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Research Article

Optimized Deep Learning Technique Based Digital Modulation Identification

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***Abstract*— In many forms of wireless communication, such as cognitive radio and signal recon, modulation detection is a crucial task. The demand for accurate identification of OFDM signal has increased due to the diversity of modulation techniques and the complex route environment. The enhanced large data processing and categorization capabilities of D-L are thought to be viable answer to these issues. In this study, an effective deep neural network (DNN)-based technique for digital modulation identification is proposed. In addition, we introduce the particle-swarm-optimization (P-S-O) approach to improve the amount of concealed layer nodes of the DNN in order to address the issue that the original D-N-N is stuck at local minimum values and the amount of concealed layer nodes needs to be explicitly selected.**

keywords — Digital modulation identification, Optimization, Deep learning technique.

I. INTRODUCTION

Modification recognition is a technique of technology used in wireless communications that enables intelligent signal receiving, processing, and classification. When the receiver is unaware of the modulation scheme the sender chose, it is crucial for consumer smart control systems purposes and signals surveillance for military purposes [1]. Moreover, it is a fundamental issue for cognitive radio' dynamic spectrum access [2]. Accurate detection of various frequency modulation at low SNR gets more difficult as the interference of multiple sounds confuses the condition and indeed the number of transmitted signals increases. The feature-based (F-B) approach has been the standard method for identifying digitally modulated patterns because it has a straightforward theoretical foundation and can perform close to optimally when properly constructed [4]. The classifier separates the received qualities based on the features that the F-B method obtains from the OFDM signal before decision. Using the focus on organizational cumulants characteristic of the signal, Guo et al. [1] suggested finding a range of modulation patterns that may effectively reduce the Gaussian white background.

The superior ability of massive data recognition and analysis, which has several uses in the area of communications [2], including handling correctly, has accelerated the development of the Deep Learning (D-L) approach in recent years. Several nonlinear transforms can be used by D-L in conjunction with the original simple features to automatically find more complex features. The research proposed a solution that combined the F-B approach and D-N-N and significantly improved efficiency for Doppler Rayleigh fading channel. Without further extracting features, a variety of OFDM signals were transformed into cluster shapes or waveforms and sent directly into the C-N-N classifier, which likewise produced well using this. According to the authors of [3], who investigated feature learning and automatic face categorization (A-M-C) using several D-L models, the Dev in double hidden units performs most effectively with a 3.2% promotion over the competition. To identify the best solution, it is necessary to artificially set the values of the D-L model because of the low identification rate of the approaches above at low SNR. Because of this Modulation identification may profit from the combination of feature fusion and specific scale. In this study, we offer a unique method for wireless communication' multiple-modulated signal detection that uses signal preprocessing technology and an upgraded D-N-N model. Our approach can recognize six different types of OFDM signal, including higher-level quadrature amplitude modulation (QAM) and Phase Shift Keying (Binary phase shift, QPSK, and 8PSK) (16QAM, 64QAM, 256QAM) [4] In this study, we offer a unique method for wireless communication' many modulations signal detection that makes use of signal preprocessing technology and an upgraded DNN typical. Phase shifting keying (BPSK, QPSK, and 8PSK) and more advanced M-ary amplitude modulation with quadrature (16QAM, 64QAM, and 256QAM) are among the six types of modulated signals that our approach can distinguish. To improve the classification of the modulation modes, our proposed technique trains a DNN on a variety of features that were retrieved from the modulation signals. Additionally, the PSO method is used to successfully address the DNN structure's flaws. The following three sections provide an overview of the paper's main features. In order to optimize the framework of the DNN and achieve the overall optimal number of nodes in hidden layers for a modulation recognition algorithm with low SNR, we offer a unique PSO optimization approach.

