

## A Filter Based Prediction Technique To Determine CKD Using Hwf-Fs, HWFE-Fs And EEA-DNN

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### Abstract

Chronic Kidney Disease (CKD) is a global problem in the wellbeing of people. The CKD function is to control the blood and remove the volume of excess electrolytes, the total amount of water is steady and hormones are also made. Elevated blood pressure, anaemia, poor nutritional health and damage to nerves and someone can develop similar technical hitches to handle them. Recognition and action can also prevent CKD from being worse at an early point. Methods of data mining was applied to CKD. The data mining is considered as a process of using conventional knowledge, to decide the normal trends and to establish potential decisions, resulting from the convergence of quite a few current developments: the decrease in the cost of a huge database and the easy way of gathering information by means of network structure; the creation of machine learning techniques for processing this sort of data; Several data mining methods for forecasting CKD have recently been added. The purpose of this work is to co-relate the efficiency of the CKD prediction-based ELM classifier, HFWE-FS algorithm and EEAw-DNN algorithm depending on the parameters such as accuracy, precision, and error rate. From the results, the goal of the EEAw-DNN-based algorithm results is more accurate than HWFFS, the HWFE-FS algorithm.

**Keywords**— Chronic kidney disease, Data Mining, ELM, Machine learning, EEAw-DNN, HWFFS and HWFE-FS.

### 1.Introduction

Data mining is noteworthy to explore accomplishments in the area of medical sciences. The methods that involve Data mining are utilized for analysing, predicting and in the detection of diseases. The applications of Data mining include management of health care, health information and in the maintenance of patient record system. It highlights a significant process of analysing the disease survivability. The techniques of Classification which include Artificial Neural Network (ANN), Naïve Bayes, decision tree, and Support Vector Machine (SVM) have been used for prediction. A feature selection algorithm has been also introduced to decrease the computation time and increases the prediction results of the classifiers. Those methods have been categorized into wrapper and filter methods. Machine learning along with data mining is able to commonly be presented successfully applied towards such issues, as they develop the effectiveness of the systems. Reduces set of features from instance is used by Machine learning methods.

The significant objective is to establish the methods that include feature selection for achieving the best results of classification through recognition of the best subset of features. The major purpose of the work is described as follows:

1. To introduce a Hybrid Filter Wrapper Embedded Feature Selection (HFWE-FS) to decrease the no. of features and improves the accuracy of classifier.
2. To introduce a Support Vector Machine (SVM) so as to detect the CKD with improved accuracy.
3. In the determination of CKD was the implementation of an Ensemble Entropy Attribute Weighted

## Deep Neural Network (EEAw-DNN) classification.

The medical field has a high impact in the process of diagnosis which is a daunting challenge due to the complexity of kidney disorders, variation in progression of the disease having various stages and the coverage of cardiovascular risk factor [1]. The prediction of the risk factor is exactly to forecast that could improve the process of individualized decision-making, improving the fundamental and sufficient patient treatment. [2]. The data mining techniques, thus provide sufficient knowledge from the huge medical repositories, that are frequently gathered, for successful clinical diagnosis [3]. But this is not a specific algorithm that helps to diagnose all types of diseases in machine learning parameters and decision taking models. The high dimensional data sets achieve a classification accuracy rate that can be reasonable and also be able to over-adjust the risks, the processing time can be higher and costly. Low-dimensional datasets will typically trigger a greater accuracy of classification accuracy with the computation that involves cost effective and the risk of over-fitting[4].

Chronic kidney disease is mostly identified as screening outputs of individuals who are likely to be complicated for kidney complications, like elevated blood pressure or diabetes and those with a CKD parent in the blood. This research, prediction of CKD is done through the use of classifiers. The classifiers used here are classifier Extreme Machine Learning (ELM), an algorithm based on HFWE-FS and EEAw-DNN. Their tests are measured according to criteria such as precision, precision, and F-measurement.

## 2. Problem Definition

With the growing prevalence, Chronic Kidney Disease (CKD) is the most significant issue in public health. A recent study depicts that the awareness level of CKD by all categories of Primary Care Providers (PCPs) is unacceptably low and poor management on CKD knowledge among family practitioners. This is even common among those with one decade of clinical practice.

