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Modified Particle Swarm Optimization Method for Handling Renal Disease

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ABSTRACT

Renal disease is a common issue in everyone's life. The toxin produced in our body is deposited in the kidneys. Kidneys will maintain the fluid level of the body. Abnormal in the fluid level causes the renal disease. Pathologic proteinuria is the most common cause of membranous nephropathy (MN). The disease is very progressive. Blood pressure encompasses a dramatic effect on the speed at which the disease progresses. Even alight rise in pressure level can quickly make nephropathy worsen. Low salt intake will reduce the blood pressure. Healthcare industry along with the rigorous growth in computer field analyzes the disease and give a boon support to the medical field. Machine Learning Methods is one of the smart manifestation practical significance for medicine. It is often accustomed classify various objects supported a series of coaching data whose result value is known. Classifiers methods have been used to identify the important attributes and uses different techniques to identify the disease. The classifier performance and also the length of selected feature subset was used as heuristic information for the proposed PSO-based method. The classifier performance and also the length of selected feature subset was adopted as heuristic information. The present work selected the best feature subset without any prior knowledge of features. Particle swarm optimization is a technique used for multidimensional space. In order to achieve good performance modified particle swarm optimization was introduced to achieve better algorithm overall performance. The proposed modified particle swarm optimization approach makes use of the class techniques Adaboost and KNN techniques for better handling the management of renal diseases.

KEY WORDS: MACHINE LEARNING, PARTICLE SWARM OPTIMIZATION, MODIFIED PARTICLE SWARM OPTIMIZATION.

INTRODUCTION

Our body has a wide range of cell types. Among the cell types most heterogeneous type of tissues are identified in the kidneys. Each area of the kidney contains a defined segment called the nephrons and portion of the collecting duct system. The filtering portion of the kidney is named as glomeruli and have a more complex structure comprising capillaries epithelium and intraglomerular mesangial cells. Endocrine functions play a vital role in kidney function. Abnormalities as a result of poisonous chemical compounds or other interventions may have profound outcomes on those functions and consequently, on overall capabilities (Padmavathi and Senthilkumar, 2020).

Membranous nephropathy (MN) is a continual sickness and its development embraces impulsive diminutions and recurrent deteriorations (Bomback et al., 2018). Nephrotic patients who do not know how to warmth into attenuation are susceptible to course to cease stage renal morbidity. People who are susceptible to high blood pressure, diabetes are more perspective to chronic kidney disease. As a symptom of membranous nephropathy, it

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triggers problem in breast for women and it is addressed that if any one of the diseases is recognized it leads to primary membranous nephropathy in lungs (Silva et al., 2018; Padmavathi and Senthilkumar 2020).

Diagnosing the disease plays an important role. Proteins with a molecular weight of much less than 20,000 skips easily throughout the glomerular capillary wall. Conversely, albumin, with a molecular weight of 65,000 Daltons and a negative charge, is confined under everyday conditions. The smaller proteins are in large part reabsorbed at the proximal tubule, and the best small amounts are excreted. Lack of protein, urine excretion greater than grams per day in 24 hours is an end result of glomerular disease. Shi and Eberhart (2001) states that the performance of the classification techniques is improved by using particle swarm optimization methods Particle Swarm Optimization (PSO) is a heuristic optimization approach displaying a relationship with evolutionary algorithms and strongly primarily based on the concept of the swarm. Normally the particle swarm optimization is used for the non-linear functions. The researchers use this particle swarm optimization method to get better performance (Shi and Eberhart, 2001; Silva et al., 2018).

PSO is based totally on the principle that every solution may be represented as a particle inside the swarm. every particle has a role inside the search space, which is represented by way of a vector xi = (xi1, x i2,..., xi D), where D is the dimensionality of the search space, debris pass within the seek space to look for the most suitable solutions therefore, each particle has a velocity, which is represented as vi = (vi1, v i2,...,vi D). At some point of the motion, each particle updates its function and speed in keeping with its very own enjoy and that of its associates. The quality preceding position of the particle is recorded as the personal satisfactory p high-quality, and the high-quality position obtained via the populace so far is known as g nice primarily based on p pleasant and g fine,

