

Compare the Performance of Distinct Neural Networks Techniques to Diagnose the Kidney Stone Disease

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Abstract: Artificial Neural Networks are excellent at identifying patterns or trends in data, which makes them perfect for forecasting or prediction. Thus, neural networks have extensive application in biological systems. The application of neural networks to kidney stone diagnosis is emphasized in this article. Kidney stone issues can be diagnosed with neural networks by applying technological concepts such as MLP, SVM, RBF, and BPA. The purpose of this research is to use three different neural network algorithms—each with its own specific design and set of properties to identify kidney stone disease. The performance of the three neural networks is compared in this research with respect to training data set size, model creation time, and accuracy. Kidney stone sickness will be diagnosed using radial basis function (RBF) networks, two layers feed forward perceptrons trained with the back propagation training algorithm, and learning vector quantization (LVQ). However, determining the best approach for any particular diagnostic had never been an easy task. Like many other illnesses, kidney stones have already been diagnosed using neural network algorithms. The main objective of this work is to recommend the best medical diagnostic instrument, such as kidney stone detection, to reduce diagnosis times and improve accuracy and efficiency.

Keywords: Kidney stone, Artificial neural network, Radial basis function, Learning vector quantization

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1. Introduction

Artificial Neural Networks (ANNs) are used to solve many problems. However, the primary problem with neural networks is that their conclusions are not easily comprehensible to the general public. The reason for this is that the neural networks' weights and biases, which serve as representations of the knowledge, are real valued parameters [1]. To complete this article, one must first understand what kidney disease and artificial neural networks are. Learning about the mathematical underpinnings of artificial neural networks, network learning, and its use in medical diagnosis and performance should therefore be the first step. Second, look into kidney stone datasets, neural network design, and the algorithmic method used to diagnose renal illness.

Objective

This research compares the classification performance of three different neural network

approaches for kidney stone disease diagnosis. The algorithms have made use of RBF, LVQ, a multilayer perceptron with back propagation algorithm, two neural network techniques (BPA and RBF), and one non-linear classifier Support Vector Machine (SVM). We've compared their accuracy and efficacy. MRIs, ultrasounds, infrared scans, and x-rays are among the imaging procedures that are carried out when a patient goes to the doctor for a checkup [2]. Through the identification and correlation of contours of interest in these photos, the physician can diagnose a condition (e.g., fractures, pneumonia, cancer growth).

It is challenging to complete the task of diagnosing every disease and anomaly in the human body within the FYP time limit by employing an artificial neural network. Because of this, we were forced to focus only on one area of the human body, which we decided to be the kidney. Moreover, kidney cancer accounts for around 3% of all adult cancers, according to the American Cancer Society; the disease results in the diagnosis of 32,000 new cases and the death of about 12,000 individuals annually [3-4]. These numbers further motivated us to search for an accurate renal diagnostic technique that can detect tumors at an early stage and increase the prognosis of patients.

Key variables that are strongly linked to various kidney disorders the patient's gender (both male and female), Left or right kidney polarity, or both (it doesn't matter), Size of kidneys (very little, small, regular, or enlarged) [5]. The kidneys' outlines can be normal, atypical, or irregular, and a CT scan may reveal an abscess, tumor, cyst, or stone. Abnormal urine may include elevated levels of creatinine, blood ureanitrogen, bacteria, proteinuria, hematuria, white blood cells, red blood cells, or combinations of these.

