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Compare the Performance of Distinct Neural Networks Techniques to diagnose the kidney stone disease

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Abstract: **Artificial Neural Networks are ideally suited for forecasting or prediction since they excel at spotting patterns or trends in data. Neural networks are therefore widely used in biological systems. An emphasis is placed on the use of neural networks in kidney stone diagnostics. Neural networks are used to diagnose kidney stone problems using technical ideas like as MLP, SVM, RBF, and BPA. In this paper is to identify kidney stone disease through the application of three distinct neural network algorithms, each with unique design and properties. This paper compares the three neural networks' performance in terms of accuracy, model construction time, and training data set size. Radial basis function (RBF) networks, two layers feed forward perceptron's trained with the back propagation training algorithm, and learning vector quantization (LVQ) will be used to diagnose kidney stone illness. But figuring out the optimum method for any given diagnostic had always been a difficult undertaking. Neural network approaches have already been used in the diagnosis of kidney stones, much like in many other disorders.**

This paper work's primary goal is to suggest the finest medical diagnostic tool—such as kidney stone identification—in order to speed up diagnosis times and increase precision and efficiency.

Keywords: **kidney stone, artificial neural network, Radial basis function.**

1. INTRODUCTION

Artificial Neural Networks (ANNs) are utilized to address a variety of issues. But the main issue with neural networks is that the conclusions they reach are hard for people to understand. This is so because the weights and biases of the neural networks—which represent the knowledge are real valued parameters. It is initially necessary to comprehend what an artificial neural network and kidney disease are in order to finish this paper. So the first step should be to learn about the mathematical foundations of artificial neural networks, network learning, and its application in medical diagnosis and performance. Second, investigate the neural network architecture and kidney stone datasets, as well as the algorithm technique employed for renal disease diagnostics.

2. OBJECTIVE

In order to diagnose kidney stone disease, the goal of this paper is to compare the classification performance of three distinct neural network techniques. Radial basis functions (RBF), Learning Vector Quantization (LVQ), a Multilayer Perceptron with Back Propagation Algorithm, and two neural network techniques—Back Propagation Algorithm (BPA), Radial Basis Function (RBF), and one non-linear classifier—Support Vector Machine (SVM)—have all been used in the algorithms. Their effectiveness and accuracy have been compared. When a patient visits a doctor for a checkup, several imaging tests are performed, including x-rays, MRIs, ultrasounds, and infrared scans. The doctor can detect a disease (cancer growth, pneumonia, fractures, etc.) by identifying and correlating contours of interest in these photographs. The issue is how to recognize these contours, connect them with one another, and diagnose the case using test results from blood, urine, and stool testing.

It is difficult to finish the mission of using an artificial neural network to diagnose all illnesses and abnormalities throughout the entire human body in the time frame allotted for the FYP. For this reason, we had to limit our work on a specific region of the human body and we chose it to be the kidney Furthermore, according to the American Cancer Society, kidney cancer makes up around 3% of all adult malignancies; every year, the disease claims the lives of roughly 12,000 people and causes the diagnosis of 32,000 new cases [1]. These figures further encouraged us to hunt for a reliable renal diagnosis method that can identify cancers early and improve patients' chances of survival.

Key variables that are strongly linked to various kidney disorders Gender of the patient (males and females), Kidney polarities left, right or both (it doesn't matter), Kidney size (extremely little, small, regular, or enlarged). The shapes of the kidney contours will be normal, irregular or abnormal, CT scan results abscess, tumor, cyst or stone. Level of creatinine, Blood ureanitrogen, Bacteria, proteinuria, hematuria, white blood cells, red blood cells, or mixtures of these may be found in abnormal urine etc.

Kidney disease classifications

There are many types of kidney disease like as Pyelonephritis due to UTI, Carcinoma of the Renal Cells, End-Stage Renal Disease, Pyelonephrosis, Hypoplastic Right Kidney, Cyst Infected or Ruptur, Epidemiological risk factors.

