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Enhancement of Medical IoT using Hybrid Neuro Fuzzy Techniques

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Abstract

Remote Monitoring in IoT plays a major role in Smart Health Data. Sensor data collected and sent for pre-diagnosis of disease with respect to blood pressure readings. Prediction of the severity of disease is detected since hypertension is a sickness which results in life threatening diseases like renal failure, heart attack, stroke and leads to major complications if undiscovered. This model is been developed to preprocess the data to diagnose and treat the hypertension patients leads to an approach of developing a hybridization of neuro fuzzy with particle swarm optimization (HNFPSO) algorithm to diagnose based on a set of symptoms and rules. The HNFPSO algorithm is presented as an expert system for the pre-processing and classification of blood pressure (BP). The HNFPSO algorithm makes use of neural network (NN), fuzzy logic and PSO algorithm. The presented HNFPSO algorithm intends to pre-process the characteristics of hypertension for classification by the use of rules provided by an expert in fuzzy system based on rules provided by an expert. Here, the rules take place using PSO algorithm for getting optimal number of rules with maximum classification results. The proposed model is validated using a benchmark hypertension dataset and the simulation results indicated the betterment of the HNFPSO algorithm in IoT framework.

Keywords: *IoT, Sensors, Blood Pressure, PSO, Neural Network, Hypertension, Neuro Fuzzy, EHR.*

1. Introduction

Nowadays, hypertension is a common health condition which results in several ailments like stroke, heart disease, renal failure, and so on [1]. The popularity of hypertension than many other types of chronic disease which is an instance of Canadian Primary Care Sentinel Surveillance Network (CPCSSN) data set [2]. Blood Pressure values such as systolic blood pressure and diastolic blood pressure helps to diagnose whether hypertension exist and at least 2 times of observation is should be done for accuracy. Evaluating the risk factors of BP is considered to be more complex based on the frequently changing ecological statuses/factors such as body mass index (BMI), age, urea, serum creatine, smoking, genetic history., etc [3]. As it is associated with more complexity with disease analysis, prediction by physicians are not so effective especially when the data is noisy or incomplete. Here, Artificial Neural Networks (ANNs) has been employed for different kinds of applications. For instance, ANNs are generally applied for detecting the stock market [4], forecast objects as well as perceived cases, and even the compressed images. Specifically, in medical domain, ANNs are well- known as it is inbuilt with the capability of analyzing medical image, developing medications, and served as a diagnostic network [5]. Medical based systems should attain a maximum efficiency, accuracy, and stability to reduce the illness of patients [6]. Machine learning (ML) acts as a possible way for doctors to find patterns that exist within the data which are prone to human error and enhance the working process of medical system [7]. Thus, medical decision support systems could combine the ML to offer a successful and précised simulation outcome which must be applied by a doctor for better analysis and provide treatment accordingly.

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These techniques provide on-time services when integrated and initially attain data to treat patients quicker. The perspective of healthcare providers is to offer preventive measures for defected individual and minimize the surgical cost. ANN meets maximum requirements of medicine and exhibits efficient tool in electronic health care record (EHR).

Recently, there is study for analyzing the risk involved in hypertension with the application of massive database. These research works concentrate on examining data with n > 100,000 for each subject group [8]. As the study has been well equipped on wider range of subjects, this model becomes a robust one when compared with traditional methods.

Conventionally, detecting hypertension for patients was conducted with the help of statistical models like, NN as well as fuzzy techniques. [9] offer a relative work and a summary of various models that identifies the risk methods of hypertension. The study offers several hypertension predictive risk methods from few works that address on the designing, verification, and impact detection of hypertension risk predictive approaches. Some comparative procedures have developed and features, detectors, method discrimination, calibration and reclassification potential, verification, as well as impact forecasting. A general predictor attribute applied for several techniques like age, gender, BMI, diabetes condition, and BP. In addition, there are many other factors such as, smoking, genetic habits, and external inefficiency. Various risk models are acceptable-to-good discriminatory potential. Most of the applications use NN method that is an evident of providing optimal results. For better comparison with ANN technique, there are few classical ANN models discussed in the following.

