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An Improved Classification Method for Diagnosing Heart Disease using Particle Swarm Optimization

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ABSTRACT
Today, the diagnosis of some of the major cardiovascular diseases, for example Coronary Artery Diseases (CAD), heart rhythm problems, Ischemic, Atrial Fabrication and so on is generally accomplished by following modern and costly therapeutic strategies performed in well-equipped medical institutions. In addition, these procedures usually require the application of invasive methods by only highly qualified medical experts. Although this approach gives a high degree of accuracy regarding diagnosis, but the number of patients having access to this facility is limited. Hence, the development of an easily accessible method for cardiovascular disease diagnosis is highly desirable. In this research work, the past work which employs the use of Deep Neural Network (DNN) for the diagnosis of heart disease is extended, CAD for four (4) different datasets was used with Particle Swarm Optimization (PSO) assisted method for DNN to enhance the accuracy of diagnosing heart disease, which is very complex in the healthcare practices was proposed. The aim of this research is to enhance the accuracy of diagnosing heart disease. A conceptual framework to analyze CAD heart disease was developed with the end goal to improve human services partner for specialists with convenience in the advancement of treatment of disease, also integration of the PSO training algorithm to train the DNN and finally, evaluation and validation of the performance of the proposed hybrid model with benchmark model Neural Network Classifier was carried out to obtain a comparison of the proposed model to the existing classification models. The research datasets are obtained from data mining repository of the University of California, Irvine (UCI) Machine learning repository. Experimental results show that training DNN using PSO results 94%, 94.9%, 95.5%, 95.0% in accuracy for Cleveland, Hungarian, Switzerland, and VaLong beach respectively. The technique puts forth can be used in CAD detection.

Keywords
Classification, Heart disease diagnosis , Coronary Artery Disease, Machine learning, Particle Swarm Optimization Neural Network

1. INTRODUCTION
Heart diseases such as Coronary Artery Disease (CAD), Atrial Fabrication, Myocarditis, Hypertension, Heart Attack etc. are mostly referred to as silent killers as they don't normally show themselves. The cause of death by various diseases among which include; stroke, respiratory infection, tuberculosis, diabetes, liver disease, diarrheal, heart disease, road injury which heart disease shows low death rate among others. Measuring how many people pass on each year and why they die is one of the most important means alongside measuring how diseases affect people to monitor the effectiveness of the world's healthcare system. [29].

For the diagnosis of CAD, different classification methods [6], [4], [25] have been described, each with its distinctive pros and cons. While conventional methods, such as decision trees [15] naive Bayes [5], etc., have some speed benefits and are easily applied to data sets, these methods cannot yield significant classification performance.

Despite the fact that J48 is one of the well-known algorithms it creates insignificant branches number which does not only decrease the usability of decision trees but also bring on the problem of overfitting [26]. Simple logistic has a convergence failure [20]. Naive Bayes is also known as a bad estimator, so the probability outputs are not reliable, it can only learn linear discriminant functions [21]. The main limitation of Random forests is their complexity. They are much harder and time-consuming to construct [10].

Particle Swarm Optimization (PSO) algorithm is based on swarm intelligence theory. This algorithm could provide effective solutions to optimization problems through intelligence generated by complicated activities such as cooperation and competition between individuals in the biology colony. Compared to evolutionary computations, PSO still maintains a population-based global search strategy, and its velocity displacement search model is simple and easy to implement. This algorithm also avoids the design of complex genetic operators, such as the crossovers and mutations. Particle Swarm Optimization algorithm was successfully applied to complex nonlinear function optimization [23], task assignment [24], reactive power and voltage control [24], and so on. Given the relative constraints of the GA-based training method, where there is an ability for the algorithm to be stuck when reaching the optimal solution, and the problem of local convergence.

In the proposed work the aim is to address the problem of diagnosing patient with heart disease thereby reducing the cost, saving time and money, removing the complication of Angiography and improving the overall medical system by improving its accuracy. Following this introductory section, the rest of the paper is organized into different section, each focusing on different features of the research work, below is the summary of the remaining section of the paper;

Section 2 provides related work with some limitation of previous work in addition to other classification methods proposed for heart disease diagnosis Section 3, 4 and 5 discusses the research methodology, including the source of data collection, experimental approach, and PSO algorithm. Section 6 and 7 entails the results & discussion and finally conclusion & future work.