ANNs are swiftly overtaking other technologies as the most often used tool for diagnosing illnesses. An expanding number of industries, including medical diagnosis, are using artificial neural networks (ANN) due to its fault tolerance, generalization, and ability to learn from information similar to the environment. The feed forward network is a widely used network topology that restricts network connections to those between nodes in the same layer and those in the layer below. A classifier called a feed-forward back propagation neural network is used to differentiate between people who are infected and people who are not. Figure 2 shows the architecture of decision-making feed-forward neural networks (MLP). In this form, the network receives three inputs. The summing function is then used to add the inputs and weights. Ultimately, the result is binary—it can be either Yes or No. Yes in the case of a sick patient and no in the case of a healthy one. The early detection of kidney stones was investigated in this work using three neural network methods: feed forward architecture with back propagation algorithms, LVQ, RBF, and RBF. In order to classify affected and unaffected individuals, the three approaches are evaluated in comparison to each other.

The objective of employing an artificial neural network to diagnose the all illnesses and abnormalities throughout the entire human body in the time limit provided for the FYP is challenging to complete. As a result, we had to focus our efforts on a single area of the body, which we picked to the kidney. Moreover, kidney canceraccountsforaround3% of all adult cancer, according to the American Cancer Society; the disease results in the diagnosis of 32,000 new cases and the death ofabout12,000 individuals annually.[1]. These figures further encouraged us to hunt for a reliable renal diagnosis method that can identify cancers early and improve patients' chances of survival.

ANNs are a potent tool that can assist doctors with diagnosis and other tasks. ANNs have a number of benefits in this regard, including:

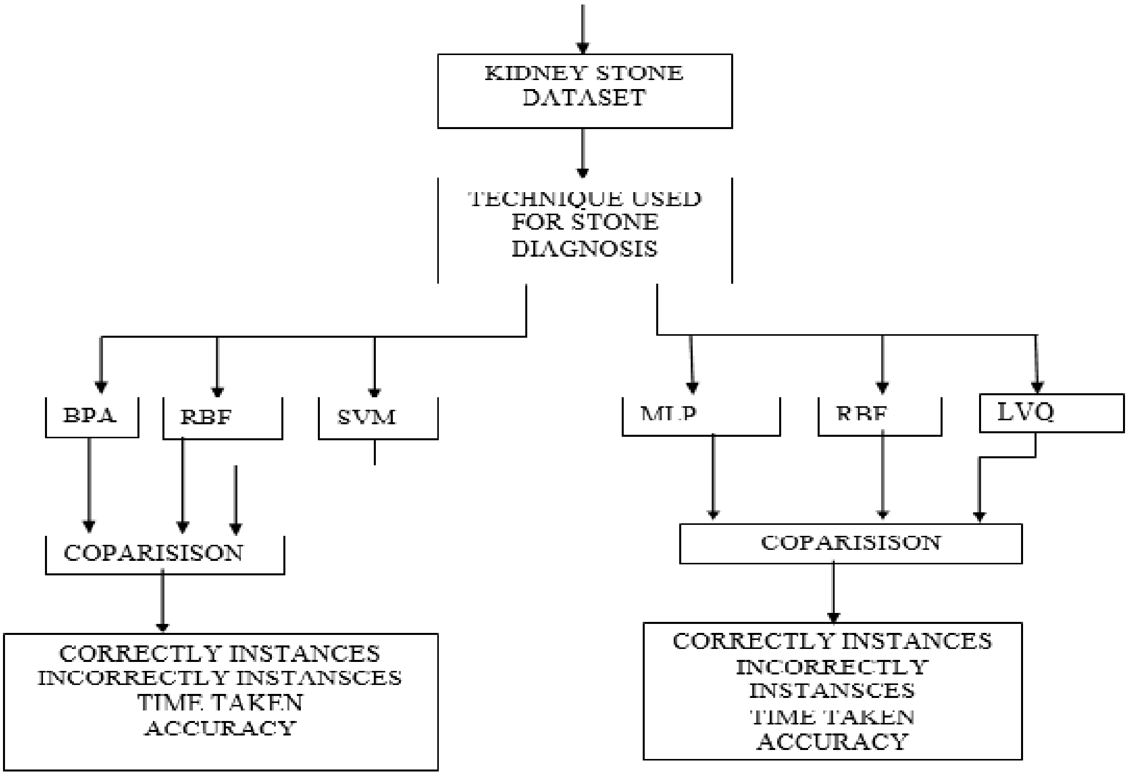
1. The capacity to handle a lot of data
2. Less chance of missing important information.
3. Shorter times penton diagnosis