In CKD diagnosis, improving the prediction accuracy of classification algorithms becomes very difficult task. The prediction accuracy of the classifier reduces because of redundant features, and irrelevant features. But the difficulty lies in reducing the characteristics of dimensionality. Methods are implemented to overcome the feature selection (FS) process to minimize the feature count from the CKD database.

At the same precision not only depends on the collection of features and on the diagnostic methods, it also detects diseases which are utilized by clinical diagnostic experts. In this job, new classifier is implemented to minimize the computation time and maximize the classifier accuracy.

## 3. Related Work

O'Seaghda et al [5] developed a risk score to estimate a person's absolute risk of incident CKD. The participants were observed for a decade to assess the growth of the CKD. To identify the risk factors of CKD a stepwise logistic regression was used. Further investigation was proposed for the effectiveness of this score in recognizing person's in the neighbourhood at high risk of CKD.

In 2015, P.Swathi Baby et al., [6] introduced a new method which the system of diagnosis depends on the mining of prediction process. Here CKD sample is utilized and investigated via Weka and Orange software. Some of the techniques that involve Machine learning are AD Trees, J48, K star, Naïve Bayes (NBs), Random Forest (RF) are utilized for the result investigation of every method which produces the arithmetical study and detecting CKD by the classifiers. This result reveals that the K-Star and RF designed for the Dataset that is being utilized, where construct the models are less time (0 sec and 0.6 sec) and the ROC values are 1.

Kunwar et al., [7] suggested the diagnosis of a condition called Chronic Kidney Condition (CKD) using such methods such as Naive Bayes and the Artificial Neural Network (ANN) used for classification. The outputs obtained via the Rapidminer tool show that the Naive Bayes (NBs) in comparison to the Artificial Neural Network have improved accuracy.

Misir et al., [8] formulated a new method for the prediction of a disease named CKD which also tried for a significant technique used for feature selection as well as to identify the minimal features that describe the set of data. Two innovative binary classification techniques are followed for the approval of the minimized set of features. The outputs of these are validated with regard to four significant validation variables. The results suggest that the minimized features show minimized uncertainty reduces time and economically effective

In 2014, K.R.Lakshmi et al.,[9] developed the performance assessment of three techniques for predicting survivability of kidney dialysis, such as ANN, DT, and Logical Regression (LR). These approaches are used to derive knowledge about the relationship between certain variables and the survival of patients. Finally, ANN is suggested to achieve enhanced results by accuracy and efficiency for kidney dialysis.

Mr. S Dayanand [10] developed the research work in 2015 using SVM and ANN to predict CKD. The purpose of this approach is to compare the outcomes of these methods, based on their accuracy and time of execution. It is seen from the results with the intent of the ANN output as compared with the SVM algorithm.

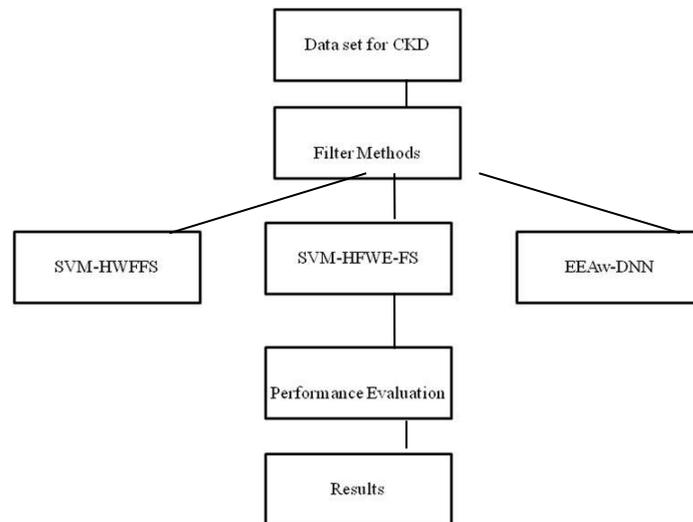
Wickramasinghe et al., [11] formulated a technique to regulate the disease utilizing the appropriate schedule for diet and to discover it with the help of algorithms meant for classification. The proposed technique functions along with the aid of different dietary schedule by analyzing potassium aspect for CKD victims as per their potassium level in their blood. Multiclass Decision Jungle, Multiclass Decision Forest, Multiclass Neural Network and Multiclass Logistic Regression are the variety of algorithms where the technique is implemented.