2. RELATED WORK

The study [13] proposed a feature selection strategy using a binary particle swarm optimization algorithm for the diagnosis of different medical diseases. The support vector machines were used for the fitness function of the binary particle swarm optimization. The proposed method was evaluated on four databases from the machine learning repository, including the single proton emission computed tomography heart database, the Wisconsin breast cancer data set, the Pima Indians diabetes database, and the Dermatology data set. The results indicate that, with selected less number of features, a higher accuracy in diagnosing heart was obtained, cancer, diabetes, and erythematosquamous diseases. The results were compared with the traditional feature selection methods, namely, the F-score and the information gain, and a superior accuracy was obtained with the proposed method. Compared to the genetic algorithm for feature selection, the results of the proposed method show a higher accuracy in all of the data, except in one. In addition, compared to other techniques using the same data, the proposed methodology has superior performance using fewer features. [30] Introduces a computer-aided diagnosis system of the heart valve disease using binary particle swarm optimization and support vector machine, in conjunction with K-nearest neighbour and with leave-one-out cross-validation. The system was applied in a representative heart dataset of 198 heart sound signals, which come both from healthy medical cases and from cases suffering from the four most usual heart valve diseases: Aortic Stenosis (AS), Aortic Regurgitation (AR), Mitral Stenosis (MS) and mitral regurgitation (MR). The introduced approach starts with an algorithm based on binary particle swarm optimization to select the most weighted features. This is followed by performing support vector machine to classify the heart signals into two outcome: healthy or having a heart valve disease, then it's classified the having a heart valve disease into four outcomes: Aortic Stenosis (AS), Aortic Regurgitation (AR), Mitral Stenosis (MS) and Mitral Regurgitation (MR). The experimental results obtained, show that the overall accuracy offered by the employed approach is high compared with other techniques. [16] Also proposes the use of PSO algorithm with a boosting approach to extract rules for recognizing the presence or absence of coronary artery disease in a patient. The weight of training examples that are classified properly by the new rules is reduced by a boosting mechanism. Coronary artery disease data sets taken from University of California Irvine, (UCI) was used, to evaluate the new classification approach. Results show that the proposed method can detect the coronary artery disease with an acceptable accuracy. Also, the discovered rules have significant interpretability as well.

[7] Propose a technique of pre-processing the data set and using Particle Swarm Optimization (PSO) algorithm for Feature Reduction. After applying the PSO, the accuracy for prediction is tested. It is observed from the experiments, a potential result of 83% accuracy in the prediction.

The performance of PSO algorithm is then compared with Ant Colony Optimization (ACO) algorithm. The experimental results show that the accuracy obtained from PSO is better than ACO. The performance measures are based on Accuracy, Sensitivity and Specificity. The other measures such as Kappa statistic, Mean Absolute Error, Root Mean Squared Error, True Positive Rate are also taken for evaluation. In 2018 [28] proposed a classifier as a Naive Bayes (NB) which is relatively stable with respect to small variation or changes in training data and Particle Swarm Optimization (PSO) which is an efficient evolutionary computation technique which selects the most optimum features which contribute more to the result which reduces the computation time and increases the accuracy. Experimental result shows that the proposed model with PSO as feature selection increases the predictive accuracy of the Naive Bayes to classify heart disease. The System [1], a Deep Neural Network based classifier for classification of CAD data sets for the purpose of diagnosing CAD was proposed. The method was tested on the Cleveland, Hungarian, Long Beach and Switzerland data sets, experimental results show that the proposed method offers the highest classification accuracy among the methods included in the experiments. It is concluded that the proposed DNN based classifier can be used to classify medical CAD data sets for the purpose of the diagnosis of CAD. Experimental results show that the deep neural network outperform other methods like Decision Table, Naive Bayes, Logistic, Random Forest and Bagging. But the [1] wasn't able to escape in the entrapment of local optimum, there by not able to attain a high accuracy.

3. METHODOLOGY

In this sections, means for the research work, source of data, the conceptual model, experimental approach and finally the PSO Algorithm are discussed.

The figure 1 is the proposed conceptual model. It starts by collecting four different medical data for Coronary Artery Disease (CAD), then it undergo data processing where the data is being pre-processed, then it proceeds to the classification model, where the Particle Swarm Optimization in combination with Neural Network (DNN+PSO) hybrid system will classify the data as being diagnosed with CAD or healthy, and finally the output of the system is utilized by authorized medical healthcare personnel (Doctor).This system could give the doctor a helping hand for effective treatment and early diagnosis of Heart disease.

4. EXPERIMENTAL APPROACH

Many packages exist for supervised learning in various programming languages such as MATLAB, Java, C++, and Python which give work in functions. Because there exist various practical challenges, they cannot be essentially regarded as black-box (basically enter the input features).Some of the difficulties are: large dimensionality of feature vectors [8] bias/variance dilemma [9], input and output noise [19], large-scale training data [3], data redundancy [27] and non-linearity among features [22].

