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# Hybrid Crow Search and RBFNN: A Novel Approach to Medical Data Classification


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*Abstract* - The Radial Basis Function Neural Network (RBFNN) is frequently employed in artificial neural networks for diverse classification tasks, yet it encounters certain limitations, including issues related to network latency and local minima. To tackle these challenges, researchers have explored various algorithms to enhance learning performance and alleviate local minima problems. This study introduces a novel approach that integrates the Crow Search Algorithm (CSA) with RBFNN to augment the learning process and address the local minima issue associated with RBFNN. The study evaluates the performance of this innovative model by comparing it to state-of-the-art models like Flower-pollination-RBNN (FP-NN), Artificial Neural Network (ANN), and the conventional RBFNN. To assess the efficacy of the proposed model, the study employs specific datasets, such as the Breast Cancer and Thyroid Disease datasets from the UCI Machine Repository. The simulation results illustrate that the proposed model surpasses other models in terms of accuracy, exhibiting lower Mean Squared Error (MSE) and Mean Absolute Error (MAE) values. Specifically, for the Breast Cancer dataset, the proposed model attains an accuracy of 99.9693%, MSE of 0.000307024, and MAE of 0.00789449. Likewise, for the Thyroid Disease dataset, the proposed model achieves an accuracy of 99.9535%, along with MSE of 0.000464932 and MAE of 0.0057098. For the diabetes dataset, the proposed model demonstrates an accuracy of 98.8073%, MSE of 0.003024, and MAE of 0.009449. In summary, this analysis underscores the enhanced accuracy and effectiveness of the proposed model when compared to traditional approaches.



*Keywords— RBFNN, neural network, back-propagation, local minima, Mean square error (MSE), MAE*

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## I. INTRODUCTION

Classification is a fundamental data mining technique, involving the organization of data into predefined categories based on shared characteristics. Its primary purpose is to discern patterns within a given dataset. Within the realm of classification, there exist three core methodologies: machine learning, statistical models, and neural network [1, 2]. Numerous classification algorithms are used by various researcher including Naive Bayes [3] and Support Vector Machine [4, 5]. Among these, the Radial Basis Function Neural Network (RBFNN) [6, 7] stands out as a prominent neural network architecture for classification tasks. RBFNN [8] is a type of artificial neural network designed for nonlinear function approximation [9]. It draws inspiration from the natural cognitive processes of the human brain, copying the computational methods used by neurons [10]. The RBFNN consists of three layers: input, hidden, and


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output layers, each comprising nodes known as neurons. Data input to the RBFNN traverses through the input layer to the hidden layer, facilitated by input weights. Subsequently, the hidden layer transmits the output to the output layer through output weights [11, 12]. Gaussian functions are commonly employed in RBFNNs for data processing. As dataset complexity increases with the number of variables, addressing the challenges associated with conventional neural networks becomes crucial. Traditional techniques, such as the multi-Quadratic and inverse multi-Quadratic functions, while commonly used, exhibit slow convergence and local minima issues [13]. Consequently, this study introduces the Crow Swarm Optimization Algorithm, a novel meta-heuristic search method [14, 15], to enhance the RBFNN's performance. This algorithm is particularly beneficial for global optimization. The research presents the modeling of neural network, the RBFNN, employing a global swarm optimization algorithm, specifically the Crow Search Algorithm (CSA). The proposed technique is evaluated using three distinct datasets. This paper present the RBFNN and the proposed CSA [16] as a learning algorithm aimed to enhancing classification techniques. Key aspects addressed in this research include:

- Implementation of Crow Search in combination with various neural network variants to mitigate gradient path oscillations and overcome local minima issues.
- An investigation into the accuracy performance of the proposed HCSRBF algorithm in training first-order neural networks like RBFNN.
- Performing a comparative analysis of Radial Basis Function and its variants through simulation, assessing Mean Squared Error (MSE) and Mean Absolute Error (MAE) on benchmark classification datasets sourced from the UCI Machine Learning Repository.

The paper is organized into multiple sections, commencing with Section II, which provides a review of related literature. Following that, Section III delves into training algorithms, introducing both the Radial Basis Function Neural Network (RBFNN) and the Crow Search Algorithm (CSA). While the subsection iii in Section III investigates the proposed optimization method for training RBFNN. Section IV outlines the techniques used to produce and analyze results. Finally, Section V provides an overall summary and conclusion for this research paper.