3. ARTIFICIAL NEURAL NETWORK IN KIDNEY DISEASE

ANNs have shown to be acceptable for accurate disease diagnosis across a range of conditions. Their use also improves the accuracy of the diagnosis, leading to higher patient satisfaction. However, despite, ether, widespread use in contemporary diagnosis, they should only be viewed as a tool to aid a clinician's final judgment, as they are ultimately in charge of critically evaluating the ANN output techniques for condensing and elaborating.

So the first step should be to learn about the mathematical foundations of artificial neural networks, network learning, and its application in medical diagnosis and performance. Second, investigate the neural network architecture and kidney stone datasets, as well as the algorithm technique employed for renal disease diagnostics.

Weka3.7.5 simulator tool was also taught because it was utilized to investigate the performance of the RBF, BPA, SVM and MLP, RBF and LVQ algorithms. The Weka 3.7.5 simulator tool was used to model an artificial neural network diagnosis for kidney diseases. This tool allows the training model's parameters, including the number of training and testing data, hidden layers, learning rate, momentum, validation threshold, error per epoch, and accuracy, to be varied and tested. The purpose of the simulations was to evaluate the effectiveness of the a for mentioned method in a range of accurately and in correctly classified instances, time taken, and accuracy condition.



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4. KIDNEY STONE INTRODUCTION

In the urinary tract, hard, solid particles known as kidney stones develop. The majorities of the time, the stones are relatively small and can easily exit the body. However, if a stone (even a small one) prevents the passage of urine, attention. The Pain, blood in the urine, gravel, nausea or vomiting, and pain when urinating are the few signs of kidney stone illness. One of the most prevalent and uncomfortable urinary tract illnesses is kidney stone formation. Kidney (renal) stone disease, a condition that happens when the urine gets too saturated with particular tiny substances, is a yearly diagnosis for thousands of Americans. They develop crystals, which eventually unite to form calculi or stones, which are hardened mineral deposits. Anywhere in the urinary system, kidney stones can form as hardened clusters of microscopic crystals. Kidney stones are detected by culturing samples of lymphocytes, mono cytes, eosinophils, neutrophils, and s. creatinine. There are several value ranges for these characteristics. According to data gathered from hospitals, people who were given a kidney disease diagnosis were present.

4.1. Kidney Stone Dataset

The kidney stone illness diagnosis data setis made up entirely of real set data. The data set used in this study was gathered from several medical facilities that test kidney stone patients. In this study, 1000 instances of patient data with 7 attributes were employed. We trained neural networks for diagnosis using the features, which are truly kidney stone symptoms. Lymphoctyes, Monocytes, Eosinophils, Neutrophils, Creatinine, Blood Sugar, and U Acid are the parameters used for diagnosis. To assist their usage in experimentally identifying the presence or absence of kidney stone disease, the dataset are split into two types. The kidney stone illness diagnosis datasetis made up entirely of real set data. The data set used in this study was gathered from various medical labs that test for the Class 1 has values that indicate the existence of disease, while class2 contains values that indicate the absence of disease. The attributes listed in Table 1 demonstrate that if a parameter falls within the attribute's actual range, a kidney stone is present; otherwise, the parameter falls beyond the attribute's actual range.