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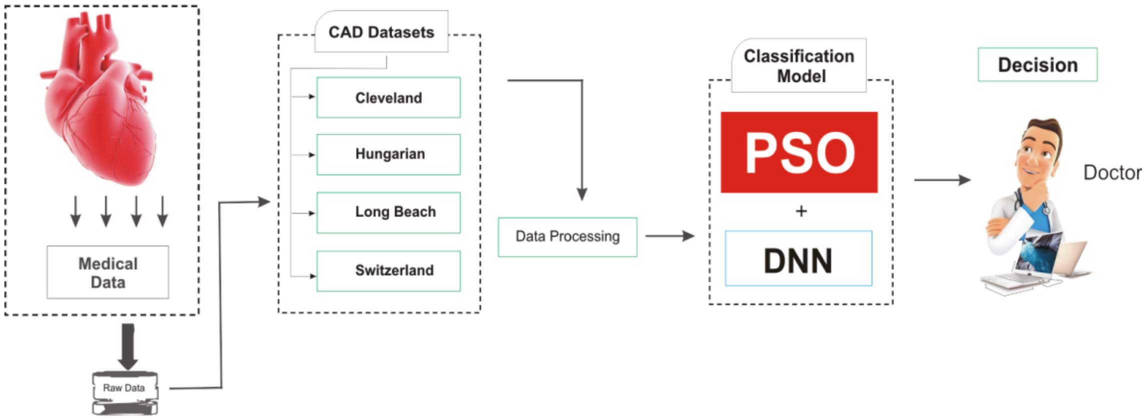

Figure 1: Proposed Conceptual Model

The proposed method employ the use of Python. Python is a general scripting language with a clear and simple syntax. With the rapid development of mature, advanced and open source scientific computing libraries and packages, Python has become one of the most common and scientific computing languages. In fact, Python has a cross-platform running feature that fits with various operating systems. , Linux, Windows, Ubuntu and so on. It has both the ability to access libraries written in a multitude of programming languages and computing environments which supports the development of small devices, embedded systems and embedded systems. In relation, Python needs a minimal setup operation to start with. Also, It uses modular and object-based programming, which is a popular methodology for organizing classes, functions and procedures in hierarchical namespaces. Each of these reasons had already made Python a famous language in a large community of researchers.

The implementation utilizes fast array manipulation with Numerical Python 'NumPy' http:/www.numpy.org/. Matrix support that use the Scientific Python SciPy (https:/www.scipy.org/) package. Precisely for the problem in binary classification. Implementation uses the powerful NeuralNetworkLibrary'neurolab'https:/pythonhosted.org/neurolab/'Home Page http:/code.google.com/p/neurolab/'

The numerical data supporting this hybrid approach are from previously reported studies and datasets which have been cited (UCI Machine learning repository). The processed data are available from the corresponding author upon request.

5. PSO ALGORITHM

Particle swarm optimization (PSO) is an evolutionary computation technique for optimization which was initially developed by Kennedy and Eberhart in 1995. It is inspired by social behaviour of bird flocking or fish schooling and swarm theory. This algorithm works by simultaneously maintaining some of the candidate solutions in the search space. Each candidate solution is called as a particle "flying" in the dimensional search space to find the best solution. In all of the iterations of the algorithm, each candidate solution is appraised by the objective function, and the fitness of that solution is calculated. Initially, like the GA, the PSO algorithm is initialized with a population of random solutions in the search space. Particle Swarm Optimization (PSO) also needs only the information that has to do with the fitness values of the particles in the population. This algorithm simply calculates the fitness values of the individuals by using the objective function. Compared to a genetic algorithm, individuals in the PSO has memory such that knowledge on particles with better solutions is retained for each individual. In other words, it promotes productive communication between each individuals share knowledge with each other. All the individuals have a location vector.

Algorithm1: PSO

For each particle

Initialize particle

End

Do

For each particle

Calculate fitness value

If the fitness value is better than its personal best

Set current value as the new Pbest

End

Choose the particle with the best fitness value of all as gbest

For each particle

Calculate particle velocity

Update particle position

End

Pseudocode

The Particle Swarm Optimization (PSO) algorithm consists of three steps.

(1) The fitness value of each particle will be calculated.

(2) Then update the local and global best positions and fitness

(3) Now measure the new velocity and position of particle with respect to the amount of inertia used to regulate the effect of the previous history of velocity.

Original PSO [12], [23], [2] takes the inspiration from the flocking behaviour of birds. The knowledge of global best found solution (typically noted gBest) is shared among the agents (particles) in the swarm. Furthermore, each particle has a memory of its own (personal) best found solution (noted *pBest*). Last important part of the algorithm is the velocity of each particle that is taken into account during the calculation of the particle movement.

The new position of each Particle is then given by (1), where x_i^{t+1} is the new particle position; x_i^t refers to current particle position and v_i^{t+1} is the new velocity of the particle.