2. Kidney disease classifications

There exist various forms of kidney disease, such as UTI-induced pyelonephritis, renal cell carcinoma, end-stage renal disease, pyelonephrosis, hypoplastic right kidney, ruptured or infected cysts, Risk factors for epidemiology [6]. ANN are quickly replacing other technologies as the most popular tool for sickness diagnosis. ANN are being used in a growing range of industries, including medical diagnosis, because of their fault tolerance, generalization, and capacity to

learn from data that is comparable to the environment [7]. A popular network topology that limits network connections to those between nodes in the same layer and those in the layer below is called the feed forward network. The block diagram of the proposed structure is depicted in Fig. 1. A feed-forward back propagation neural network is a type of classifier that is used to distinguish between infected and non-infected individuals. The architecture of feed-forward neural networks (MLPs) used for decision-making is depicted in Fig. 2. Three inputs are sent to the network in this format. The inputs and weights are then added using the summing function. In the end, the outcome is binary, meaning it can be either Yes or No. When a patient is ill, the answer is yes; when the patient is well, the answer is no. In this work, three neural network techniques—feed forward architecture with back propagation algorithms, LVQ, RBF, and RBF—were used to examine the early detection of kidney stones [8]. The three methods are compared with each other in order to categorize persons as impacted or unaffected. It is difficult to accomplish the goal of using an artificial neural network to diagnose every disease and anomaly affecting the entire human body within the allotted time frame for the FYP. We were forced to concentrate our efforts on just one body part as a result, and we chose the kidney. Furthermore, according to the American Cancer Society, kidney cancer represents nearly 3% of all adult cancer cases; each year, the disease results in the diagnosis of 32,000 new cases and the death of roughly 12,000 people [1]. These numbers further motivated us to search for an accurate renal diagnostic technique that can detect tumors at an early stage and increase the prognosis of patients [9-10]. ANNs are a potent tool that can assist doctors with diagnosis and other tasks. ANNs have a number of benefits in this regard, including

- The capacity to handle a lot of data
- Less chance of missing important information.
- Shorter times penton diagnosis

3. Artificial neural network in kidney disease

ANNs have demonstrated their suitability for precise disease diagnosis in a variety of scenarios. Utilizing them also increases diagnosis accuracy, which raises patient satisfaction.

They should only be seen as a tool to support a clinician's final decision, though, as they are ultimately responsible for critically assessing the ANN output techniques for condensing and elaborating, despite their widespread use in contemporary diagnosis [11].

Learning about the mathematical underpinnings of artificial neural networks, network learning, and its use in medical diagnosis and performance should therefore be the first step. Second, look into kidney stone datasets, neural network design, and the algorithmic method used to diagnose renal illness. Because the Weka 3.7.5 simulator tool was used to examine the performance of the RBF, BPA, SVM, and MLP, RBF, and LVQ algorithms, it was also taught. We modelled an artificial neural network diagnosis for kidney illnesses using the Weka 3.7.5 simulator tool. The training model's parameters can be adjusted and evaluated using this tool [12-13]. These parameters include the quantity of training and testing data, hidden layers, learning rate, momentum, validation threshold, error per epoch, and accuracy. The simulations' goal was to assess the method's efficacy across a range of precisely and correctly identified cases, time taken, and accuracy circumstances.

3.1 Kidney Stone Introduction

Kidney stones are hard, solid particles that form in the urinary tract. Most of the time, the stones are rather tiny and are easily expelled from the body. But pay attention if a stone—even a tiny one—obstructs the flow of pee [14]. The few symptoms of kidney stone illness are discomfort, blood in the urine, gravel, nausea, and pain during urination. Kidney stone production is one of the most common and unpleasant urinary tract infections. Each year, thousands of Americans are diagnosed with kidney (renal) stone disease, a condition that arises when the urine becomes overly saturated with specific microscopic substances.

They produce crystals that eventually come together to form deposits of hardened minerals called calculi, or stones. Kidney stones can occur anywhere in the urinary system as hardened clumps of tiny crystals. Samples of neutrophils, eosinophils, monocytes, lymphocytes, and s. creatinine are cultured in order to identify kidney stones [15-16]. There are several value ranges for these characteristics. According to data gathered from hospitals, people who were given a kidney disease diagnosis were present.