II. The Contribution of the Work

In this study, we provide a better overall technique to identify the properties derived from the modulation identification with AWGN, and to build a net which can improve recognition effectiveness in low signal-to-noise situations (SNR). Our suggested approach trains a DNN on a variety of traits that were extracted from the signal that has been modulated in order to enhance the categorization of the modulation mode. Additionally, the drawbacks of the D-N-N structure are successfully addressed using the PSO approach. The main contribution of this study are summarized as following:

1- A novel PSO optimization approach that can optimize the D-N-N architecture is proposed and obtained the total optimal quantity of the hidden layer nodes.

2- The effectiveness of the suggested method is assessed in this essay. The simulation outcomes show that, in terms of the various SNR recognition rates, our scheme performs noticeably better than the other two conventional recognition procedures. We also do comparative simulations with D-N-N optimized by a different optimization method. The simulations also demonstrated that our suggested strategy had a faster rate of convergence. We therefore declare that the improved PSO detection algorithm is reliable and powerful [7].

3- We conduct detailed, in-depth testing and case analyses, which validate the effect of particle amount on the rate of recognition and include an examination of overall categorization rates. The best-performing criteria are subsequently incorporated into the design approach [5][7].

III. PSO-DNN Based Digital Modulation Identification

In this article, we select the digital modulation approaches for detection based on communication technology currently in use. The wireless L-A-N standard and OFDM both use a variety of PSKs depending on the required data rate [9]. To increase spectrum efficiency, the communication systems engagement high-density M-QAM constellations, which provide greater transmission. As a result, we select the following schemes (Figs. 1 and 2) to alter the raw data [11]:

In this study, we focused on the PSO algorithm and proposed a new pattern for how the algorithm works in order to obtain a lower margin of error in addition to increasing accuracy and reliability during implementation by proposing the studied algorithm and clarifying its scheme. In reality, the receiver constantly picks up a signal that has been tainted by noise, hence the complicated baseband signal's interpretation is [9][10]:

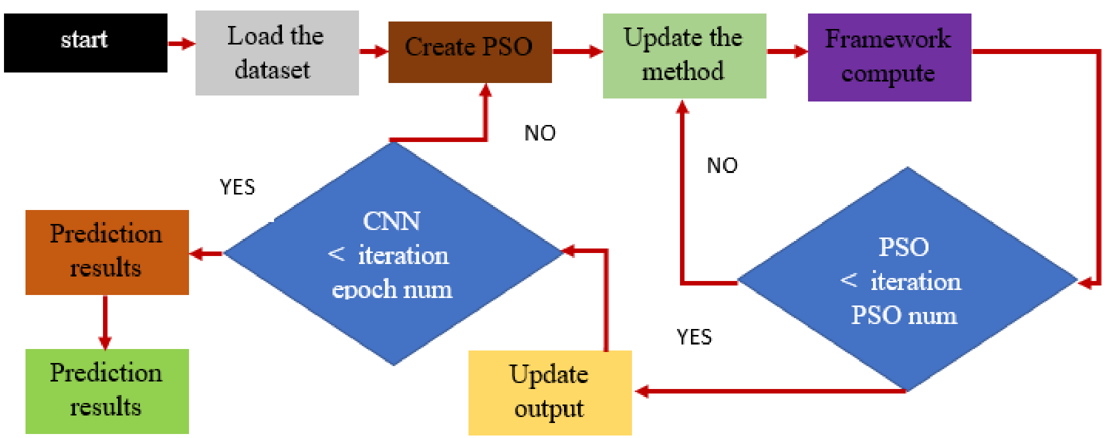

Fig.1 PSO-DNN based Digital Modulation Identification.