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (1)$$

To calculate the new velocity the distance from *pBest and gBest* is taken into account alongside with current velocity (2)

$$v_i^{t+1} = w \cdot v_{ij}^t + c_1 \cdot Rand \cdot (pBest_{ij} - x_{ij}^t) + c_2 \cdot Rand \cdot (gBest_{ij} - x_{ij}^t) \quad (2)\ [14]$$

Where:

v_i^{t+1} - New velocity of the ith particle in iteration $t + 1$. (Component *j* of the dimension D).

w - Inertia weight value, several different approaches for setting the value of inertia weight are described in [18]

v_{ij}^t - Current velocity of the ith particle in iteration t. (component *j* of the dimension D).

c1, c2 - Acceleration constants.

$pBest_{ij}$ - Local (personal) best solution found by the ith particle. (Component *j* of the dimension D).

$gBest_{ij}$ - Best solution found in a population. (Component *j* of the dimension D).

x_{ij}^t -Current position of the ith particle (component *j* of the dimension D) in iteration *t*.

Rand - Pseudo random number, interval (0, 1).

After the movement, the particle evaluates the quality of its new position and compares it with its personal best solution (*p*Best). If a better value was discovered, the *p*Best is updated. Similarly, if the new best solution in the neighborhood (swarm or sub-swarm) was discovered, the gBest is updated.

The basic PSO algorithm consists of three steps, namely, generating particles' positions and velocities, velocity update, and finally, position update. Here, a particle refers to a point in the design space that changes its position from one move (iteration) to another based on velocity updates.

First, the positions and velocities of the initial swarm of particles are randomly generated using upper and lower bounds on the design variables values, *rand* is a uniformly distributed random variable that can take any value between 0 and 1. This initialization process allows the swarm particles to be randomly distributed across the design space.

The second step is to update the velocities of all particles using the particles objective or fitness values which are functions of the particles current positions in the design space. The fitness function value of a particle determines which particle has the best global value in the current swarm and also determines the best position of each particle i.e. in current and all previous moves. The velocity update formula uses these two pieces of information for each particle in the swarm along with the effect of current motion to provide a search direction for the next iteration. The velocity update formula includes some random parameters, represented by the uniformly distributed variables, *rand*, to ensure good coverage of the design space and avoid entrapment in local optima. The three values that effect the new search direction, namely, current motion, particle own memory, and swarm influence, are incorporated via a summation approach as shown below with three weight factors, namely, inertia factor, *w* , self confidence factor, *c*1 , and swarm confidence factor, *c*2 , respectively.

6. RESULT AND DISCUSSION

The original PSO algorithm uses the values of 1, 2 and 2 for *w*, *c*1, and *c*2 respectively, and suggests upper and lower bounds on these values as shown in Equation above. However, this research work found out that setting the three weight factors *w*, *c*1, and *c*2 at 0.9, 1.494, and 1.49 respectively provided the best convergence rate for all test problems considered. Other combinations of values usually lead to much slower convergence or sometimes non-convergence at all. The tuning of the PSO algorithm weight factors is a topic that warrants proper investigation but is outside the scope of this work. For all the problems investigated in this work, the weight factors use the values of 0.2 – 0.9, 1.494 and 1.49 for Minimum *weight-Maximum weight*, *c*1, and *c*2 respectively. Position update is the last step in each iteration. The position of each particle is updated using its velocity vector as shown in Equation 2.
The three steps of the velocity update, position update, and fitness calculations will be repeated until the necessary convergence criterion has been met. There was no suggestion in the literature on swarm size in the PSO. Some researchers use 10 to 50 swarm sizes, but there is still no well-established guideline. Table (3) demonstrates the outcome of Particle Swarm Optimization for the following datasets in Cleveland, Hungary, Switzerland and VaLongBeach. In order to achieve useful statistical results, we have the swarm population size = 100 and the number of iterations = 10.The dataset is divided into two (2) 64% for training and 36% for testing for each dataset (Cleveland, Hungary, Switzerland and VaLongBeach). The following table shows the results obtained from the proposed model for only 30 simulations in order to obtain a good statistical result, showing the execution time with specific accuracy for training and testing.

A. Cleveland

Table 1 displays the result of the execution time, the test accuracy and the training accuracy of the Cleveland dataset and the related chart and graph shown in fig 1.1 and fig. 1.2 respectively.