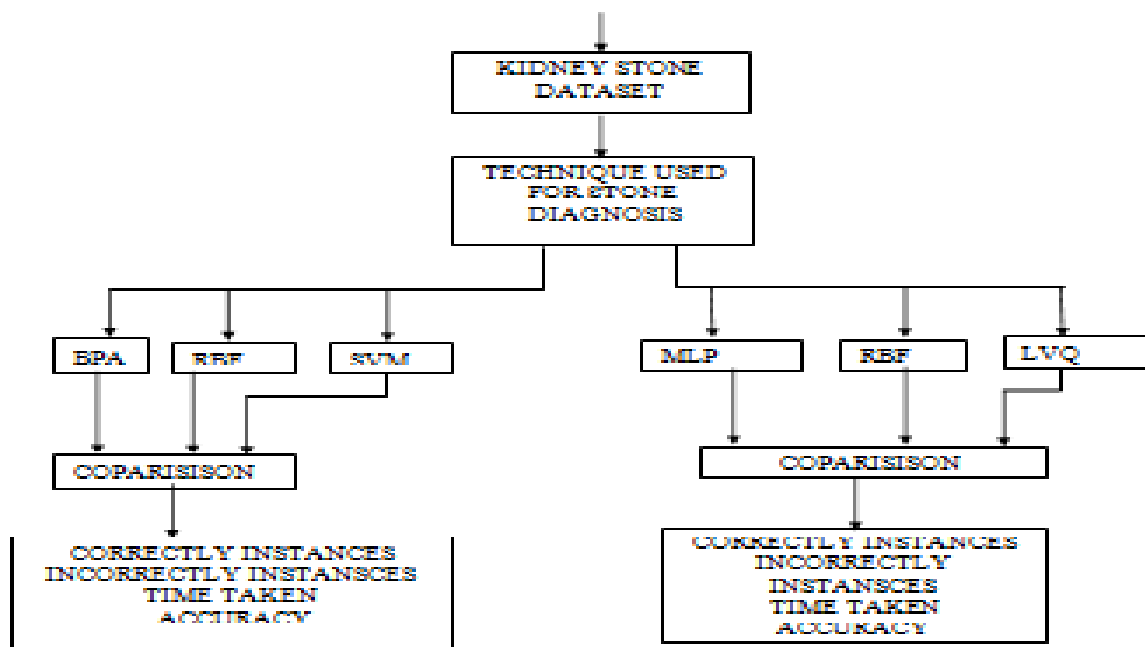


Fig.1: Block diagram of kidney diseases diagnosis using ANN

3.2 Kidney Stone Dataset

All of the data in the kidney stone sickness diagnosis data set are genuine set data. The kidney stone patient testing facilities provided the data set used in this investigation. One thousand patient data instances with seven attributes were used in this study. The features represent real symptoms of kidney stones, and we used them to train neural networks for diagnosis. The markers used for diagnosis include lymphocytes, monocytes, eosinophils, neutrophils, creatinine, blood sugar, and uric acid. The datasets are divided into two categories to facilitate their use in experimentally determining the presence or absence of kidney stone disease. All of the real set data in the kidney stone sickness diagnosis dataset is used. The study's data set was collected from many medical laboratories that test for Class 1 and Class 2 diseases, respectively. Class 1 results indicate the presence of disease, while Class 2 values show its absence. A kidney stone is present if a parameter comes within the attribute's actual range; if not, the parameter falls outside of the attribute's actual range in Table. 1.

Table. 1: Sample report for kidney stone

Attributes	Weight	Actual range
Lymphocytes	30.0gms	21-15%
Monocytes	1.0gms	1-6%
Neutrophil	2.0gms	1-4%
S. Creatinine	61.0gms	50-69%
Eosinophils	3.0gms	4-11%

3.3 Detail of data set

Medical records of patients collected from different hospitals make up the kidney stone disease data set. This study made use of 1199 occurrences, or patient data. Age, sex, lymphocytes, monocytes, eosinophils, neutrophils, and s. creatinine were the seven characteristics of each occurrence.

