studied and assessed with the help of eight classifiers, chronic renal disease was divided into two orders (patient or not).[9] the study describes, three machine learning classifiers were used: Logistic Regression (LR), and Decision Tree (DT). A bagging ensemble system was used to improve the developed model's results. Finally, the Kidney Disease Collection is categorized and divided into non-linear features. In the decision tree case, this system produced the best results with the highest accuracy.

[13] When compared to other algorithms for classifying the Individuals with various stages of CKD the probabilistic neural networks algorithm has the highest overall classification accuracy percentage of 96.7%. The Multilayer Perceptron, on the other hand, requires the shortest execution time (3s), whereas this takes 12s for the probabilistic neural network to finish the analysis [15]. The tree in a decision forest with the highest probability has the biggest impact on the outcome. The prediction procedure takes less time as a result. It will enable medical professionals to start treating CKD patients. Earlier and to diagnose more patients in a shorter period [14]. These experimental results show that of the six classifiers tested, Decision Stump and Rep Tree performed better in terms of accuracy than the other algorithms. K-Star has a higher accuracy measure in ROC. Decision stump and Rep tree algorithms produce better results with lower error rates, and it is expected that the designed system, backed up by the classification algorithms used, will be used to anticipate, or analyze data about other disorders [21].

We employed bagging, random forest, AdaBoost, and Gradient Boosting as four-ensemble methods. AdaBoost and Random Forest had a higher F1-score and AUX of 100% than bagging and Gradient Boost. According to [17], a feed forward neural network with a 0.99 f1-score, 0.97 precision, o.99recall, and 0.99 AUC score is the best method for diagnosing CKD [19]. Four supervised machine learning classifiers with a 99.7% AlUC, 100% specificity, and 98.98% sensitivity were employed to predict the disease [6] In this study, six classifier algorithms a random tree and logistic regression among others. C5.0, Chi-square automatic interaction detector, an artificial neural network, a linear support vector machine with penalty L1 and L2, and Chi-square automatic interaction detector. The essential feature selection method was applied to the dataset as well.

The results for each classifier were calculated using the following techniques. Full features, least absolute shrinkage and selection operator retrogression, least correlation-based feature selection, wrapper method feature selection, and synthetic minority over sampling technique, and full features combined with least operator for absolute shrinkage and selection retrogression. The outcomes show that LSVM with penalty L2, offers the greatest accuracy [20], employed decision tree, logistic regression, K-NN and SVM as their four machine learning classifiers (SVM). To choose the best classifier, the outcomes of these tests were compared SVM stood out among the others as the top classifier, having s sensitivity of 99% [5]. Proposed a system using machine learning techniques such as decision tree, SVM, and others for Chronic Kidney Disease Prediction and discovered that using SVM as a classifier shortens the prediction process; additionally, SVM outperforms the decision tree algorithm in terms of accuracy [11]. Many length patterns that are derived from photos, videos, audio, music, etc., and the recommended class-specific IMK based SVM allo for the classification of expressed as sets of continuous valued local feature vectors.

[18] In this classification, problem SVM classifies the output into two classes with CKD and without CKD. The main objective of this learning was to forecast patients with CKD using fewer number attributes while maintaining a higher accuracy. Considering the related work based on prediction CKD describes that the SVM shows good results comparing other classifiers however SVM is often prone to errors during the classification [24]. Characterize the hard margin classification error rate and the soft margin. SVMs precisely. [12] proposed Result-based Re-computation (RBR) as an efficient scheme for implementing soft error tolerance for classification using Support Vector Machines (SVMs); the proposed scheme has a significantly lower computational overhead than traditional Time-Redundancy (TR) schemes.

3 Proposed Work

See Fig. 1.

3.1 Preprocessed Data

Preprocessing data is a critical step in the data mining process. It refers to the process of transforming and integrating data to prepare it for analysis. The purpose of data preprocessing is to enhance data quality and make it more suited for the specific data mining activity at hand.