Table 1: Cleveland result

Experiment	ExecTime(Min)	trainAcc%	testAcc%
1	14.11718559	100	94.89927
2	13.93806696	100	93.763908
3	13.91404343	98.5	93.858802
4	14.43357658	96.5	94.066607
5	13.67086768	98	93.665238
6	13.74293327	30.5	93.255746
7	13.7619462	100	95.272506
8	13.70785141	98.5	96.008723
9	13.79798222	97.5	94.576254

10	13.74188256	100	93.09836
11	13.82190919	99.5	94.786361
12	13.66785979	1	95.008625
13	13.9170444	100	93.896504
14	13.81494689	66.5	93.987917
15	14.02209282	91	95.92241
16	13.87702703	100	96.47133
17	14.16533089	98	93.619471
18	13.71480989	97.5	92.563087
19	13.90407848	100	93.442382
20	13.78797436	91	95.203352
21	13.90398431	77	92.765055
22	13.81499505	100	92.971576
23	13.84398293	100	93.300221
24	13.82999206	86	94.321805
25	13.88201141	100	92.690845
26	13.92409778	100	96.302183
27	14.38043213	100	92.710171
28	14.69673753	99.5	95.076488
29	14.7017839	100	93.805412
30	14.16533089	98	93.619471

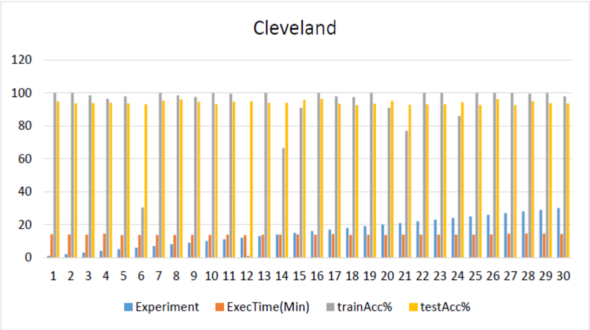

Figure 1.1: Cleveland

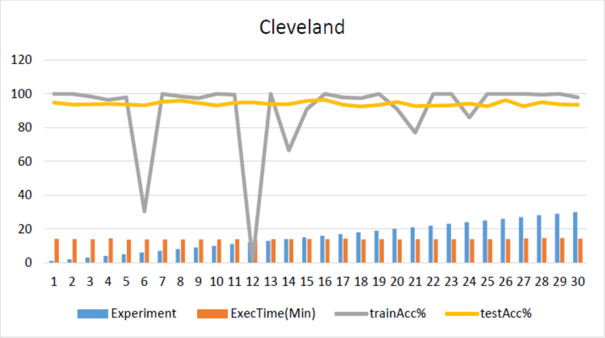

Figure 2.2: Cleveland

B. Hungarian

Table 2 shows the results of the execution time, the test accuracy and the training accuracy of the Hungarian dataset and the corresponding chart and graph shown in fig 2.1 and 2.2 respectively.

Table 2: Hungarian result

Experiment	ExecTime(Min)	TrainAcc%	TestAcc%
1	13.97209811	92.16	94
2	14.08820748	92.12	94
3	13.80394101	92.23	93
4	13.60074759	92.31	94
5	13.61171222	92.17	94
6	13.74091196	92.31	93
7	13.88701677	92.03	94
8	13.78892946	92.05	93
9	14.09524727	92.28	94
10	14.10226583	92.02	93
11	13.86800981	92.29	93
12	13.83397269	92.08	94
13	14.26036906	92.23	93
14	13.92901492	92.16	93
15	13.66480923	92.01	93
16	14.22133422	92.16	93
17	14.07319331	92.04	94
18	13.98210669	92.10	93
19	14.04316735	92.12	93
20	13.81299925	92.08	94
21	14.14128923	92.29	94
22	13.80994678	92.17	94
23	13.89802814	92.05	94
24	13.60980892	92.10	94
25	13.89707518	92.01	93
26	14.10822797	92.16	94
27	13.79693484	92.10	93
28	13.72986984	92.28	94
29	13.93706942	92.28	93
30	13.74688697	92.28	94