The primary technique was established by [10] that employs ANN named Hyper net for diagnosing and provide treatment for people affected with hypertension. These methods are divided into several effective feed-forward network modules with diverse complexity to revise the difficulty of physicians. Therefore, the system obtains anamnestic data and a time sequence of BP observing data as inputs for producing the final outcome that specifies the superiority of antihypertensive drugs for all patients. A non-hypertension can be identified when no output is produced & deployed a Levenberg-Marquardt Back Propagation Neural Network (BPNN) in Matlab with a greater number of input nodes and single output node which is comprised with massive hidden layers to analyze hypertension. Some of the input factors are BP, serum proteins, albumin, hematocrit, cholesterol, triglycerides, and hemorheological features. Additionally, developers are estimating the variations of functions on the basis of hidden nodes and layers to compute the best performance. Finally, a deep network with higher number of nodes in the first hidden layer and five nodes in 2nd hidden layer tends to optimal accuracy. Many researchers have addressed that, this model has attained maximum accuracy under the application of rich data set gathered from last decades at Hemorheology Laboratory of the Indian Institute of Technology Bombay (IITB) hospital in Mumbai, India. employed a comparison over the working function of 3 Decision Tree (DT) techniques, 4 statistical frameworks and 2 ANN technologies, for detecting the risk of hypertension disease. According to the metrics of sensitivity and precision analysis of techniques, this research reveals that the features employed for optimal predicting attributes that diagnose the hypertension and ANNs are good modules to increase the learning ability to overcome the factors of statistical methods [11] implied a fuzzy soft computing scheme for classifying 5 various levels/grades of blood pressure range such as very low, minimum, gradual, maximum, very high. These methods are not capable of performing as ANNs and based on the description of fuzzy utilities. [14] illustrates that the feed-forward BP-NN of 8 input variables, 4 hidden variables, and 2 output variables accomplish the simulation outcome for doctors. Therefore, accuracy and subject values are not added for this method respectively. This study develops a hybridization of neuro fuzzy with particle swarm optimization (HNFPSO) algorithm to diagnose the disease of different patients based on a set of symptoms and rules depending on blood pressure range. The HNFPSO algorithm is presented as an expert system for the classification of blood pressure (BP). The HNFPSO algorithm makes use of neural network (NN), fuzzy logic and PSO algorithm. The presented HNFPSO algorithm intends to model the characteristics of hypertension for classification in fuzzy by the use of rules provided by an expert. Here, the rule optimization takes place using PSO algorithm for getting optimal number of rules with maximum classification results. The proposed model is validated using a IoT sensor data for hypertension dataset and the simulation results indicated the betterment of the HNFPSO algorithm.

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2. Proposed method

The Particleral Neuro Fuzzy Hybrid Model where the input is applied as a data of BP for an individual, then it is induced for NN and 2 results are attained, that has been established as inputs for fuzzy system which is generalized with particletic model to accomplish good simulation outcome as final result. Also, Fig. 1 illustrates a particular neuro-fuzzy hybrid that depicts the working function of this method.

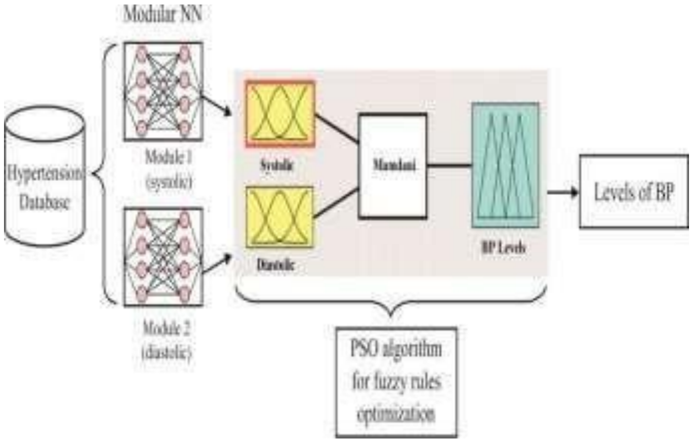

Fig. 1. Overall process of proposed method

2.1. Modular Neural Network

Modular neural network are mainly employed to give the input data, that is a systolic as well as diastolic pressures which is acquired by all patients, where every information is passed to every module of this neural network, and understands the develops a data to send fuzzy system for classifying in a viable options to provide best diagnosis which assist the physicians for making decision of every patients. This technique choose a network which is associated with the following modules, layers of 1 to 3, neurons values of 1 to 20, that helps for training the modular neural network: 1000 epochs, learning value of = 0.01, then, error goal is about 0.0000001, three setback/delays are assumed with partial data and training model of Levenberg-Marquardt (trainlm) approach.