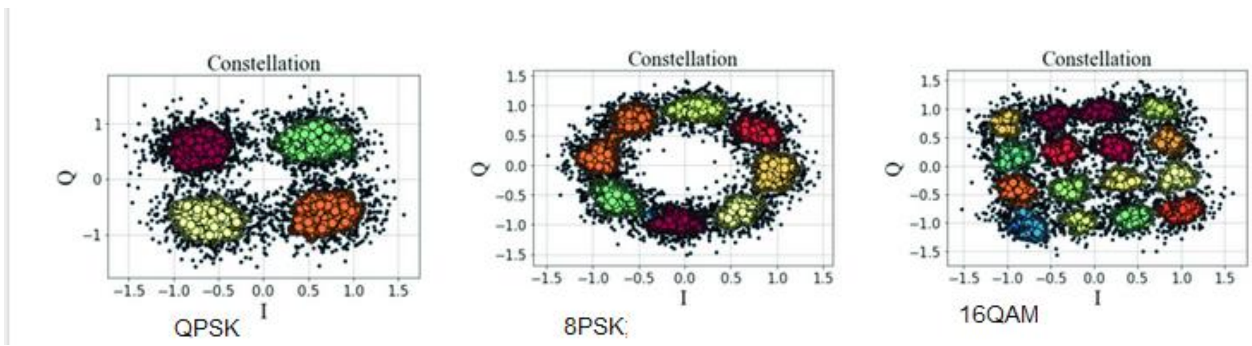

Fig.2 Various modulations' constellation diagrams at SNR D 10

$$s(t) = x(t) + n(t)$$
$$= \sum_n a_n \sqrt{E}\, p(t - nT_s) e^{j(2\pi f_c t + \theta_c)} + n(t) \quad (1)$$

where s(t) denotes the signal demodulate upon reception. Depending on the modulating mode, x(t). E depicts the signal's energy. The signal with finite energy and a T_s duration is called p(t). The length of the received binary symbol series is indicated by n =1, 2,.. N. The carrier bandwidth and cycle are denoted by f_c and c, correspondingly. n(t) is the AWGN signal with zero means. Meanwhile, the SNR is expressed as

$$SNR = 10 \log_{10} \frac{S^2}{N^2} \quad (2)$$

where the effective powers of the noise with signal, respectively, are S and N [11]. As shown in Fig. 3, a constellation pattern of the six modulated audio signals is interfered with by A-WGN at S-N-R- D 10(dB). We adopt the assumption that the period has been corrected at the receiver in order to fairly compare our approach to conventional techniques. In accordance with the constellation diagram's mapping relation and the digital signal's modulating theory, the two symbol sequences an The formula below can be written as follows:

$$a_{MPSK} = exp\left(\frac{j2\pi\,(n-1)}{N}\right) \quad (3)$$
$$a_{MQAM} = I_n + jQ_n = \sqrt{I_n^2 + Q_n^2}\, e^{j\varphi_n} \quad (4)$$

where φ_n represents the phase of the complicated information within a location frame of polar coordinate system, and a_{MPSK} and a_{MQAM} are the PSK and QAM modified symbol sequences, correspondingly. I_n and Q_n location the values of the in-phase portion and quaternary component.

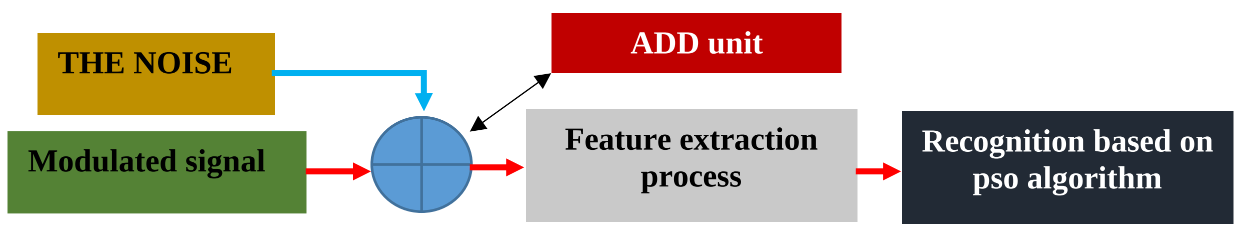

Fig. 3 Foundation for feature-based recognition.