Chetty et al., [12] formulated certain model for classification which is constructed using various classification algorithms like Wrapper subset parameter valuator and excellent search mechanism to identify and classify the CKD and non-CKD victims. The proposed models are imposed on recently gathered CKD set of data take from the TICI database. The outputs of these models have provided good response in the classification of CKD and non-CKD issues. Comparison is performed on various models. The comparative results prove that classifiers yielded good performance on the minimized set of data than the actual set of data.

Chen et al.,[13] performed a symptom analysis related to CKD's progressive development, focusing on risk identification for CKD through clinical symptom data combined with multivariate methods. K-Nearest Neighbor (KNN), SVM, and Soft Independent Class Analogy Modeling (SIMCA) are three commonly used multivariate methods. Such approaches were tested using the probability of 386 cases depending on the sequence of medical information collected from the repository containing UCI machine learning.

#### **4. Methodologies Involved**

The major contribution of this work is to introduce a new feature selection algorithm and classification algorithms for prediction of CKD. The proposed work consists of three major contributions which are described in section 4.1, 4.2 and 4.3.



**Fig1.1 Architecture of proposed work**

#### 4.1. Methodology I

The filter methodology is independent of any learning algorithms that pick the characteristics whose ranks are the maximum between the subset and then use the same characteristics for certain classifiers (Chao-Ton and Yang,[14]. HFWFS is being suggested in this work in order to decrease the number of features for CKD prediction. Filter functions use an ordinary method to pick essential features from the set of data. The Wrapper Feature Selection (WFS) algorithm uses the Enhanced Immune Clonal Selection (EICS) algorithm to select the features optimally. The extraction of Datasets is from a regular machine learning server at the University of California Irvine (UCI).

Filter functions pick the features that stand superior to the few other related features, and then some classifier algorithm can be used for the selected subset features. In this work, the following three types of filter functions are Knowledge Gain (IG), Correlation-based Feature Selection (CFS), and Consistency-Based Subset Evaluation (CS).

Gaining knowledge is evaluating the variance, with two distributions of probability. It calculates a function X by measuring the knowledge obtained from the class variable Y by looking at it.

Correlation-based selection of features (CFS) is a filter method with a view to sub-sets of results. Redundant features are differentiated because they are more associated by multiple features in determining.

CS tests the reliability time for the class as per the measure of evaluation. The idea plan is to get a collection of features to separate the new subset-addicted dataset that integrates the majority of a single class.

The wrapper approach calculates the scores of feature sets to base the predictable results as a black box through the classifiers. This characteristic increases the space of each and every subset element.

For this work, the Clonal Selection Algorithm (CSA) is used within the B cell that reacts against invaded antigen during the modification of the receptor called an antibody. Cloning, hypermutation, and selection are the three major steps are implemented to select the key features within the samples of the CKD datasets. The Enhanced Immune Clonal Selection (EICS) algorithm is written in real numbers and each feature item of a collection of features is evaluated as a gene component. Any logical movement of gene parts would create a new B cell, related to the recombination in immunology. Finally, SVM has a great ability in aspects of classification. Using Hybrid Filter and Wrapper-based Feature Selection (HFWFS), the performance of the SVM classifier are enhanced. It is capable of expanding generalization results by managing high-dimensional features by mapping the

inputs and assessing the issue of CKD prediction. It can locate the optimum hyperplane with disjunctive effect.

## 4.2 Methodology II

A Hybrid Filter Wrapper Embedded based feature selection (HFWE-FS) was implemented in this process to pick an appropriate feature subset from CKD dataset. This algorithm HFWE-FS blends filter, wrapper, and embedded algorithm procedures. Depending on the three main functions: Relief, One-R, Gain Ratio and Gini Index, the filter algorithm is implemented. Improved Bat Algorithm (IBA) was used in the Wrapper method. The embedded algorithm is performed to select analytical attributes from the CKD dataset, that depends on the Support Vector Machine- t-statistics (SVM-t). The outputs of all selection algorithms for features are combined and called as HFWE- FS algorithms. At last SVM-based prediction algorithm is used to predict CKD is proposed.