2.2. Design of Fuzzy Classifier

More number of samples are performed with Neuro Fuzzy Hybrid Model where the fuzzy classification is improved, where the fuzzy system has 2 inputs, like systolic and diastolic pressures of 8 membership functions (MF) and 1 outcome with 8 MF, fourteen fuzzy rules, of Mamdani type. Alternatively, it has been decided to develop with a greater number of feasible rules which depends upon the MF of inputs and applying the combination of above model has attained 49 fuzzy rules. The main objective is to monitor the classifier function where it is not better to apply the entire rules and determine the final outcome achieved for optimizing fuzzy system along with particletic frameworks and identifies a greater number of rules to enhance the final outcome and relate the classification task. Therefore, the numbers of rules in a full set of rules are same as:

$$TNPR = \prod m_i \tag{1}$$

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Where TNPR denotes the overall count of possible rules; $m_i$represents the count of MF for input i and n indicates the input values. The third fuzzy classification model comprises 2 inputs, like systolic and diastolic pressures along with 7 MF and result with 10 MF, 49 fuzzy rules that are probable and fuzzy system of Mamdani type. The initial input system named systolic, which has the range from 20 to 300, whereas alternate input system termed as diastolic, which has the range from 20 to 130 as well as the output has the BP levels, like Hypotension, High, Moderate, High Normal, Grade 1 hypertension, Grade 2 hypertension, Grade 3 hypertension as well as isolated systolic hypertension Grade 1, isolated systolic hypertension Grade 2 and isolated systolic hypertension Grade 3, the above mentioned modules are associated with fuzzy rules. Fig. 2 shows the architecture of classification model 3, Fig. 3 and 4 illustrates the inputs and Fig. 5 demonstrates the result of classifier 3:

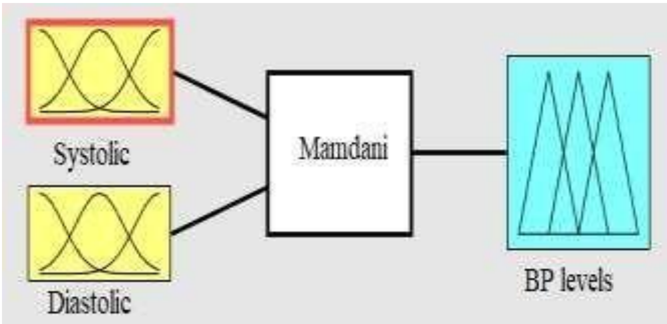

Fig. 2. Structure of the fuzzy logic classifier

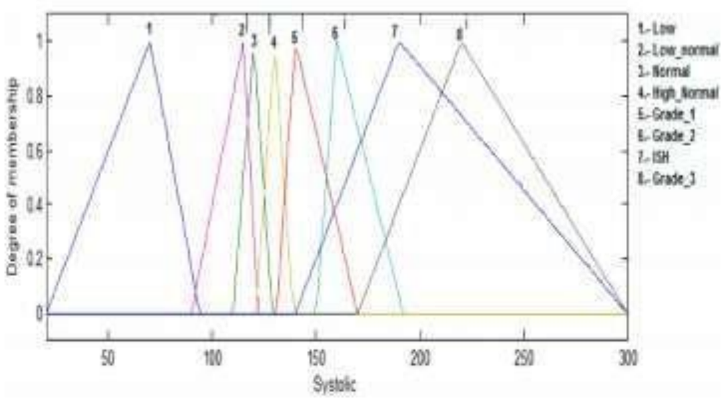

Fig. 3. Systolic for the fuzzy logic classifier 3

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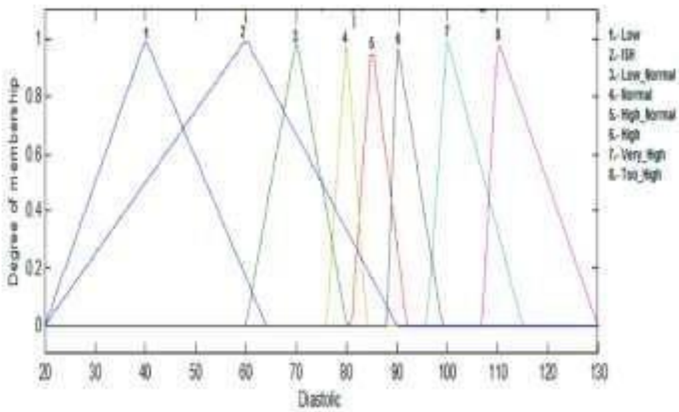