The method of extracting, merging, and modifying features to acquire representative data of the signals in the sphere of interaction is known as characteristic engineering [13]. The features extractor and recognition algorithms make up the two subsystems that make up the FB recognition framework, as can be seen in Fig. 4 [9][11].

The primary definition of the signal's amplitude is:

$$X = \frac{1}{M} \sum_{m=1}^{M} |T| \quad (5)$$

where T= $a(m)$. In a similar manner, the amplitude accumulation of signal 2's adjusted square root value can be expressed as:

$$X_2 = \frac{1}{M} \sqrt{\sum_{m=1}^{M} |T|} \quad (6)$$

The following characteristic is hybrid order seconds v_{20}, which is denoted by:

$$v_{20} = \frac{M_{4,2}(y)}{M_{2,1}^2(y)} \quad (7)$$

where a(m) and a(m) are conjugated, and $M_{p+q,p}(y)$ indicates $E[a(m)^p\, a(m)^{*q}]$. The modulated signal's high-order cumulants, which are represented by the equations below [12], make up the remaining features.

$$C_{20} = Cum(T,T) = E[T^2] \quad (8)$$
$$C_{21} = Cum(T,T^*) = E[|T|^2] \quad (9)$$
$$C_{40} = Cum(T,T,T,T) = M_{40} - 3M_{20}^2 \quad (10)$$
$$C_{41} = Cum(T,T,T,T^*) = M_{41} - 3M_{20}M_{21} \quad (11)$$

As a result, standardizing the data may bring the weighting of each feature dimensions match the goal function and speed up the process of convergence of the incremental solution. Eigenvalues from data samples are transformed into a single dimension, which corresponds the data from 0 to 1.

IV. PSO and DNN Techniques

We will offer an advanced deep neural network built around PSO to apply modification detection and optimization action in future interaction, which is predicted to address the current condition. This is motivated by employing PSO to maximize DL model settings and increase C-N-N performance. D-N-N issues and a low identification rate in dynamic channels scenarios that are getting more complicated. We begin by quickly outlining the PSO method's fundamental components. The progress of D-N-N learning is then described. The final section outlines the precise phases of our suggested approach [14][16].

A. PSO algorithm:

The algorithm of PSO, also referred to as the flock feeding algorithm [16]. It creates a random solution initially, and then iteratively searches for the best-fitting optimal solution. The Back Passage (B-P) neural network technique has seen extensive application of this type of algorithm due to its benefits of simple implementation, high precision, and quick convergence. Furthermore, it was initially used in the field of D-L and has shown superior at solving real-world issues The PSO algorithm's fundamental structure consists of a collection of particles that interact with one another to continually arrive at the ideal location. The method updates each particle's velocity, position, and fitness value according to mathematical formulae in order to solve the problem. The position of the particles serves as a potential solution to the issue at hand and is noted as the personal best solution, p_{ibest}. The shifting of position is steered toward the global best position g_{best}, which corresponds to the global fit value g_{fit} among every outcome in the entire space, by its own unique greatest fitness value p_{fit}, that is the least Got to value in earlier iterations [17][19]. The following equations can be used to express the PSO method [19].

$$V_i[k+1] = w\,V_i[k] + c_1 rand_1\left(p_{ibest} - P_i(k)\right)$$

$$+c_2 rand_2(g_{best} - P_i(k)) \quad (12)$$

$$P_i[k+1] = P_i[k] + V_i[k+1] \quad (13)$$

The weight of inertia, or w, aids the particles' movement throughout the interior to a more advantageous position [20]. The location vector is $P_i[k]$ and vector of velocity is $V_i[k]$ of the i-th particle, at the k-th iteration, and the $P_i[k]$ is updated by $V_i[k + 1]$. c_i represent the constants that are used and $rand_i$ represents the uniform random value.