## II. RELATED WORK

This paper provides an overview of several prior research studies that focus on the utilization of Radial Basis Function Neural Networks (RBFNNs) in various applications: The author in [17] employed RBF-NN for breast cancer data classification and reported excellent accuracy. The study assessed the model's precision using breast cancer X-ray CT scans and MRI datasets collected under radiologist supervision. The proposed RBFNN achieved an accuracy of 91.49%, surpassing the comparative model (BPNN) with 69.47% accuracy. Similarly [18] introduced a neural network approach for quicker identification of depression data using RBF and Back Propagation Algorithm (BPA). Their model, developed for categorizing depression, showed improved performance through the combination of these two algorithms. Further in [19] this paper developed RBFNN and BPNN models for breast cancer image classification. The proposed RBFNN outperformed the comparative BPNN model, achieving an accuracy of 70.4% compared to 59.0%. another paper in [20] introduced an RBFNN method called SOM-RBF for automatic epilepsy diagnosis, leading to a detection precision of 97.47%. This hybrid approach aimed to improve the accuracy of epilepsy diagnoses and reduce incorrect seizure disorder diagnoses. Further in [21] the author suggested ANN and RBFNN models for heart disease prediction, achieving high accuracy (97% for CBR integrated with ANN and 98% for RBFNN). Where [22] applied RBFNN to two satisfiability programming problems, comparing no-training and half-training techniques. The study found that the half-training technique was more effective. In [23] this paper explored the use of RBFNN in combination with various algorithms to optimize results for the σ value. Their research demonstrated the superiority of the RBFNN with Kohonen's unsupervised learning in terms of accuracy. Where else [24] used RBFNN for classifying mammography images for breast cancer, with RBFNN outperforming MLP in accuracy (79.166% vs. 54.1667%). Further in [25] the author presented metaheuristic techniques for enhancing RBFNN architecture. The study used the Firefly algorithm and Prey-Predator algorithm to train RBFNNs, providing insight into RBFNN behavior under different conditions. In [26] proposed MLP and RBFNN for lung cancer dataset classification, with MLP demonstrating higher accuracy compared to RBFNN. Shao in [13] suggested a quantum RBF network for data classification, showcasing the potential of quantum RBF networks for solving binary classification tasks. Similarly [27] Demonstrated the effectiveness of the AIS algorithm in training RBFNN-2SATRA, achieving higher accuracy and convergence rates compared to other training methods. In [28] employed MLP and RBFNN to calculate the solution gas-oil ratio based on reservoir temperature, API, and gas specific gravity, outperforming empirical correlations. These studies collectively highlight the diverse applications and successes of RBFNNs in various fields, showcasing their potential in solving complex problems and improving accuracy in data analysis and prediction.

## III. TRAINING ALGORITHMS

### *A. Radial Basis Function Neural Network*

An RBF Neural Network, or RBFNN for short, holds significant importance in the realm of neural networks. It adopts a three-layer multilayer perceptron structure, comprised of an input layer, a hidden layer, and an output layer, with each layer containing nodes [21, 29]. The RBF Neural Network is distinctly characterized by its single hidden layer, serving as both an input and an output layer for the nodes. The linkage between input and output is established through a distance measurement, which allows for approximations to be made [30]. In the process of obtaining these approximations, an input pattern undergoes evaluation through a series of fundamental functions, each associated with an RBF center. These functions are then scaled by coefficients and aggregated linearly to produce the final results [18]. Numerical representation of the RBFNN is given in equation (1).

$$h(x) = exp\ exp\left(-\frac{(x-C)^2}{\gamma^2}\right) \tag{1}$$

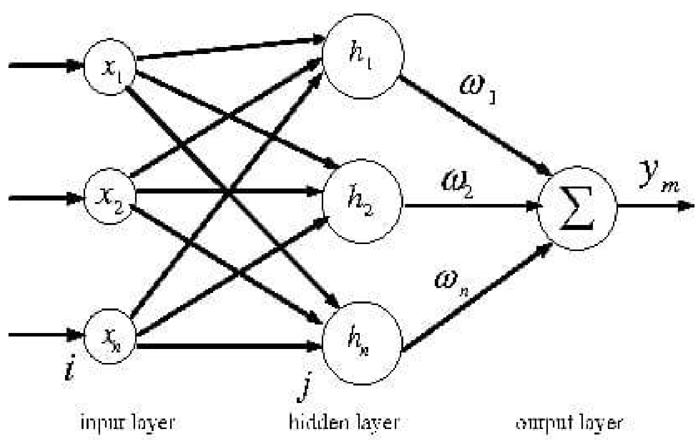


Figure 1. Radial-basis Function Neural Network (RBFNN)

### *B. Crow Search Algorithm*

The Crow Search Method is a unique meta-heuristic optimization technique that draws its inspiration from the collective intelligence of crow swarms [31, 32]. The algorithm is fundamentally rooted in the behavioral patterns of crows, which are renowned for their exceptional intelligence. One of the key principles behind the Crow Search Algorithm (CSA) is based on the concept that crows store extra food in hidden locations, retrieving it when necessary [15]. They exhibit remarkable social intelligence by recognizing and alerting one another in the presence of perceived threats.

A set of guiding principles of the CSA as given below:

- Crows live in social groups.
- Crows possess the ability to remember the specific locations of their food caches.
- Crows engage in strategic planning to potentially steal food from each other.
- Crows take precautions to safeguard their food stores from accidental theft.