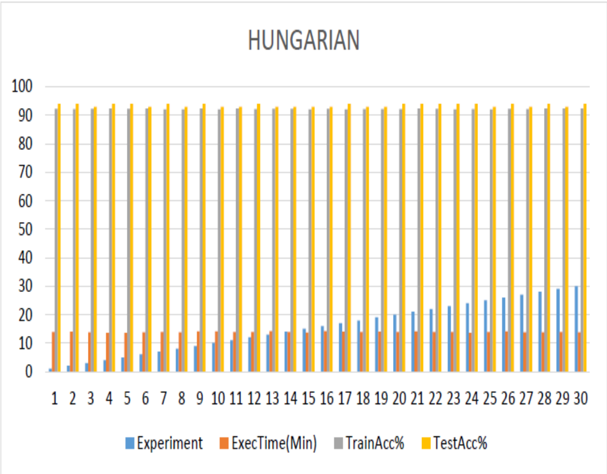

Figure 2.1: Hungarian

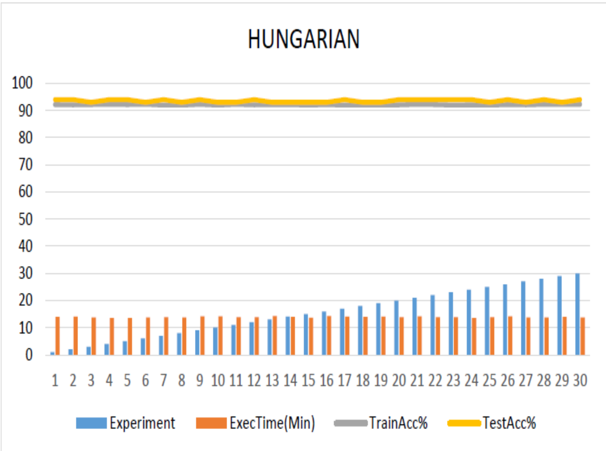

Figure 2.2: Hungarian

C. Switzerland

Table 3 shows the result of the execution time, the test accuracy and the training accuracy of the Swizerland dataset and the corresponding chart and graph shown on the fig. 3.1 and 3.2 respectively, respectively.

Table 3: Switzerland result

Experiment	ExecTime(Min)	trainAcc%	testAcc %
1	7.1036129	98.7654321	96
2	7.071562767	88.8888889	95
3	7.39893198	100	95
4	7.214760542	100	96
5	7.343884468	95.0617284	95
6	7.209758759	100	95
7	7.325868607	98.7654321	96
8	7.328775406	4.9382716	95
9	7.262806416	100	96
10	7.277821302	100	96
11	7.256803989	98.7654321	95
12	7.232782364	92.5925926	96
13	7.379915714	98.7654321	95
14	7.474003792	48.1481481	95
15	7.452990055	100	96
16	7.25980711	98.7654321	95
17	7.429967642	98.7654321	95
18	7.265812635	93.8271605	96
19	7.282822847	75.308642	95
20	7.270816088	96.2962963	95
21	7.308853388	100	95
22	7.131688833	96.2962963	95
23	7.293838978	60.4938272	96
24	7.198750734	66.6666667	95
25	7.2628057	100	96
26	7.1056602	86.4197531	96
27	7.329865932	88.8888889	96
28	7.215764046	100	96
29	7.226736069	98.7654321	96
30	7.083642483	98.7654321	96

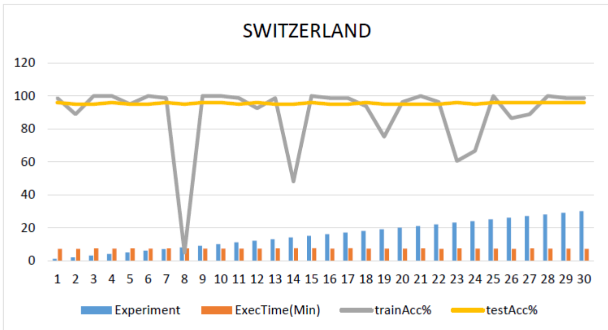

Figure 3.1: Switzerland

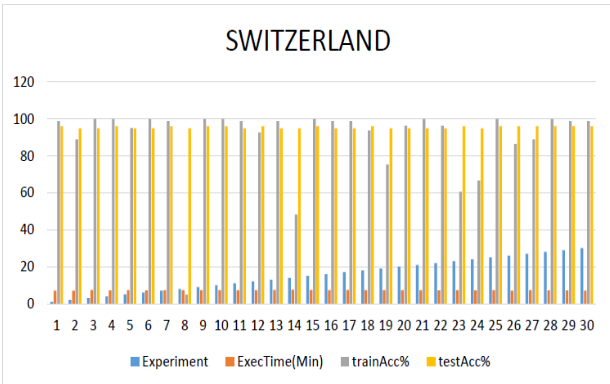

Figure 3.2: Switzerland

D. *ValongBeach*

The table 4 shows the result of execution time, testing accuracy and training accuracy of the VaLongBeach dataset and the corresponding Chart and graph showing on fig 4.1 and 4.2 respectively.

Table 4: ValongBeach result

Experiment	ExecutionTime(Min)	trainAcc %	testAcc%
1	10.01138639	89.2818	94.26107
2	10.26562452	89.1203	95.28173
3	10.06743836	89.6699	95.71659
4	9.996401787	89.3152	94.87131
5	10.26061797	89.3147	94.93224
6	10.26963091	89.4061	95.09214
7	10.15757108	89.9777	95.32196
8	10.03240657	90.0148	95.8981
9	10.25761485	89.6654	94.22749
10	9.926305532	89.919	95.57667
11	9.966346264	89.3869	94.197
12	10.07243896	89.7346	94.68703
13	10.39278793	89.4043	95.27773
14	9.939315081	90.1484	94.00149
15	9.907288551	89.8319	95.45987
16	10.04241085	90.1686	94.52232
17	10.52186251	89.3982	95.56663
18	10.01938891	89.6158	95.15833
19	10.09046197	89.3376	95.76756
20	10.19660974	90.0051	95.04711
21	10.41876936	90.0397	95.27916
22	10.28764176	89.9973	95.47863
23	10.31266689	89.2063	95.09494
24	10.58392334	90.18	94.75407
25	9.958379507	89.9395	95.47529
26	10.11351013	90.0325	95.73667
27	10.2285893	90.0707	94.00487
28	10.12552214	90.1806	94.34839
29	10.28964114	90.2795	94.85991
30	10.16553259	90.1657	94.39674