3.2 Data Collection

The chronic renal disease dataset is used for this investigation. The input dataset for chronic kidney disease was retrieved from the UCI repository. The chronic renal disease dataset is used for this investigation. The input dataset for chronic kidney disease was retrieved from the UCI repository. There are 400 examples in this collection, along with 24 qualities; the objective attribute has been separated into two classes in order to designate CKD or non-CKD. Moreover, it lacks values. This dataset has 400 occurrences

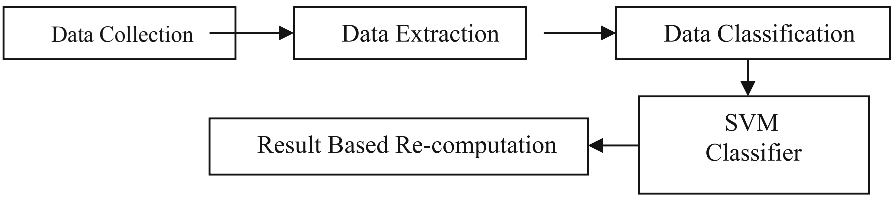

Fig. 1. Structure of proposed work

Table 1. Input and Description of Chronic Kidney Dataset.

Inputs	Descriptions
Age	Patient's ID
BP	Blood Pressure of the Patients
RBC	Red Blood Cells
PC	Pus-Cells
Hemo	Hemoglobin
WBC	White Blood Cells
CI	Blood Cholesterol Level
Ba	Bacteria
AI	Albumin
Su	Blood Sugar Level
Bu	Blood Urea
Sc	Serum Creatinine
Sod	Sodium
Pot	Potassium
Rc	Red Blood Cell counts in per microlitre
Wc	White blood cell counts in per microlitre
Dm	Diabetes Mellitus
Cad	Coronary Artery Disease two value Yes or No

with 24 attributes, including 1 target attribute. The target attribute is divided into the CKD and non-CKD categories. The dataset came from various hospitals in 2015 and was collected there. The Table 1 represents the inputs for CKD diagnosis.

3.3 Data Extraction

The process of gathering or obtaining diverse types of data from a variety of sources, many of which can be sloppy or entirely unstructured, is known as data extraction. Here the input attributes such as Blood cholesterol level, Resting BP level, and Fasting Blood sugar level were found sufficient to predict the Chronic Kidney Disease Prediction of Patients. Data centralization, processing, and upgrading are made possible by data extraction so that it can be retained in a central area to be converted. The process of gathering or regaining remote types of data from a range of sources, many of which may be completely or only partially unstructured, is known as data extraction. It makes it possible to combine, analyze, and refine data so that it can be turned into relevant facts and stored for further use and manipulation. The process of data extraction typically transforms dissipated and unwieldy raw data into a more usable, measured form that may be utilized for further processing. Now, input attributes such as blood cholesterol level, resting blood pressure level, and fasting blood sugar level have been determined

Table 2. Extracted Data of Chronic Kidney Disease.

Age	Sex	Resting-Bp	Cholesterol	Blood Sugar
65	male	162	285	150
66	male	125	230	108
38	male	130	250	129
46	female	136	208	182
58	male	124	236	172
62	female	140	268	178
57	female	120	354	160
63	male	130	254	163
53	male	147	203	147
57	male	140	198	156
59	female	143	294	148
56	male	132	259	153
44	male	127	264	142
52	male	172	199	173
57	male	150	168	162
48	female	110	229	174
49	male	140	239	168
64	male	130	275	167
58	male	110	266	139
58	male	150	284	171
58	male	132	224	160
63	male	145	233	173

to be sufficient for predicting patients' chronic kidney disease. Table 2 shows the Data of Chronic Kidney Disease.

3.4 SVM Classification

In a data mining can be processed of removing information from a sizable database. Classification is a crucial machine learning job. Support Vector Machines, one of the most widely used classifiers, have been extensively employed to solve practical applications because of its reliable generalization and accuracy. Yet, classification issues make up a large portion of its use. In the SVM algorithm, each data point is represented as the value of a certain coordinate and is treated as appoint in n-dimensional space. Additionally, we accomplish classification by altering the hyper plane that effectively distinguishes the two classes. A Support Vector Machine is a sort of Classifier that is technically described as a discriminational classifier by a separating hyperplane. The algorithm

Table 3. Confusion Matrix

Confusion Matrix	**Ckd (Predicted Value)**	**Non Ckd (Predicted Value)**
Ckd (Actual Value)	True Positive (TP)	False Negative (FN)
Not Ckd (Actual Value)	False Positive (FP)	True Negative (TN)

creates an ideal hyperplane that classifies fresh cases. This hyperplane is a line in two-dimensional space that divides a plane into two sections, with each class on each side. To establish its class, a value is calculated using SVM utilizing a kernel function and several support vectors. Only the terms that potentially change the classification result are identified using the SVM result, and they must be reevaluated. In this system Blood-Pressure, serum-Cholesterol, and Fasting- Blood sugar terms are used for classification to predict chronic kidney disease.