B. Deep Neural Networks

D-L, which consists of numerous H(hidden) layers and brain nodes, serves as the basis for many contemporary artificial intelligence (A-I) applications. Currently, it is heavily used in voice the process, image identification, and other areas, leading to some advancements in communicating. With the quick development of D-L, modulation acceptance processing of digital transmissions transitioned from the conventional method to the D-N-N method. This new approach can also be seen as a notion for learning, moving from "learning the system model" to "learning the signal features." In actuality, using D-N-N as a classification may be seen of as combining machine learning with signal feature analysis. (ML). A data that is multidimensional vector is supplied in the visible layer as the input of the D-N-N, which is also known as the training example. Following that, each hidden layer makes a sequence of not linear adjustments can be summed up as next [22].

$$Y = sig\,(W * A + b) \quad (14)$$

However, the model used by D-N-N is a black box, making it impossible to monitor how it functions or the traits it learns, which causes a number of issues [17][23].

As a result, we apply the PSO algorithm to address the issue that the D-N-N is prone to falling into the nearest minimum values and that the total amount of nodes in the hidden layer is not set, hence increasing the precision of modulation identification.

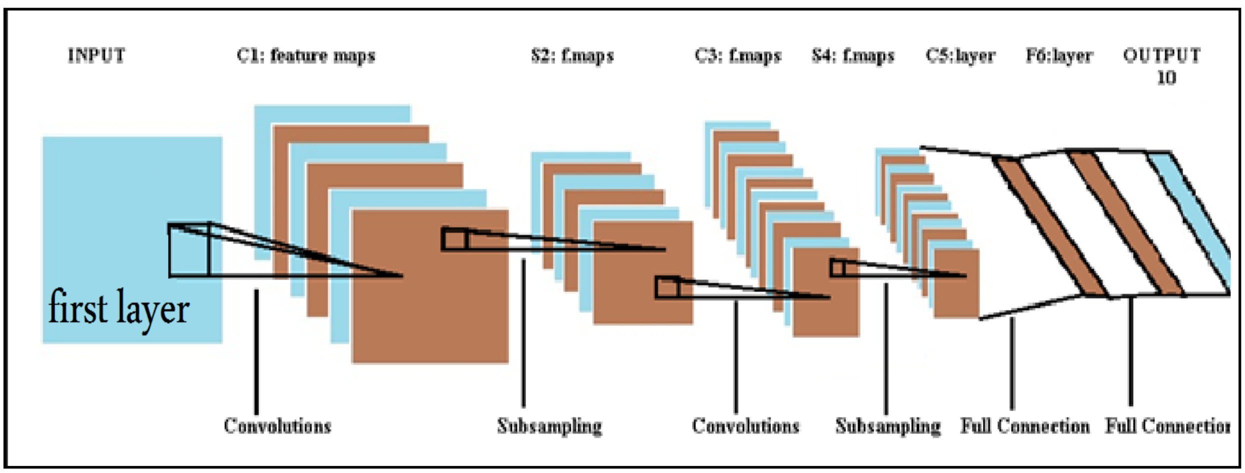

Fig.4 The proposed PSO-DNN model

V. Digital Modulation Identification using PSO-DNN

In our suggested approach, modulation recognition is carried out by combining the algorithm known as PSO and the D-N-N architecture after training the D-N-N, as illustrated in Figure 4. The network model receives its input from the modular feature vector. Then, based on the acquired M-S-E monitoring, the total amount of doubly nodes in the hidden layer in D-N-N is dynamically modified utilizing the universal optimization capability of the PSO method to reach the ideal number of nodes and enhance the recognition accuracy. with an objective Better outcomes monitoring is achieved by the use of the Softmax function, which normalizes the output of the function to provide the final For each output node, the rate at which it is recognized can be expressed [23].