Table 4.1: Sample Report for Kidney Stone

ATTRIBUTES	WEIGHT	ACTUALRANGE
LYMPHOCTYES	30.0gms	21-15%
MONOCYTES	1.0gms	1-6%
NEUTROPHIL	2.0gms	1-4%
S.CREATININE	61.0gms	50-69%
EOSINOPHIS	3.0gms	4-11%

Detail of data set

The data set for the kidney stone disease is compiled from patient medical records gathered from various hospitals. The 1199 patient data, or 1199 instances, were used in this study. Each instance had seven attributes: age, sex, lymphocytes, monocytes, eosinophils, neutrophils, and s.creatinine.

Table 4.2: 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

The data set on kidney stone disease is shown here. The attribute mentioned above is displayed in this data set in table 4.2. This dataset supports the use of 5 attributes. These properties have two possible values: YES or NO. These characteristics fall into a specific range, which is discussed in table 1. If the patient reports a number in this range, it indicates that they have kidney stones and contains the value YES; otherwise, it contains the value NO. The experiment is conducted in the same way that WEKA advises. The remaining 25% of the data is utilized for testing, while the remaining 75% is used for training.

All data in WEKA is regarded as instances, and the characteristics of the data are referred to as attributes. Several items are highlighted in the simulation results for quicker study and evaluation. The first examples that are successfully and wrongly classified are divided into numerical and percentage values, and the Kappa statistic, mean absolute errors and root mean square error are then only available in numerical values. For references and evaluation, we additionally display the relative absolute error and the root relative squared error in percentage.

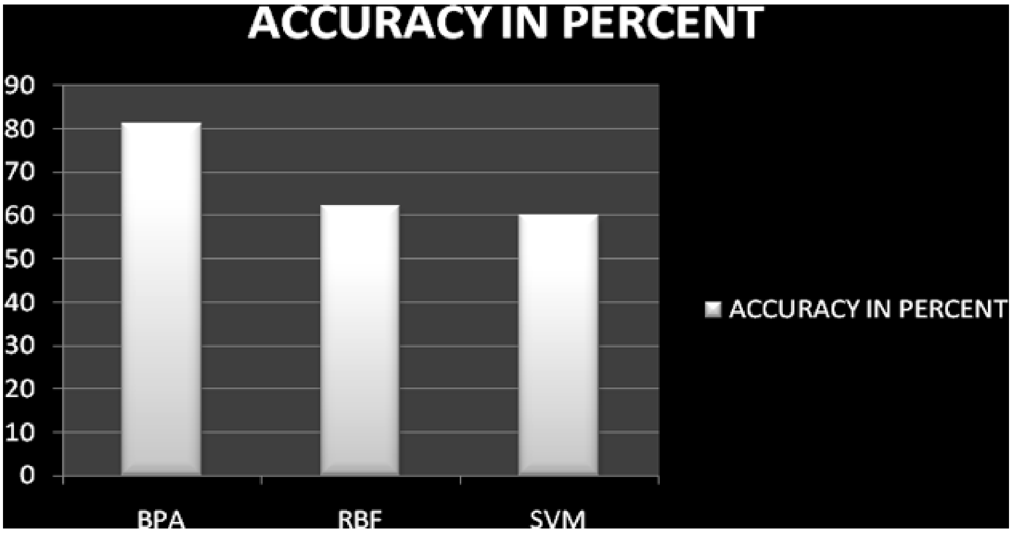

Figure 2

Figure 3 below displays the performance curve we obtain following the successful training and testing of neural networks. The curve shows how, as the number of cases increases, the back propagation method's classification accuracy begins to rise.