3.5 Result Based Re-computation

In this study, result is based on the re-computation is proposed. RBR is an effective strategy for protecting SVMs from kernel function errors. That is the most difficult aspect of the SVM implementation. As described in this study, an effective defense tactic called Result Based Re-computation is proposed. In this study, an effective defense tactic called Result-based Re-computation (RBR) is proposed. RBR makes use of input data to decrease errors during SVM classifier classification. Constraints such as blood cholesterol, blood pressure, and blood sugar levels are taken into consideration for the re-computation process, which has a significant influence on the SVM classification outcome. The outcomes show a list of normal people as well as patients with chronic kidney disease before and after the re-computation procedure.

4 Performance Analysis

4.1 Performance Evaluation Measure

Many assessment matrices were utilized the classifier's performance. The confusion matrix was used to achieve this goal. Due to the two classes in the dataset, it is a 2X2 matrix. The confusion matrix offers two kinds of classifiers that make accurate prediction, as well as two kinds of classifiers incorrect predictions. Table 3 shows the confusion matrix, and Table 4 describes the matrix.

4.2 Precision

A key component of the model performance evaluation matrix is precision. The percentage of linked occurrences among all retrieved instances is what this term refers to. It is a forecasted value that is positive. The precision of an equation is calculated as follows:

$$\text{Precision} = \text{TP}/\text{TP} + \text{FP}.$$

Table 4. Confusion Matrix Description

Class	Description Matrix
TP	True Positive means output as positive such that predicted result is rightly classified.
TN	True Negative means output as negative such that predicted result is rightly classified.
FP	False Positive means output as positive such that predicted result is wrongly classified
FN	False Negative means output as negative such that predicted results is wrongly classified

4.3 Recall

Recall is other crucial component of the model performance evaluation matrix. It represents the proportion of related occurrences among all retrieved instances. Equation calculates the recall as follows:

$$\mathrm{Recall} = \mathrm{TP}/\mathrm{TP} + \mathrm{FN}.$$

4.4 F-Measure

F Score is another name for it. To assess test accuracy, the F-measure is computed. Equation calculations are done using the precision and recall data.

$$\mathrm{F{-}Measure} = 2 \times \mathrm{Precision} \times \mathrm{Recall}/\mathrm{Precision} + \mathrm{Recall}.$$

4.5 Categorical Data

The nominal data transformed into 0 and 1 based numerical data. For example, the nominal value of "Gener" can be labeled as 0-for female, and 1-for male. The final CSV file contain all the integer data after preparing the data and more over float values for many CKD related characteristics. Prior to training nay models, it is crucial to normalize numerical features since many methods, like nearest neighbors, support vector machines and deep learning requires scaling as a prerequisite. There are various scaling methods, and Z-score normalization was employed in this study. On the basis of the signify and regular deviation, the values for a feature are normalized.

$Z = X\text{-}\mu/\sigma$.
If $x =$ feature value.
$Z =$ score value.
$M =$ mean value.
$\Sigma =$ standard deviation.

The Performance comparison shows the before and after re-computed attributes are classified by SVM. It also shows the number of normal and defected patient details before and after re-computed in Table 5.

Table 5. Before And After Recomputed Attributes

Sl. No	Diseases	Before Re-Compute NormalPatients	After Re-Compute Normal Patients	Before Re-Compute Defected Patients	After Re-Compute Defected Patients
1	**BLOOD-PRESSURE**	97	183	206	120
2	**SERUM-CHOLESTEROL**	5	84	298	219
3	**FASTING-BLOOD SUGAR**	37	264	266	39
4	**CKD**	238	258	65	45

The calculated accuracy measurements of RBR with SVM method also viewed in this module. The comparison of RBR-SVM with existing 6 methods precision, recall and F1-Measure values showed in Table 6 (Fig. 2).