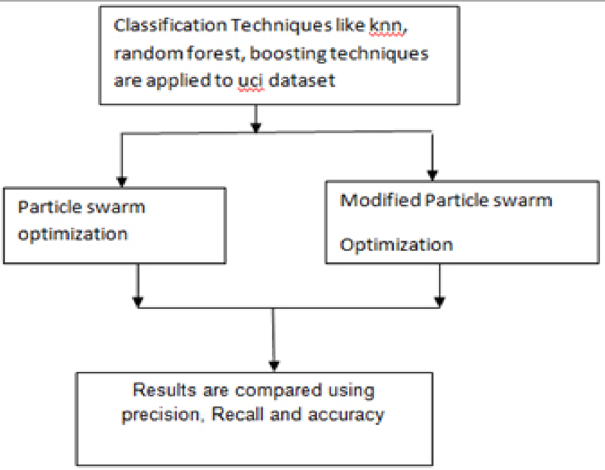
PSO searches for the most effective solutions through updating the velocity and the placement of every particle consistent with the subsequent equations. K-Nearest Neighbor, Random forest and boosting methods have been taken for the optimization techniques. The accuracy degree of every classifier has been calculated earlier (Silva et al., 2018; Padmavathi and Senthilkumar 2020). Then the modified particle swarm optimization has been used to get higher performance. Assessment of PLA2R autoimmunity is crucial for an affected man or woman management. The classifiers are applied to the AntiPLA2R dataset to enhance the overall performance. Normally, feature choice is a multi-goal problem. It has two foremost objectives, which can be to maximize the type overall performance (reduce the classification errors rate) and to reduce the variety of features (Padmavathi and Senthilkumar 2020).

MATERIAL AND METHODS

The research work has been implemented on MATLAB software tool and utilized it as a user-friendly interface. For the experimental tests, UCI Repository dataset was used in this framework. Monitoring the PLA2R and diagnosing the disease plays a key role in this research work. Kaplanmeier statistical analysis was done and hypothesis method was introduced and proved that p value was significant. Machine learning methods was introduced and the performance of the classifiers was done along with classifiers bagging and voting, which was introduced and the performance of the bagging gave better result for the disease prediction. Weka toolkit 3.8.2 was used to obtainbetter results modified using methods of earlier workers (Rakhlin, 2006; Padmavathi and Senthilkumar, 2019).

Optimization based feature selection method has also been used, where teaching learning-based optimization method has been used. Hybrid based learning method was used for one of the supervised learning method support vector machines, (SVM) and its performance was calculated, based on the time period following the methods of workers like, (Dhayanand and Vijayarani1, 2015; Padmavathi and Senthilkumar, 2019). Class problems often have a big wide form of functions in the records units, but now not they all are beneficial for class irrelevant and redundant functions may additionally even reduce the overall performance. Characteristic selection targets to choose a small number of relevant skills to gain similar or perhaps higher magnificence normal overall performance than the use of all capabilities (Padmavathi and Senthilkumar, 2019).

Figure 1: Optimization Based Selection System



It has fundamental conflicting objectives of maximizing the category performance and minimizing the quantity of capabilities. In the proposed method, the modified PSO technique we alternate the fitness feature (distance calculation) for every statistic. Here we alternate the match cost each new release, each new release the threshold cost is increased. Ultimately, we discover the solution of the iteration value based totally on the p best and b best values. Every iteration discovers the solution of facts based totally on generation and locates the first-class answer value in a few particular iterations and then we set the edge cost.

The particle swarm optimization was found to be fee effective and its technique is being used in many fields. Modified-PSO algorithm becomes a parameters optimization method, progressing to improve the sitting of the parameter values of system learning algorithms KNN, RF, Boosting, this model was designed to help the physicians reliably in identifying the abnormalities in pancreatic cancer. KNN, Random Forest and Boosting methods have been taken for the optimization methods. The source of data was taken from the UCI Repository dataset. The particle swarm optimization was applied to this dataset. A total of twenty-five attribute was taken for the calculation of the accuracy (Padmavathi and Senthilkumar, 2019).

This model is designed to handle the renal disease membranous nephropathy. The classification techniques like knn, Random forest and boosting techniques are considered for optimization-based selection system. Particle swarm optimization and modified particle optimization methods are applied. Then the accuracy of the classification techniques is calculated. PSO algorithm work details: PSO is an evolutionary algorithm inspired from the flocks of birds or schools of fish in coordinated motion.