Fig. 4. Diastolic input for the fuzzy logic classifier 3

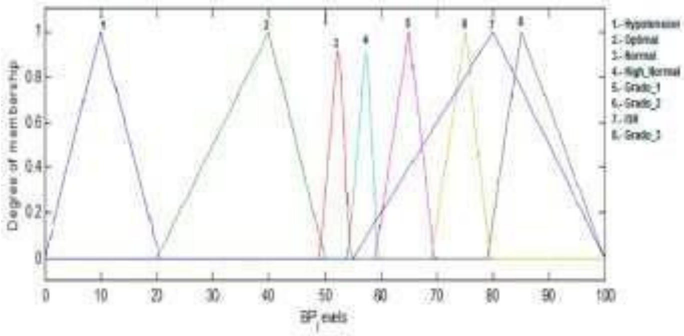

Fig. 5. BP Levels is the output of the fuzzy logic classifier 3

2.3. Optimization with PSO algorithm

The classification 4 has been optimized under the application of particletic models, which contains a particle for optimizing the fuzzy system, where the particle is constrained with 122 particles, that helps to optimize the structure of fuzzy system for fuzzy rules as well as MF, Particles with 1–72 enable to handle the attributes of MF for inputs and output, and particles with 73–121 are named as rules. Therefore, particle 122 permits to decrease the rule count and trigger/deactivate the models.

PSO algorithm:

PSO is simulated with the behavior of social organisms in sets, namely bird and fish schooling. From the technique follows the interaction among members to distribute data. PSO have been executed to frequent regions in optimization and in combination with other predefined techniques. In this technique executes explore of the best result during agents, assigned to as particles, whose trajectories are changed with stochastic as well as deterministic module. Every particle is controlled with 'optimal' obtained position and the set 'optimal' position, however tend to move arbitrarily. The particle i is determined
with position vector, xi and its velocity vectorv_i. All iteration, every particle modifies its position based on the novel velocity.
where $xBest$ and $gBest$ indicate the optimal particle position and optimal set position and the parameters w, c_1, c_2, $r_1 and r_2$ are correspondingly inertia weight, 2 positive constants as well as 2 arbitrary parameters in [0, 1].

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3. Performance Validation

3.1. Dataset used

The effectiveness of the HNFPSO model has been tested using a Hypertension dataset, which comprises a total of 1424 instances. A set of 19 features were present in the dataset with a total class labels of 6. A total of 77 instances fall into the category of Athero, 147 instances under Conn, 912 instances under Essent, 112 instances under Fibro, 87 instances under Pheo and 89 instances under Poly is depicts in Table 1. The figure 6 shows the frequency distribution of the dataset