This data set pertains to kidney stone disease. Table. 2 presents the attribute that was previously discussed in this data collection. The use of five attributes is supported by this dataset. There are two possible values for these properties: NO and YES. These qualities fit into a particular spectrum that Table. 3 discusses. If the patient reports a number within this range, the value YES indicates that they have kidney stones; if not, the value NO is present. The experiment is carried out in compliance with WEKA's recommendations. 75% of the data are used for training, and the remaining 25% are used for testing.

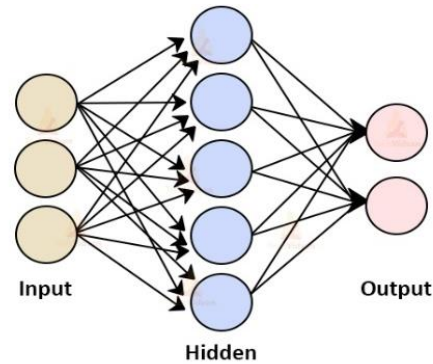


Fig. 2: Feed forward ANN

Table. 2: Sample of kidney stone dataset

Age	Sex	Lymph.	Monoc	Eosinp.	Neutro.	S. creat
48	F	Yes	Yes	No	No	Yes
40	M	No	Yes	Yes	Yes	No
51	M	Yes	No	No	No	Yes
23	F	Yes	No	Yes	No	No
57	F	Yes	No	Yes	No	No