In PSO, individuals are called particles and the population is called a swarm. Each and every particle search for the best point and this is based on the particle movement and intelligence. Thus, each particle motion is to find the particle current location (lbest), particle best location (pbest), sum of best location (gbest). The current location of the particle is estimated by the fitness function which is obtained from the fitness value (Padmavathi and Senthilkumar, 2019).

Steps: 1) Find the Objective (target to be achieved), 2) Let as Assume the Fitness value as 1 by Objective 3) Initialize Velocity and number of Iteration a) For each iteration calculate the local best from the population. b) Compare the local best with the previous local best to update the current lbest and velocity 4) Recalculate the Global best.5) Compare with the fitness if reached stops the iteration 6) Else continue to the next step. The accuracy level of each dataset is considered and it is tabulated.

Table 1 Describes the performance of the classification techniques by PSO. Based on the time factor accuracy is calculated for the Anti PLA2R DATASET.

Table 2 describes the performance of the classification techniques by PSO algorithm. Based on the time factor accuracy is calculated.

RESULTS AND DISCUSSION

PSO provides a valuable high level data points for the initial selection for further classification. Particles or potential solutions are represented having a position and rate of the change in d-dimensional space. In PSO, a number of solutions are encoded as a swarm of particles in search space. The initial values of a particle are randomly chosen. Each particle maintains a record of its best achieved since the beginning of the iteration. Also, each particle has a defined neighborhood. Particles make decision based on the performance of its neighbor and itself (Padmavathi and Senthilkumar, 2019).

Table 1. Accuracy level of the particle swarm optimization-based classification techniques

Algorithm	Accuracy	Precision	Recall	F measure	Time period
PSO_KNN	92	89	90	90	4.2
PSO_RF	95	92	94	93	3.7
PSO_BOOSTING	97	95	94	95	3.3

Table 2. Accuracy level of the optimization-based classification techniques

Algorithm	Accuracy	Precision	Recall	F measure	Time period
PSO_KNN	90	87	89	89	4.6
PSO_RF	93	90	91	92	4.2
PSO_BOOSTING	95	91	93	94	3.8

This method without feature selection total 25 attributes features based data given UCI data set (age, Level of specific gravity, sugar, rbc, pus cell clumps, bacteria, hypertension, diabetes mellitus, coronary artery disease, Appetite, pedal edema, pus cell clumps, age, blood pressure, blood urea, serum creatinine, sodium, potassium, hemoglobin, packed cell, wbc).Using modified pso algorithm improve the algorithm and optimized the features there given 25 it reduced the feature attributes our proposed method selected most relevant feature 19 from 25.

Table 3 describes the performance of the classification techniques by modified particle swarm optimization. Based on the time factor accuracy is calculated. In this modified pso method the distance is measured and its threshold values is calculated.

Figure 1: Showing the accuracy of the particle swarm optimization being determined.

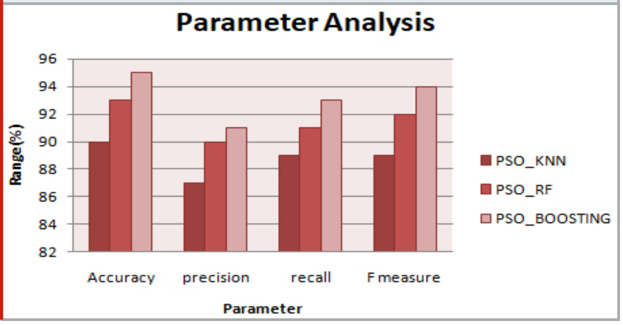


Figure 2: The accuracy of the particle swarm optimization determined on the basis of time.

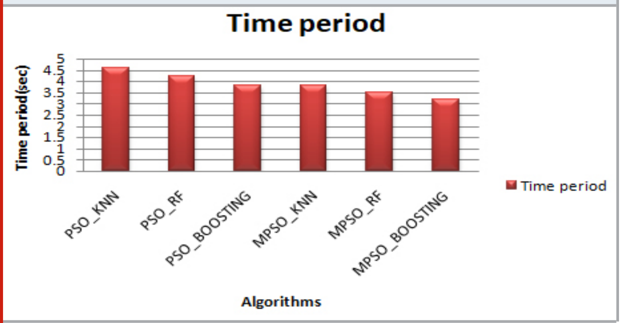


Table 3. Accuracy level of the Modified Particle swarm optimization algorithm for the classification techniques