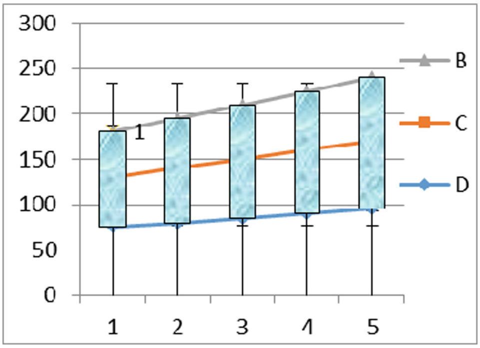

Fig. 2. Comparison of RNN and SVM

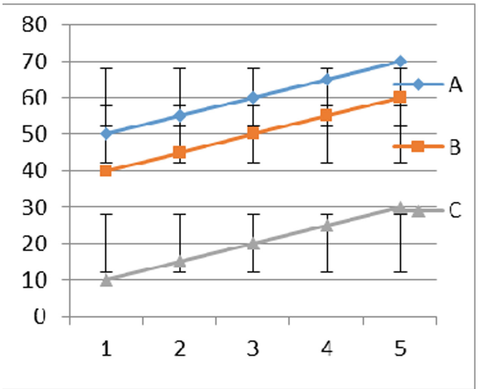

Fig. 3. Comparison of RBR and SVMRNN

The regression analysis for the prediction methods employed will be based on the above diagram K-nearest observation from the dataset in a determined value. Let B,C,D be the other dataset that can be utilized to determine a metric for a particular distance, and let K be the smallest number of neighbours in a data distribution. The dataset is split into preparation of the numbers and examination of the data used for the expected values of the following K-neighbours using schemata analysis. So, the highest value is determined by C5.0 for the F-measure is 94.80%.

RBR-SVM

The dataset for the values are depicted in the Fig. 3. Diagram up top. This method gives the classifier a small number of observations. The inside, outside, and extremely outside values of the dataset can be found by using the graphical representations of three zones, such as A,B and C. The above diagram SVM prediction analysis is the greatest value is approximately 70% has been improved, compared to the existing analysis.

The comparison graph of total 7 methods is displayed in the following Fig. 4 shows the measure value of ANN, CHAID, LSVM,KNN, RBR-SVM, LOGISTIC, C5.0, The maximum value of RBR-SVM is 97.26 regression value is the best.

Table 6. Comparisons of Various Classification Algorithms

SI. No	Method	Precision-Value in %	Recall –Value in %	F-Measure in %
1	**ANN**	93.4	92.00	92.61
2	**C5.0**	92.40	97.30	94.80
3	**Logistic**	56.48	98.60	71.80
4	**CHAID**	93.50	96.00	94.74
5	**LSVM**	90.00	96.00	92.90
6	**KNN**	59.01	96.00	73.09
7	**RBR-SVM**	96.56	97.98	97.26

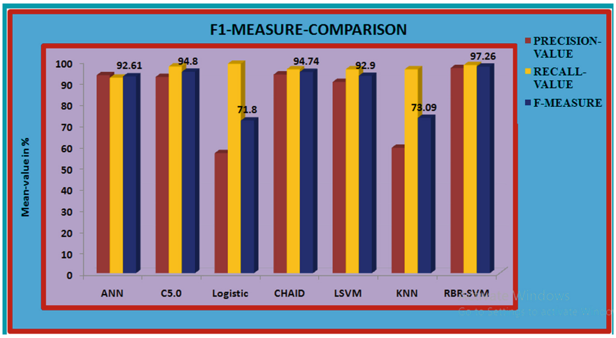

Fig. 4. Comparison Graph

5 Results and Conclusion

In our proposed study, we processed the UCI dataset as well as the real-time dataset. A non-linear SVM classifier was developed. RBR is an effective way for safeguarding SVMs from mistakes. It is used as an error-tolerating approach. The SVM result is utilized to identify words that may affect the only those terms that were classified correctly must be recalculated.This approach uses blood pressure, serum cholesterol, and fasting blood sugar levels to predict chronic kidney disease. For CKD accuracy prediction, the SVM-classified words are updated, compared to KNN and ANN and random forest, which are some other classifications and other machine learning classifiers, RBR SVM classification achieves 97.26% accuracy. Additionally, the CKD results are being recomputed, and it indicates the number of patients who have been switched from the CKD category to the Normal category by monitoring the Blood-Pressure, Serum-Cholesterol, and Fasting-Blood-Sugar terms. The project's objective was to be defined. The goal of this work was to identify patients with CKD using fewer attributes while keeping a greater accuracy; Additionally, it makes the SVM classifier error-tolerant in foretelling theses results. As a result, it is important to investigate the application of an RBR based SVM classification technique to handle incorrect classification in database because it may one day be associated to numerous diseases.

6 Future Scope

The proposed model assists experts in making quick decisions; it is preferable to create a mobile-based system that allows experts to track the status of patients and allows patients to use the system to determine their status; similarly, RBR incorporated in SVM classifier set up to be useful for producing the system error tolerant with the highest accuracy when compared to other classification algorithms. In the future, this concept of Result Based Re-computation can be utilized to forecast multiple diseases to deliver a high-quality prediction.

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