Relief-F is an instance-dependent algorithm for the selection of attributes that defines features from several classes by how fine its meaning differentiates examples with the intent, but are comparable to each other. One-R is an easy algorithm [15], it creates one rule in the training data for each feature, and then chooses the rule with the lesser error. It considers each and every numerically valued attribute to be continuous, and uses a simple algorithm to isolate the set of values addicted to a number of intervals of disjoint. It handles missing data as a valid value, by handling "missing."

This is individual to the primitive methods of the majority. Depending on one attribute it simply creates simple rules.

The gain ratio is the non-symmetrical calculation with the purpose being developed in the equilibrium direction designed for the IG bias [16]. For each function, IG is calculated independently and the features with the top-k values are chosen as the correct features.

Gini index is supervised by the filter measure's multivariate FS algorithm to evaluate the capability of a function to distinguish between groups. Specified C classes, a function's GI can be calculated as GI is capable of taking the full value of 0.5 for a double classification. The additional appropriate features have smaller GI values.

Bat Algorithm (BA) is an efficient developmental algorithm but has some weakness in exploration [17], so it can be stuck directly in the most multimodal test functions belonging to the local minimum. To solve this typical BA issue, two modifications are being implemented to increase BA's ability to investigate and develop. BA's ability to grow is improved by adding linearly decreasing weight factor inertia. The weight factor inertia governs BA's research and growth. The BA is similar to local search algorithm when the weight value for inertia is less. Else when the weight of inertia is higher is more like global scanning. The effect of earlier velocity decreases gradually with the linear decreasing inertia weight factor. A feature selection solution in BA is assigned to any randomly generated frequency value, and this value of frequency will have the similar effect on each and every aspect of such feature selection solution. At this point, the difference between all the features of a solution doesn't make sense.

The embedded algorithm is performed to select analytical attributes from the CKD dataset, based on the Support Vector Machine- t-statistics (SVM-t). SVM only use help vector information in the context of generating the maximum hyper plane partition and find the classes for each CKD dataset. The support vector, the closest CKD dataset points position between two classes, plays a significant role in selecting feature. The proposed SVM-t approach allows use of the CKD dataset points' most important feature subset (i.e., SVs) to establish the selection criteria for the feature.

## 4.3 Methodology III

Classification of the Ensemble Entropy Attribute Weighted Deep Neural Network (EEAw-DNN) has been helped to estimate CKD in this methodology. The EEAw-DNN's accuracy rate is surveyed using data reduction, using feature selection. To pick the best subset of CKD dataset features Hybrid Filter Wrapper Embedded (HFWE)-based Feature Selection (FS) is designed. This technique of

HFWE-FS combines filter, wrapper and algorithm together. The EEAw-DNN-based technique is utilized for the purpose of prediction and diagnosis of CKD. The research repository is utilized as "CKD" which is implemented with the help of MATLAB software. The results show that the EEAw-DNN classifier merged with the algorithm of HFWE allows a higher prediction level when compared with a few classification algorithms such as NB, ANN and SVM in the CKD severity prediction.

The EEAw-DNN classifier selects can be joined by the main item giving a vote, aggregating all the votes in accordance with every class and choosing the class in order to receive the votes in a large number. At the same time as voting in a large number is the widely common rule of combination; a key issue of voting in a large number is with the intention of taking into account simply the decision of each DNN group, not including the distribution of decisions. In particular, through different theories, each and every one of the potential methods in the theory space may be misused with the imagination of their own independent options and the relations. Here, using a Bayesian-based system to combine individual classifiers.