Algorithm	Accuracy	Precision	Recall	F measure	Time period
MPSO_KNN	94	93	92	93	3.8
MPSO_RF	96	93	94	93	3.2
MPSO_BOOSTING	98	96	94	95	2.9

Table 4. Accuracy level of the optimization based classification techniques

Algorithm	Accuracy	Precision	Recall	F measure	Time period
MPSO_KNN	93	90	92	92	3.8
MPSO_RF	95	92	94	94	3.5
MPSO_BOOSTING	97	95	95	96	3.2

Figure 3: Applying parameter analysis for the machine learning techniques using PSO

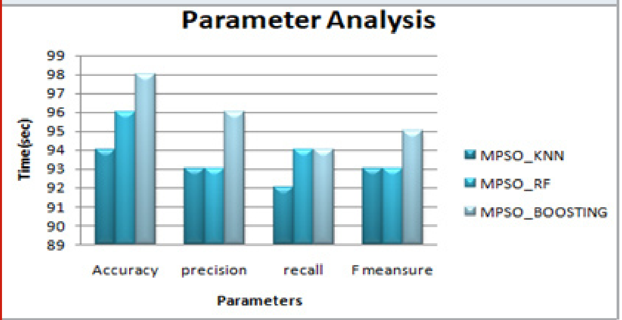


Figure 4: Applying parameter analysis for the machine learning techniques using pso for Anti –Pla2R dataset.

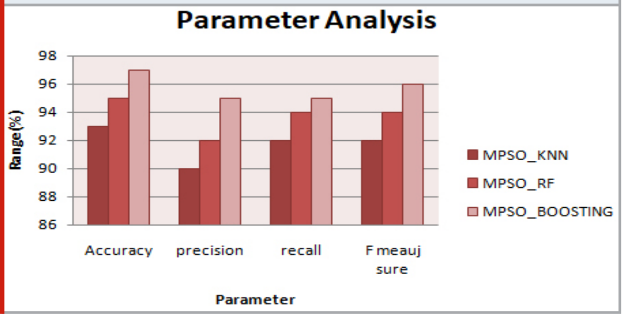


Table 4 describes the performance of the classification techniques by modified pso algorithm. Based on the time factor accuracy has been calculated

Figure 4: Applying parameter analysis for the machine learning techniques using pso for Anti –Pla2R dataset.

This present model has been designed to help the physicians reliably in identifying the abnormalities in pancreatic cancer. KNN, Random Forest and Boosting methods were taken for the optimization methods. The source of data is taken from the UCI Repository dataset.

The particle swarm optimization was applied to this dataset. A total of twenty-five attribute was taken for the calculation of the accuracy as the method of Padmavathi and Senthilkumar, (2019). The above process discusses about the comparison of previous work with the proposed work Modified particle swarm optimization. The accuracy of the ensemble methods bagging and boosting proves to be higher with the time factor 3.8.

Recently Trujillo et al (2020) have provided a new way of understanding membranous nephropathy, similar to our work where two datasets are used to improve the classification performance. The input parameters for boosting methods were optimized using modified version of PSO algorithm. In both the datasets the boosting algorithm performance is very high compared with the other classification techniques knn and Ada boost techniques

Table 5. Comparison of previous work.

Description	Algorithm used	ACCURACY	PRESCISION	RECALL
Feature selection process	SVM	90	89	90
	DT	93	91	92
	ES	96	93	95
Modified Optimization techniques	KNN	93	90	92
	RF	95	92	94
	Boosting	97	95	95

CONCLUSION

Membranous nephropathy may be a relatively common autoimmune disorder with a heterogeneous prognosis and its detection persists within the timely treatment of the patients. Different classification techniques have been used to improve the performance. KNN method was applied to boost up the accuracy. In this proposed method classifiers along with the particle swarm optimization methods were used. Two datasets were used to improve the classification performance. The input parameters for boosting methods were optimized using modified version of PSO algorithm. In both the datasets the boosting algorithm performance was very high as compared with the other classification techniques, the knn and Ada boosted techniques. We anticipate that future research will specialize for a far better understanding of autoimmune antibodies and to enhance with the applications of Artificial Neural Network.

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Conflicts of Interest: The authors declare that they have no conflict of interest.

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