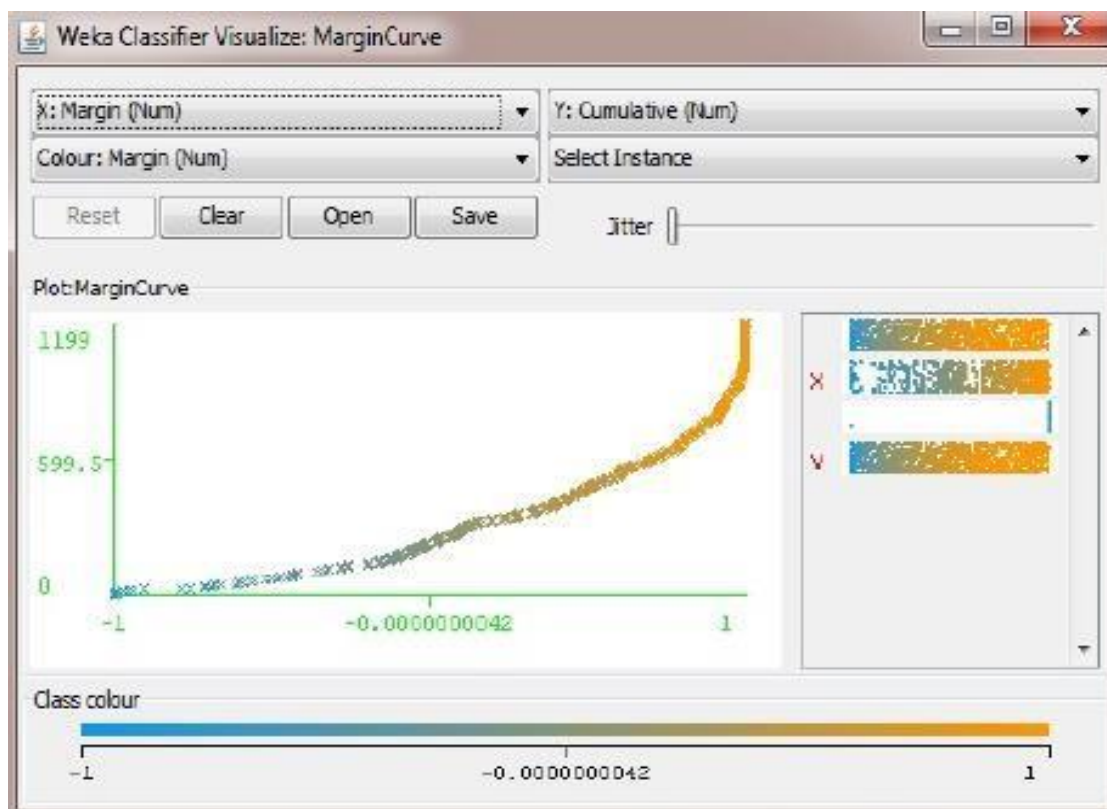


Fig. 3: Performance curve for BPA

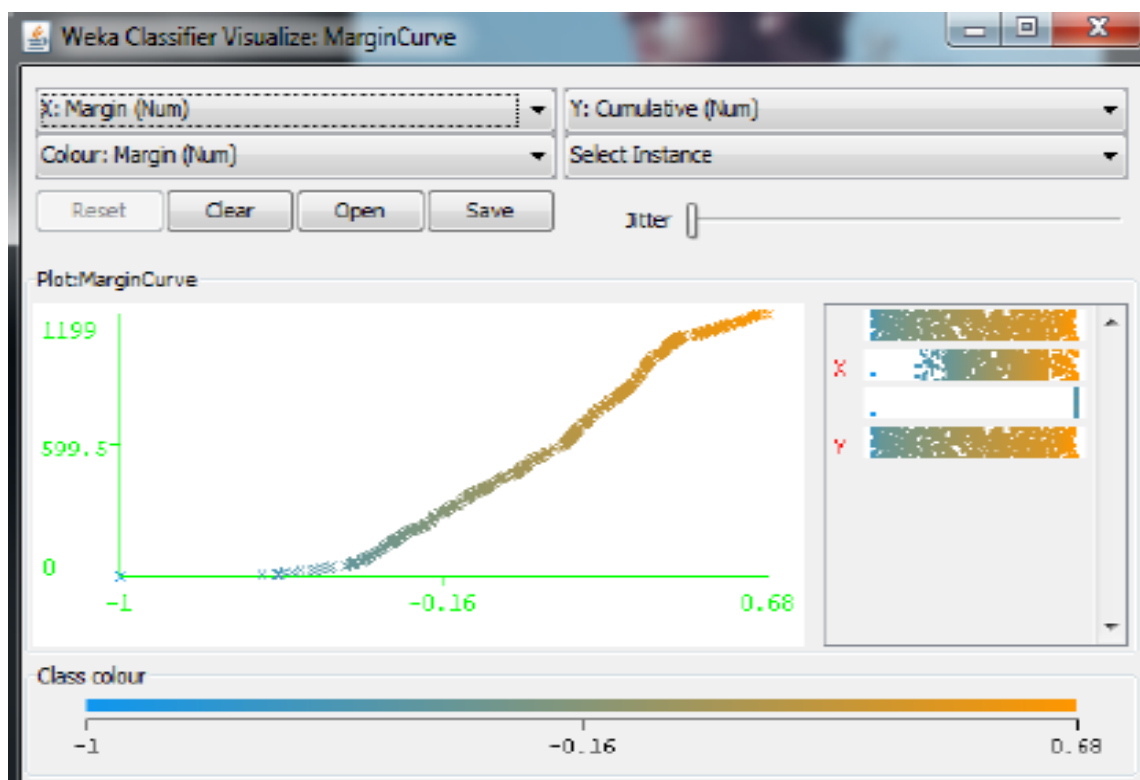


Fig. 4: Performance curve for RBF

In WEKA, all data are considered instances, and the attributes are the properties of the data. The simulation results highlight a few items for easier analysis and review. The first instances of correctly and incorrectly classified are separated into numerical and percentage values. Only numerical values are then accessible for the Kappa statistic, mean absolute errors, and root mean square error. We also show the root relative squared error in percentage and the relative absolute error for evaluation and references. The performance curve we acquire when neural networks are successfully trained and tested is shown in Fig. 3. The figure illustrates how the classification accuracy of the back propagation approach starts to rise as the number of cases increases. Fig. 4 showing performance curve that we obtain after successful training and testing of Neural Networks. The curve indicates that as the number of cases increases, the RBF Network's categorization accuracy first rises and then declines.