Deep Neural Networks (DNNs) are commonly used as a group extractor for the base classifier. From one point of view, EEAw-DNN consists of various preparatory layers for learning portrayals of knowledge with specific deliberative dimensions. Then again, two depictions of separate minibatch orders will combine into different configurations in the midst of the training phase of an individual deep neural network. Those previews also have the comparable false rates, but make independent mistakes. These can be misused by assembling, in which various snapshots are standard inspection and then merged with the major component producing a yield sheet, which changes the similar arrangement that is followed to the details, e.g.  $P(h)$ , where  $x$  is the CKD data verifies and certifies the class environment. Pruning is typically able to increase the ensemble outcomes in the classifier ensemble. Using the Genetic Algorithm (GA) to prune the ensemble here. GAs is commonly used to produce high-quality outcomes that are mutation, convergence and selection for optimization with operators.

The feature attribute weight is called entropy. A population of binary weight vectors originally developed from the function called entropy in EEAw-DNN pruning, where '1' refers to the means the classifier remains. Secondly, the repetition of the population is involved, where a vector  $Aw$ 's fitness is based on the set of validation  $V$ , i.e.  $f(Aw) = PVAw$  ( $P$  defines the predictive rate). At last, pruning of equal ensemble is carried out using the vector having the best weight ( $Aw$ ) created.

### Dataset used

CKD is divided into stages I – V as per the predictable Glomerular Filtration Rate (GFR). The measures where GFR is supposed to inhibit the equations involving the mathematics using serum creatinine, age, sex, body size, ethnic origin etc[19]. The wastes of the blood can build up to higher levels, if the regular kidney function is degraded to an extent.

A collection of CKD data from the UCI repository which has 24 attributes and an extra class (binary) attribute[20]. This consists of 400 samples of two variety of classes (CKD 250 cases; "NOTCKD" 150 cases). In this work, 160 sample numbers are used from entire samples.

The performance metrics evaluation (**Table 3**) uses the confusion matrix to reflect the efficiency of the classification algorithms.

**Table 3. Confusion matrix**

| Confusion Matrix |          | Prediction |          |
|------------------|----------|------------|----------|
|                  |          | Positive   | Negative |
| Actual           | Positive | TP         | FN       |
|                  | Negative | FP         | TN       |

## 5. Results and Discussions

The system's efficiency is predicted by the computation of Classification Accuracy (CA), specificity, sensitivity, precision, F-measure and Error Rate (ER) as these are considered to be the parameters which are significant for the very detection of systems performance leaving out the knowledge of data distribution. To further compute the performance parameters True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are computed.

Classification accuracy - Shows the classifier algorithm's potential to predict classes in the dataset.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \times 100 \quad (1.1)$$

Sensitivity -indicates the degree of precision of the occurrence of the target type. (Eq1.2).

$$\text{Recall} = \text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100 \quad (1.2)$$

Specificity is correlated with the test's ability to identify patients precisely, without any condition. (1.3)

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100$$

Precision may also be defined as a the prediction of positive value that is meant to be the fraction of relevant instances in the retrieved instances.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100 \quad (1.12)$$

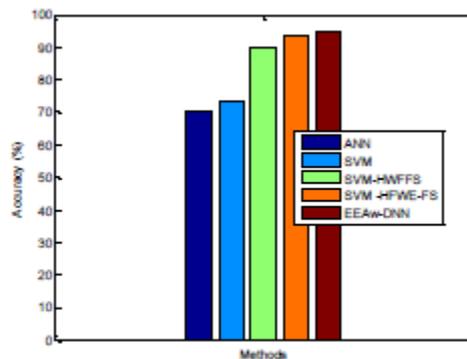
F-measure is mean average of precision and recall. It is evaluated as:

$$\text{F - measure} = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \times 100 \quad (1.4)$$

Table 3 shows comparison for performance metrics and classifiers.