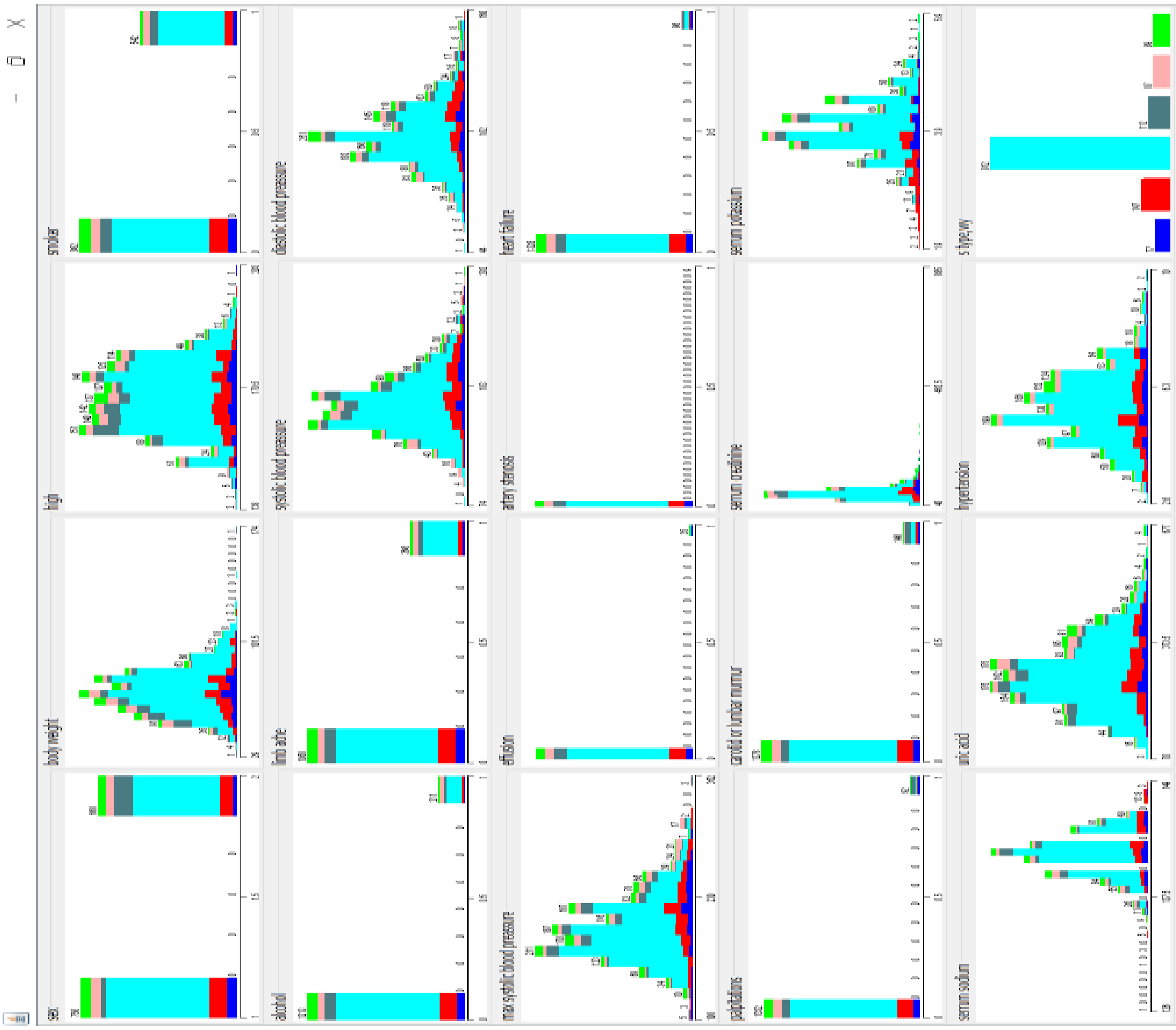

Fig. 6. Frequency Distribution of Dataset

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Description	Hypertension
No. of Instances	1424
No. of Features	19
No. of Class	6
No. of Athero Samples	77
No. of Conn Samples	147
No. of Essent Samples	912
No. of Fibro Samples	112
No. of Pheo Samples	87
No. of Poly Samples	89
Data sources	[15]

Table 1 Dataset Descriptions

3.2. Results analysis

Table 2 and Figs. 7-8 show the classifier results analysis of diverse models on the tested dataset.

Methods	Precision	Recall	F-measure	ROC	Accuracy	Kappa
HNFPSO	90.00	94.00	92.00	95.00	93.47	90.34
DT	61.00	65.00	62.00	72.00	64.88	31.17
RF	64.00	69.00	65.00	84.00	69.45	37.03
RT	57.00	54.00	55.00	69.00	54.21	23.21
LR	69.00	72.10	68.00	84.00	72.12	41.51
KNN	85.00	86.00	84.00	92.00	87.80	64.90

Table 2 Classifier results analysis of HNFPSO with existing models

While determining the results in terms of precision, it is noted that the RT model has offered inferior classification with a least precision value of 57%. On continuing with, the DR and RF models offered slightly better results with the precision values of 61% and 64% correspondingly. In line with, the LR model has offered moderate results by attaining a precision value of 69% whereas the KNN model has shown competitive classifier results by achieving a higher precision value of 85%. However, superior classifier results are provided by the proposed HNFPSO model, which has attained a maximum precision value of 90%.