3.4 Diagnosis using support vector machine

Demonstrates support vector machine results. The findings demonstrate that support vector machines are capable of correctly classifying 722 out of 1199 instances that we offer to neural networks as inputs, demonstrating a 60% accuracy in disease detection. Model construction took 0.53 seconds. The kappa statics is 0.1775, while the root mean square error is 0.6307. The relative absolute error is 80.4111,

and the root relative squared error is 126.8168. Fig. 5 Training windows for SVM

Performance curves that we receive after successfully training and testing the SVM are displayed in Fig. 6. The support vector machine's classification accuracy increases initially before declining as the number of occurrences increases, as indicated by the curve. Here, the SVM curve's declining level exceeds that of the RBF Network.

3.5 Comparison result

Table. 3: Comparison BPA and RBF algorithm

Technique	Correctly classified data	Incorrectly classified data	Time taken	Accuracy
BPA	81.4012	18.5988	35.26 sec	81%
RBF	62.2185	37.7815	0.12sec	62%
SVM	60.2168	39.7832	0.56sec	60%

4. Experiment results for MLP, RBF and LVQ Algorithm

The black-box method is using neural networks to diagnose medical conditions. A network is selected, and it is trained using examples from every class. The system is capable of diagnosing unknown cases and making predictions after a successful training phase.