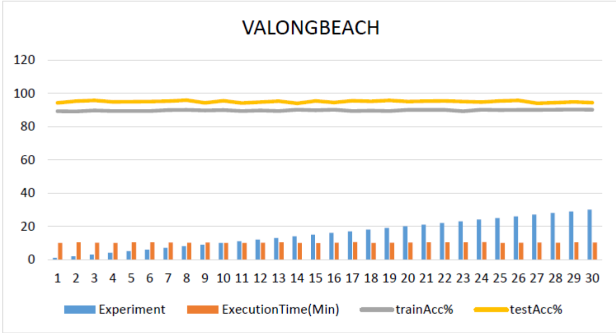

Figure 4.1: VaLongBeach

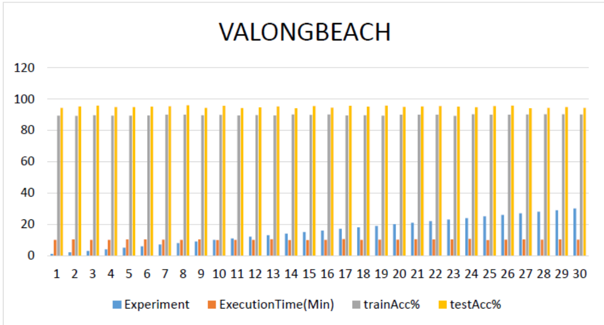

Figure 4.2: VaLongBeach

The Accuracy comparison is shown in Table 5 in comparison with the existing [1] method result and the proposed method. Deep Neural Network could only achieve 85.2 per cent, 83.5 per cent, 92.2 per cent and 84 per cent accuracy for Cleveland, Hungarian, Switzerland and VaLongBeach datasets to classify the subject under study whether or not it has CAD. However, our proposed model, which uses the PSO Neural Network, was able to achieve 94 per cent, 94.9 per cent, 95.5 per cent and 95.0 per cent accuracy for the Cleveland, Hungarian, Swiss and VaLongBeach datasets, respectively, to classify patients whether or not they have CAD. The results of the accuracy, sensitivity and specificity of the existing model result, the proposed method and the corresponding graph with the confusion matrix table for each data set are also presented.

Table 5: Accuracy

Data sets	**Accuracy**	
	DNN	DNN + PSO
Cleveland	85.2%	94%
Hungarian	83.5%	94.9%
Switzerland	92.2%	95.5%
VaLong beach	84%	95.0%

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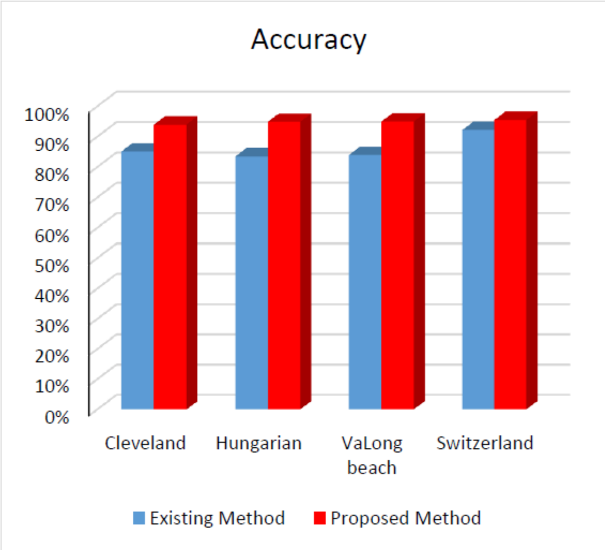