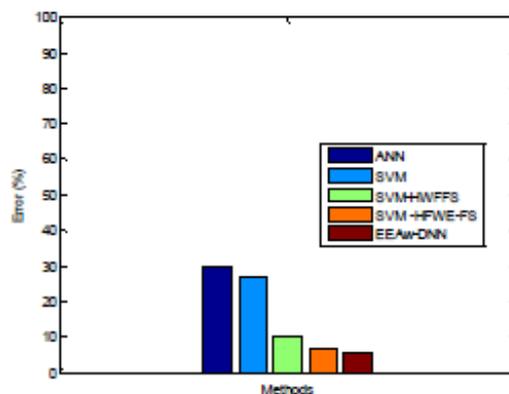
**Table 3. Performance metrics vs. classifiers**

| Methods     | Results(%)  |             |           |           |          |            |
|-------------|-------------|-------------|-----------|-----------|----------|------------|
|             | Sensitivity | Specificity | Precision | F-Measure | Accuracy | Error rate |
| ANN         | 76.19       | 55.56       | 80.00     | 78.05     | 70.00    | 30.00      |
| SVM         | 77.27       | 62.50       | 85.00     | 80.95     | 73.33    | 26.67      |
| SVM-HWFFS   | 90.91       | 87.50       | 95.24     | 93.02     | 90.00    | 10.00      |
| SVM-HFWE-FS | 95.45       | 87.50       | 95.45     | 95.45     | 93.33    | 6.67       |
| EEAw-DNN    | 97.30       | 87.50       | 95.58     | 96.43     | 94.70    | 5.30       |



**Figure 1. Accuracy performance comparison vs. Classifiers**

Figure 1 shows the result of the formulated EEAw-DNN technique which produces higher level of accuracy having 94.70% when compared to various classifiers like ANN, SVM, SVM-HWFFS, SVM -HFWE-FS with the results of accuracy as 70%, 73.33%, 90% and 93.33%.



**Figure 2. Error rate performance comparison vs.shows Classifiers**

Figure 2 shows the results of the proposed EEAw-DNN algorithm produces a less error rate having the result of 5.30%, but the other classifiers like ANN, SVM, SVM-HWFFS, SVM -HFWE-FS yields the results of accuracy of 30%, 26.67%, 10% and 6.67%.

## 6. Conclusion and Future Work

To predict CKD via the Support Vector Machine (SVM) classification from the datasets the Hybrid Wrapper and Filter-based FS (HWFFS) algorithm is implemented to identify the optimal subset of features. There are 24 features used from the UCI repository for the prediction purpose of CKD or non-CKD. From those 16 features HWFFS chooses. The main objective of this work is to correctly predict CKD or non-CKD with technical correctness via HWFFS algorithm among the identified features. HWFFS approach makes use of the filter and wrapper algorithm algorithms. Enhanced Immune Clonal Selection (EICS) based wrapper algorithm is proposed to figure out the features are selected that define the data set much better, thereby increasing the classifier's accuracy. In this research, the filter functions are Information Gain (IG), Correlation-based Feature Selection (CFS), and Consistency-Based Subset Evaluation (CS). Finally, an SVM classifier for CKD prediction was suggested.

Secondly, to predict CKD result from a dataset a novel Feature Selection (FS)-based Hybrid Filter Wrapper Embedded (HFWE) algorithm was implemented to select an optimal subset of features. In this analysis, the accuracy rate of the classifiers with selection of features is investigated. Wrapper, filter and embedded based FS algorithms are used for the diagnosis of CKD to decrease the dimensions of features and thus SVM has been used to classify features. Filter is based on three key features: Relief, One-R, Gain Ratio (GR) and Gini Index (GI). To pick analytical attributes from the CKD dataset, the wrapper algorithm is performed using the Improved Bat Algorithm (IBA) The embedded algorithm is to select analytical attributes from the CKD dataset, depending on the Support Vector Machine-t-statistics (SVM-t).

Final formulations used in the prediction of CKD is Ensemble Entropy attribute Weighted Deep Neural Network (EEAw-DNN) for data-focused detection of the CKD. The developed EEAw-DNN prediction method is designed to classify deep classifier components in an adaptive manner at many repetitions of the entire neural network. In addition, the ensemble is introduced as a Bayesian system for weighting and combining of the classifier attributes. The results show that the EEAw-DNN classifier using HFWE-FS approach produces high precision in CKD prediction when co-related to other methods.

It is important to handle the new classifier with missing and noisy values as future research. Similar data mining findings are checked in the context of determining the factors with the greatest complications on CKD by means of the qualified systems. The rule defined through data mining methods is the type of association rules to explain the role of CKD factors.

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