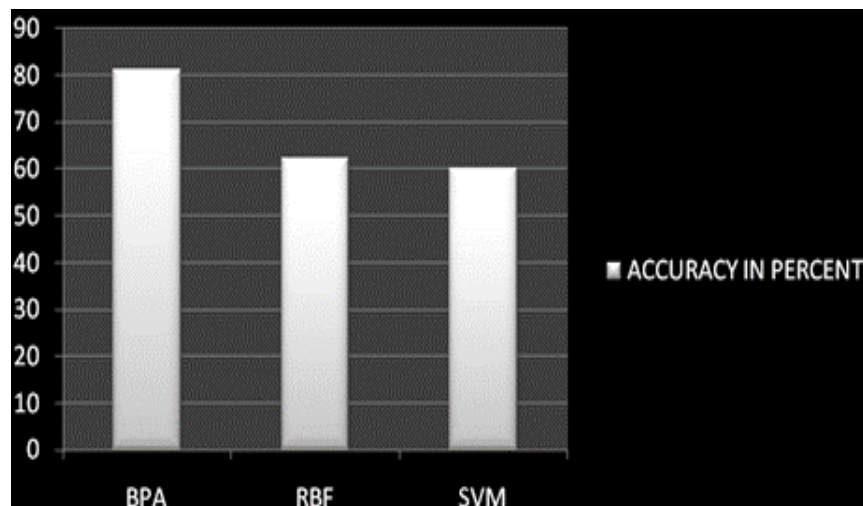


Fig. 5: Training windows for SVM

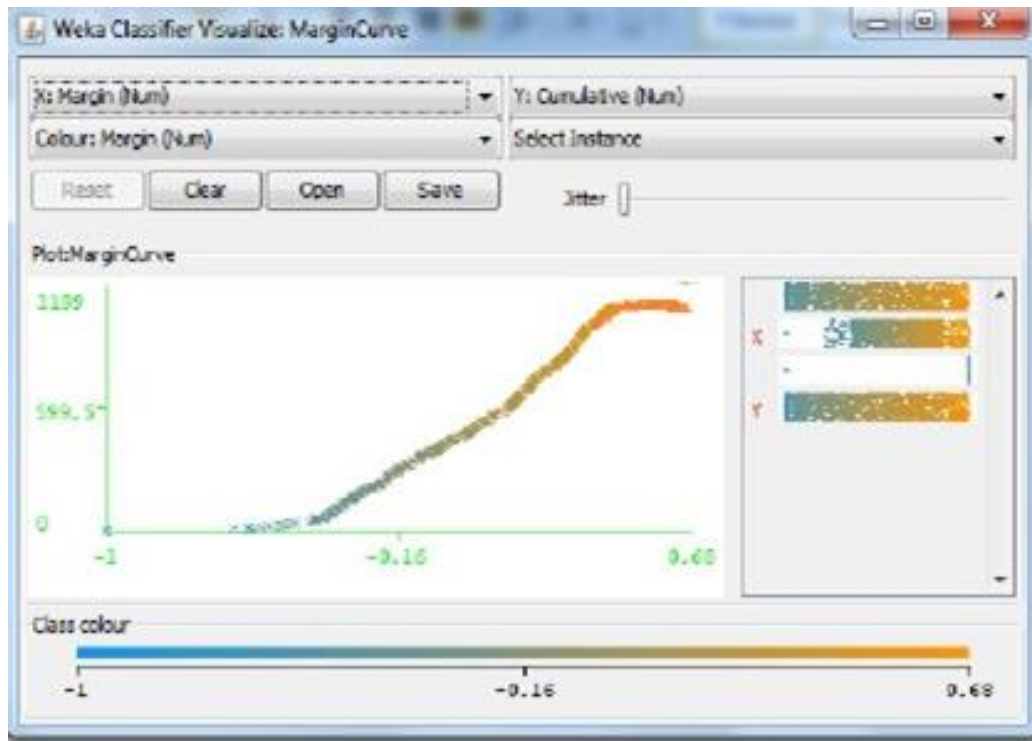


Fig. 6: Performance curve for SVM Network

In this investigation, we used three neural networks to classify and diagnose individuals with kidney stone illness. The tables below display the experiment's findings. Table. 4 demonstrates that neural networks are tested using 150 data instances after being trained on 1000 instances or data items. Two hidden layers are used, which is sufficient for all categories. For training and testing, the learning rate and momentum are, respectively, 0.3 and 0.2. This particular figure was picked because using these parameters, the highest level of accuracy is possible. Error per epoch is 0.013, and the validation threshold is 20.

Table. 4: MLP parameter with high accuracy

Parameter	Value
No. of training Data	1000
No. of testing Data	151
No. of hidden layers	2
Learning rate	0.30
Momentum	0.20
Validation threshold	20
Error per epoch	0.0131
Accuracy	98%

Table. 5 shows the parameters we used for training and testing of different networks. There are two hidden layers, two hidden instance numbers, 1000 total instances, 150 instances used for testing, a 0.3 learning rate for the network, and a 0.2 momentum. In learning, the size of weight and bias changes is controlled by the learning rate, and momentum simply adds a portion m of the previous weight update to the current one. The system is kept from convergent to a local minimum or saddle point by the momentum parameter. A high momentum parameter may also aid in accelerating the system's convergence. The system may become unstable if the momentum parameter is set too high since it increases the chance of the minimum being over fit.

Table. 5: Results of classification after training and testing

ANN	Kappa statistics	Mean absolute error	Root	Relative absolute error	Root relative error
MLP	0.96131	0.02831	0.12072	5.711%	24.25%
RBF	0.87320	0.07743	0.2052	15.62%	41.22%
LVQ	0.84591	0.07514	0.2741	15.16%	55.10%

Table. 6 shows different parameters which play critical role in the accuracy and performance of the

neural networks. The degree of agreement between the classification and the true classes is measured using kappa statistics, which corrects for chance. It is computed by subtracting the agreement anticipated by chance from the observed agreement and dividing by the greatest amount of agreement that may be achieved. All remaining parameters are some sort of mistakes.