Figure 5.1: Accuracy of existing and Proposed method

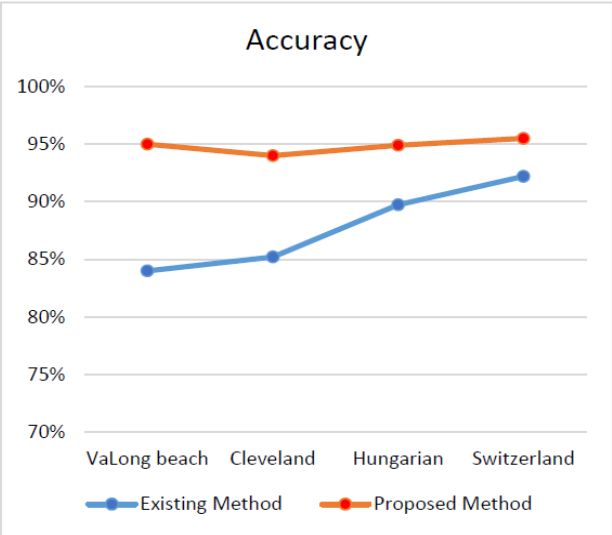

Figure 5.2: Accuracy of existing and Proposed method

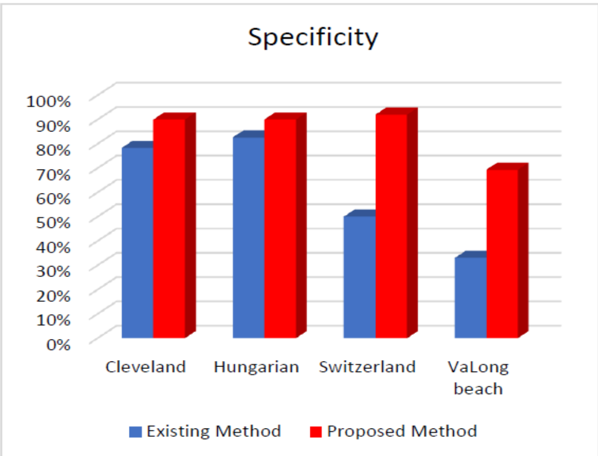

Figure 6: Specificity of existing and proposed method

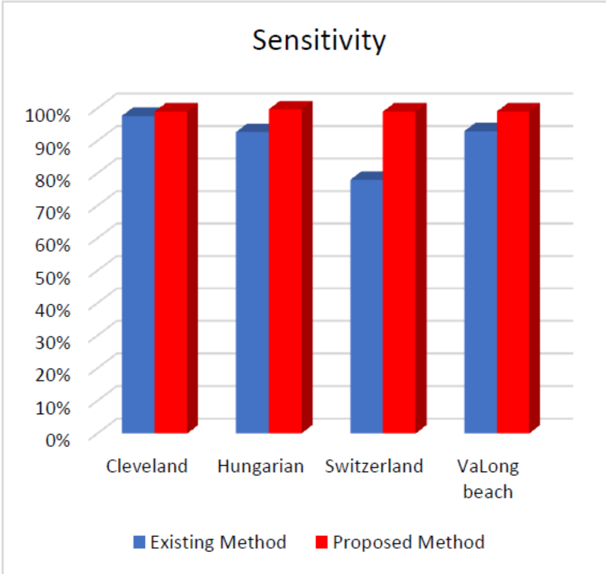

Figure 7: Sensitivity of existing and proposed method

The remaining tables shows the results of confusion matrix for each dataset.

Table 6: Confusion Matrix of Cleveland dataset

CLEVELAND DATASET	**TN = 91.79**
ACCURACY = 94	**FP = 9.93**
SENSITIVITY = 99	**FN = 0.29**
SPECIFICITY =90	**TP = 93.18**

Table 7: Confusion Matrix of Hungarian dataset

HUNGARIAN DATASET	**TN = 95.53**
ACCURACY = 94.9	**FP = 9.85**
SENSITIVITY = 99.7	**FN = 0.27**
SPECIFICITY =90	**TP = 94**

Table 8: Confusion Matrix of Valongbeach dataset

VALONGBEACH DATASET	**TN = 96.06**
ACCURACY = 95.0	**FP = 42.47**
SENSITIVITY = 99	**FN = 0.21**
SPECIFICITY =90	**TP = 94.98**

Table 9: Confusion Matrix of Switzerland dataset

SWITZERLAND DATASET	**TN = 93.93**
ACCURACY = 95.5	**FP = 7.53**
SENSITIVITY = 99	**FN = 0.23**
SPECIFICITY =92	**TP = 95**

7. CONCLUSION

A new hybrid method has been proposed to improve the performance of the neural network. The method was tested on four datasets of CAD heart disease to the best of our knowledge, and we found that there is an improvement in its performance. The method used improved the performance of the neural network as regards the detection of CAD. Although this method is used, CAD can be detected without angiography, which can help to eliminate high costs and major side effects. In addition to the Particle Swarm Optimization algorithm, there are many powerful evolutionary and natural-inspired meta-heuristic optimizers, such as Gray Wolf Optimizer, Ant Colony Optimization (ACO), Whale Optimization Algorithm, etc. As for future work, if there is any further improvement, we can use one of these methods to experiment.

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