Here, we produce sets of data, where n is the number of swarming particles. The least error in identification related to the ideal number of node in the i.th group is represented by the person's best fit value (p_{fit}) and the global best fit value (g_{fit}), respectively [20][24]. The ideal nodes numbers in i.th group and the entire group are represented, respectively, by the particular best value p_{ibest} and the global best value g_{best}. The structure of the algorithm is as follows:

Step 1: initialize P randomly, a variable with a size of 2, the numerous dual H(hidden) layer nodes, and V, the adjusting variable. P is used to educate the D-N-N and calculate the initial fitness value $p_{fit}(i)$ for each particle. Select P's g_{best} and g_{fit} commands.

Step 2: Modify P using the fine-tuning option V.

Step 3: Find the new $p_{fit}(i)$ by training the D-N-N using the updated P.

Step 4: Assign the new $p_{fit}(i)$ to p_{ibest} if its value is lower than that of the previous step. If the value for the fresh $p_{fit}(i)$ is less than g_{fit}, update g_{fit} and g_{best} with the updated $p_{fit}(i)$ and p_{ibest}, respectively.

Step 5: Determine whether the g_{fit} value is less than the target error; if so, the repetition is terminated; otherwise, return to step 2 and repeat the procedure. until the cycle is finished or the necessary condition is met.

The system will then return the optimal neural nodes and those with the least error in step six. To specify the precise optimization process, utilize Algorithm 1.

```
Required Number of particle in a swarm α, Cognitive coefficients c, Inertia weigh
w
Required Initial velocity V, Initial the nodes of double
hidden layers P
Required Initial individual best fitness value pfit, Individual
best value pibest
Required Initial global best fitness value gfit calculated by
DNN, Global best value gbest
While gfit > 0 do
For each i D 1: α do
Calculate update: Vi wVi−1 C c1rand1(pibest − Pi−1)
Cc2rand2 .gbest − Pi−1/
Calculate update: Pi Pi−1 C Vi
Calculate pfit(i) through DNN using Pi
If pfit(i) < pfit(i − 1) do
Update global best value: pibest Pi
Ifpfit .i/ < gfit do
```

Algorithm 1: OPtimizationProcess

VI. *Simulation Results*

Measuring the degree to which the genuine responses of the data models observed match one another is important for better describing the accuracy of predictions of the PSODNN model.

As a result, the modulation recognition performance is measured using the likelihood of success identification (PSR) based on the classifier's output. PSR can be determined using the formula below [23].

$$PSNR = \frac{samples\ of\ success\ recognition}{all\ samples} \times 100\% \qquad (15)$$

In the practical section, we conducted the necessary training for the system in order to improve the proposed (PSO) algorithm in the modification of digital signals [21]. The following chart shows the proposed training system for the algorithm according to the performance and accuracy curves:

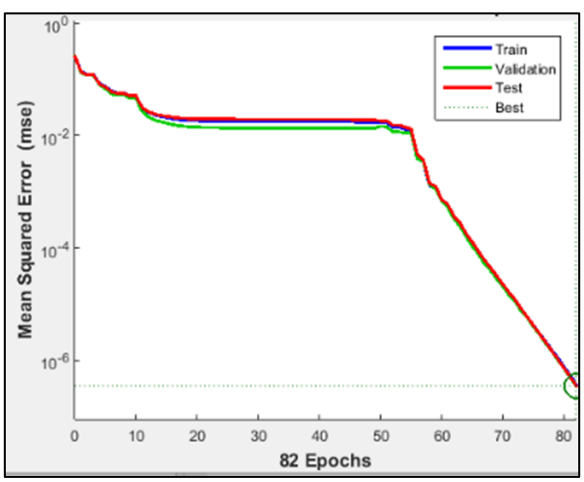

Fig.5 Work curves and results of the proposed system (PSO) according to the training system

The following figure shows the time spent in the processing and performance process so that we have a representation of the studied system according to the PSO algorithm and it was modeled according to a training system in order to raise work efficiency and obtain more accurate results and higher returns in the classification and modification of digital signals and their classifications [21][23]