While determining the results in terms of Recall, it is noted that the RT model has offered inferior classification with a least Recall value of 57%. On continuing with, the DR and RF models offered slightly better results with the Recall values of 61% and 64% correspondingly. In line with, the LR model has offered moderate results by attaining a Recall value of 69% whereas the KNN model has shown competitive classifier results by achieving a higher Recall value of 85%. However, superior classifier results are provided by the proposed HNFPSO model, which has attained a maximum Recall value of 94.00%. While determining the results in terms of F-measure, it is noted that the RT model has offered inferior classification with a least F-measure value of 57%. On continuing with, the DR and RF models offered slightly better results with the F-measure values of

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61% and 64% correspondingly. In line with, the LR model has offered moderate results by attaining a F-measure value of 69% whereas the KNN model has shown competitive classifier results by achieving a higher F-measure value of 85%.

However, superior classifier results are provided by the proposed HNFPSO model, which has attained a maximum F-measure value of 92.00%

On continuing with, the DR and LR models offered slightly better results with the ROC values of 61% and 64% correspondingly. In line with, the RF model has offered moderate results by attaining a ROC value of 69% whereas the KNN model has shown competitive classifier results by achieving a higher ROC value of 85%. However, superior classifier results are provided by the proposed HNFPSO model, which has attained a maximum ROC value of 95.00%.

While determining the results in terms of Accuracy, it is noted that the RT model has offered inferior classification with a least Accuracy value of 57%. On continuing with, the DR and RF models offered slightly better results with the Accuracy values of 61% and 64% correspondingly. In line with, the LR model has offered moderate results by attaining a Accuracy value of 69% whereas the KNN model has shown competitive classifier results by achieving a higher Accuracy value of 85%. However, superior classifier results are provided by the proposed HNFPSO model, which has attained a maximum Accuracy value of 93.47%. While determining the results in terms of Kappa, it is noted that the RT model has offered inferior classification with a least Kappa value of 57%. On continuing with, the DR and RF models offered slightly better results with the Kappa values of 61% and 64% correspondingly. In line with, the LR model has offered moderate results by attaining a Kappa value of 69% whereas the KNN model has shown competitive classifier results by achieving a higher Kappa value of 85%. However, superior classifier results are provided by the proposed HNFPSO model, which has attained a maximum Kappa value of 90.34%.

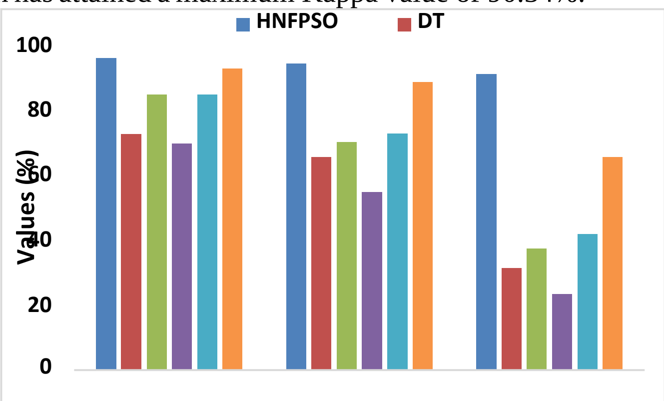

Fig 7. Classifier results analysis of diverse models

From the above-mentioned table and figures, it can be concluded that the HNFPSO model has offered optimal classification results on the hypertension dataset by achieving maximum precision of 90%, recall of 94%, F-measure of 92%, ROC of 95%, accuracy of 93.47% and kappa value of 90.34%.

4. Conclusion

This paper has developed a HNFPS algorithm to pre-process data and to diagnose risk of different patients-based onset of symptoms and rules. The HNFPSO algorithm is presented as an expert system for the classification of BP. The HNFPSO algorithm makes use of NN, fuzzy logic and PSO algorithm. The presented HNFPSO algorithm intends to model the characteristics of hypertension for classification by the use of rules provided by an expert in fuzzy system. Here, the rule optimization takes place using PSO algorithm for getting optimal number of rules with maximum classification results. The proposed model is validated using the data collected from blood pressure sensor to have

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the hypertension dataset and the results indicated the betterment of the HNFPSO algorithm. It can be concluded that the HNFPSO model has offered optimal classification results on the hypertension dataset by achieving maximum precision of 90%, recall of 94%, F-measure of 92%, ROC of 95%, accuracy of 93.47% and kappa value of 90.34%.

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