Three neural network algorithms have been examined for the diagnosis of kidney stone illnesses in this area of the study presented. We are successful in finding the optimal model for kidney stone detection based on the aforementioned data. The most effective model for detecting kidney stone illness is a multilayer perceptron with two hidden layers and a back propagation method. The diagnosis of kidney stone illness is 92% accurate. 977 out of 1000 cases were accurately classified. Both of the other networks under examination fall short of in terms of classification accuracy, a multilayer perceptron trained using the back propagation technique excels. Even MLP's error is lower than that of the other two methods. Consequently, we conclude that multilayer perception training.

Table. 6: Comparison result for applied MLP, RBF and LVQ Algorithm

ANN's	Correctly Instances	Incorrectly classified instances	Time taken	Accuracy
MLP	976	23	0.440	92%
RBF	926	75	0.420	87%
LVQ	911	90	0.571	84%

It demonstrates that multilayer perception taught with a back propagation method properly classified the majority of examples, yielding a 92% accuracy rate in 0.44 seconds. Two hidden layers are used in multilayer perception; these layers have learning rates and momentums of 0.3 and 0.2, respectively. Compared to MLP, RBF finds instances 87% of the time correctly and takes less time, but it makes more mistakes. LVQ used more time than other networks and correctly identified 84% of occurrences. For various applications, radial basis function networks are said to perform better than multilayer perceptrons by many researchers; nevertheless, other researchers

found the opposite. However, the effectiveness of RBF in our work is limited to small data sets; as the number of data set instances increases, RBF's performance declines.

5. Conclusion

The application of artificial neural networks to medical diagnostics is examined in this thesis. The analysis is carried out step by step, with a focus on kidney diagnostics. Detecting disorders greatly aids doctors in saving lives. Future study will involve mathematically modeling neural networks to analyze medical diagnoses using a permissible set of parameters. My thesis's primary goal is to evaluate the three algorithms BPA, SVM, and RBF in order to determine which one is the best for treating kidney stone illness. The best model for kidney stone illness is back propagation. The diagnosis of kidney stone illness is 81% accurate. 976 out of 1199 cases were accurately classified. A model is constructed in 35.26 seconds. RBF and SVM are less accurate than BPA. RBF's accuracy rate is 62%. It properly categorized 746 out of 1199 occurrences. A model can be built in 0.15 seconds. Additionally, SVM accuracy is 60%. 722 out of 1199 cases were correctly classified. A SVM model may be constructed in 0.56 seconds. Compared to RBF and SVM, back propagation has a lower error rate (0.2418). Additionally, back propagation has a higher kappa statistic than both RBF and SVM. As a result, the back propagation algorithm (BPA) considerably enhances the utilization of the traditional classification technique in the medical industry.

The second section of this thesis looks at three neural network algorithms for diagnosing kidney stone illnesses. Our goal of determining the best model for kidney stone detection based on experiment results has been accomplished. The best model to identify kidney stone disease is a multilayer perceptron that uses backpropagation and two hidden layers. Kidney stone disease can be diagnosed with 92% accuracy. Of 1000 cases, 977 were correctly classified. In terms of classification accuracy, the two additional networks under investigation are not as good as a multilayer perceptron trained using the back propagation technique. The inaccuracy of MLP is even less than that of the other two techniques. This

leads us to conclude that multilayer perceptron training.

Future scope

In the developing field of bio-medical engineering, each person needs to be given care. There is an urgent need for both prevention of and treatment for life-threatening diseases in the modern world, which is negatively impacted by earthquakes and tsunamis. Neural networks are used with caution to diagnose modern diseases including the swine-flu, chicken pox guinea worms, brain tumor, and brain-fever, among others. In order to obtain the intended outcome with the necessary level of accuracy, mathematical modeling of neural networks will be the main focus and numerous parameters will be used.

Conflict of Interest

The authors declared "No conflict of interest".

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