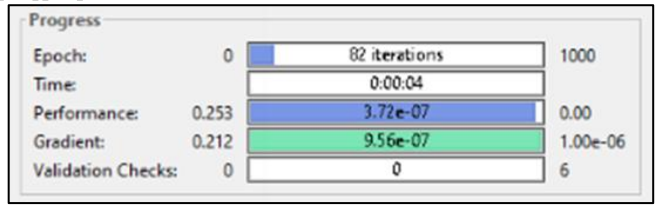

Fig.6 The evolution of the process according to the proposed system

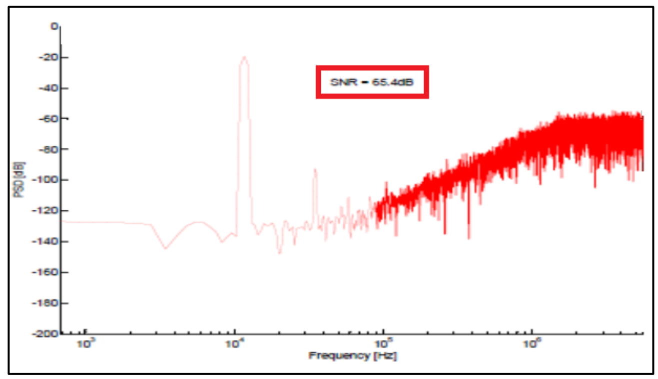

Fig.7 The evolution of the process according to the proposed system

Kennedy, Eberhart, and Shi are the authors of PSO, which was initially created to simulate social behavior by stylizing the movement of creatures in a fish school or bird flock.

The algorithm was made simpler, and optimization was seen to be taking place.

An elementary version of the PSO algorithm operates by generating a population of potential solutions (referred to as a swarm or particles). A few basic equations are used to move these particles around in the examination space. The positions of the particles in the swarm, as well as their particular greatest known positions within the search space, aid as a management for their travels. These will finally start to direct the swarm's motions once improved sites are found.

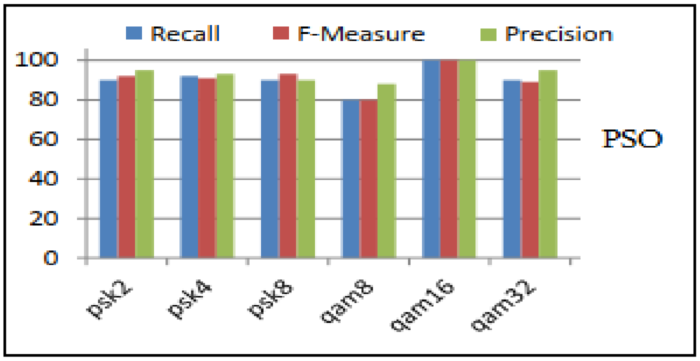

Fig.8 PSO classification Accuracy with optimization of multi types

VII. Conclusion

In our study, first we suggest a particle swarming D-neural-network framework that is optimal for identifying digital modulation modes. The method can recognize six different sorts of digital signals in a chaotic environment. The altered signals are pre-processed in our method before being fed into the neural network. The D-N-N structure is then optimized using the PSO technique. Finally, we perform modification recognition using both the suggested method and the conventional method. Our method described in our search accomplishes higher prejudice The rate of accuracy with advancement of 8.7% to 9.5% compared to the traditional D-N-N technique and the S-V-M similar approach under the circumstance of low value ((S-N-R)), despite the time intricacy being high in the event or component quantity of big data sets for training. It also addresses the issue of artificially adjusting the total amount of nodes in the hidden layer and exemplifies the best functionality of the suggested approach. Wireless communications is a field. However, our approach was used. Future work will concentrate on using existing patterns to utilize this method on unidentified changed signals.

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