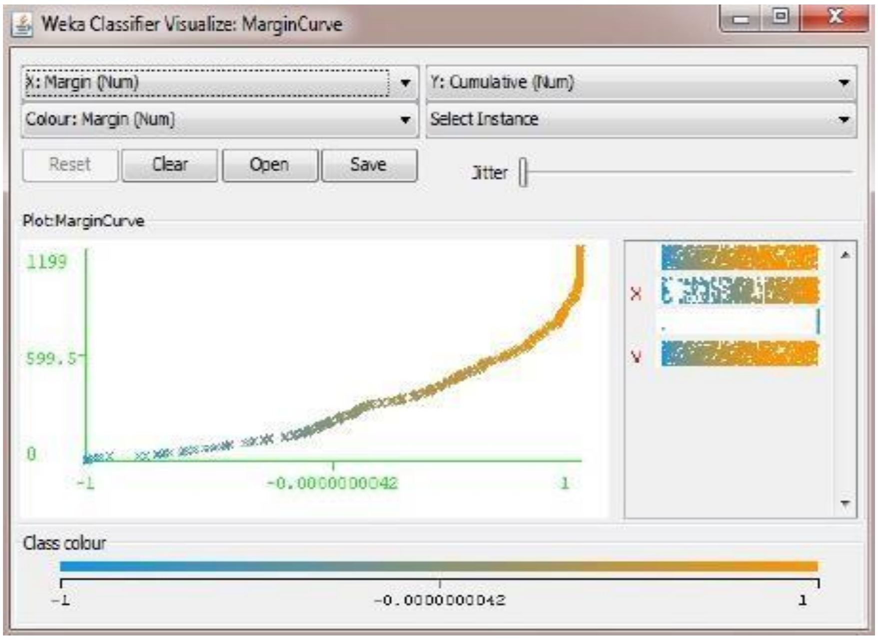

Figure 3: Performance curve for BPA

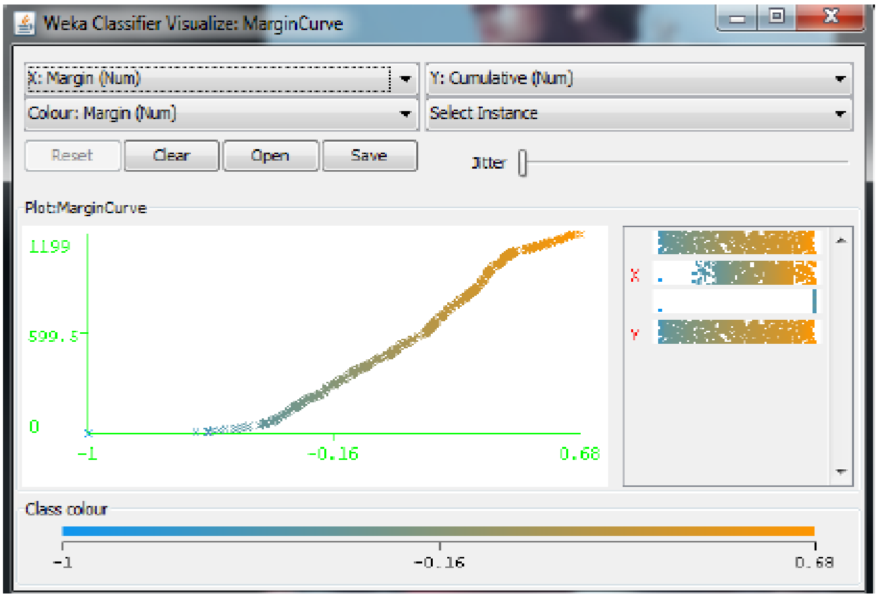

Figure 4: Performance curve for RBF

Figure 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.

5. COMPARISON RESULT

Table 5.1: 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%

6. CONCLUSION

The application of artificial neural networks to medical diagnostics is examined in this paper. The analysisis carried out step by step with a focus on kidney diagnostics. This paper primary goal is to evaluate the three algorithms BPA 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. 976out of 1199 cases were accurately classified. A model is constructed in 35.26 seconds. RBF is 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, Compared to RBF and SVM, back propagation has a lower errorrate (0.2418). As a result, the back propagation algorithm (BPA) considerably enhances the utilization of the traditional classification technique in the medical industry.

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