*C. Proposed Crow S_RBFNN Algorithm*

The initial step involves configuring the parameters for the Crow Search (CS) and RBFNN. Subsequently, input the preprocessed dataset, alongside the transformed input weights and bias, into the RBFNN architecture, effectively converting them into objective functions. The CS algorithm will utilize this objective function to compute the appropriate weight values. It will then proceed to adjust these weight values based on the discrepancies it identifies between the model's output and the desired data. The CS algorithm operates on the premise that each particle signifies a potential solution with a unique set of weight vectors. The following presents a concise overview of the CS algorithm used to train the RBFNN. The pseudo of the proposed model is given as below:

1. Start.
2. Begin by reading the data, where $X_i$ represents a vector of length M, and $\mathrm{N} * 1$ class labels.
3. Normalize the data.
4. Allocate 70% of the data for training purposes, reserving the remaining 30% for testing.
5. Initialize a population of crows with random solutions.
6. Evaluate the fitness level for each crow.
7. Randomly assign weights ($W_x$) for each connecting link in the RBFNN.
8. While (While iterating < $iter_{max}$ )
9. Calculate the RBFNN's output.
10. Determine new positions for each crow.
11. Update weights using the following equation:
$$w_x^{n+1} = w_x^n - \Delta v_t^{(k+1)} \tag{2}$$
12. Update the position of each crow using the equation:
$$x^{i,iter+1} = x^{i,iter} + r_i \times fl^{i,iter} \times \left(m^{i,iter} - x^{i,iter}\right) \tag{3}$$
13. Calculate the mean error for each crow.
14. Update the weights using the equation:
$$w_x^n = w_x^n - w_x^{n+1} \tag{4}$$
15. Determine the best position among the crows.
16. End the iterative process, marking the conclusion of step 9.
17. Conclude the overall procedure.

*D. Data Collection*

The dataset utilized in this study was sourced from the UCI website, which is easily accessible online. This specific dataset focuses on cancer and comprises 9 input attributes, featuring 2 distinct classes: Benign and Malignant. The attribute values are integers ranging from 0 to 1, with the output attribute being binary, indicated as 2 for benign and 4 for malignant. These values are directly employed, rescaled to a standardized 0 to 1 range, and represented using a two-unit binary output format. In the case of the second dataset, specifically the thyroid dataset, the encoding method aligns with the original data file. It employs a 1-of-3 encoding technique to replace the class numbers (1, 2, or 3), representing them as (1 0 0, 0 1 0, or 0 0 1). In previous studies, the initial 3772 thyroid records were designated as the training data, while the remaining 3428 records were reserved for use as test data. Datasets can be acquired from various online sources, including /uciml/datasets and https://archive.ics.uci.edu/ml/index.php.

*E. Performance Parameters*

The dominant method for evaluating classifiers and evaluating system efficacy primarily hinges on two fundamental metrics: accuracy and Mean Squared Error (MSE). Accuracy is computed by dividing the number of accurately predicted observations by the total number of observations or real values. A higher accuracy value signifies superior system performance, effectively showcasing the model's alignment with the training data. Conversely, MSE measures the average squared difference between predicted and actual values within the training dataset.

## IV. RESULT AND DISCUSSION

### *A. Thyroid Dataset*

The table 1, summarizes the performance of four different algorithms, namely Artificial Neural Network (ANN), Radial Basis Function Neural Network (RBFNN), Flower Pollination (FP) RFBNN, and Crow Search-based RBFNN (CROW S_RBFNN), on thyroid dataset divided into a 70% training and a 30% testing subset. The key metrics used to assess the algorithms are accuracy (ACC), mean squared error (MSE), and mean absolute error (MAE). On the training dataset, FP_RFBNN and CROW S_RBFNN outperform ANN and RBFNN in terms of accuracy, achieving a remarkable 99.5591%, while the latter two models attain 93.6018%. This means FP_RFBNN and CROW S_RBFNN have a superior ability to correctly classify data in the training set. Additionally, FP_RFBNN and CROW S_RBFNN show the lowest MSE and MAE values, which measure the accuracy and precision of predictions. This indicates that they have the smallest differences between predicted and actual values in the training dataset. Moving to the testing dataset, FP_RFBNN and CROW S_RBFNN continue to demonstrate higher accuracy, achieving 98.3087%, compared to ANN and RBFNN's 93.8865%. However, there is a trade-off in the form of slightly higher MSE values for FP_RFBNN and CROW S_RBFNN compared to ANN and RBFNN. In terms of MAE, FP_RFBNN and CROW S_RBFNN maintain their superiority with the lowest values. In conclusion, FP_RFBNN and CROW S_RBFNN display excellent accuracy and precision, particularly on the testing dataset. Figure 2 show the convergence of the proposed model in term of MSE MAE and accuracy.

Table 1. Performance Evaluation on Thyroid Dataset

| Algorithm | ANN | RBFNN | FP_RFBNN | CROW S_RBFNN |
|---|---|---|---|---|
| 70% Training dataset | | | | |
| ACC | 93.6018 | 93.6018 | 99.5591 | 99.5591 |
| MSE | 0.005924 | 0.005924 | 0.004409 | 0.00440 |
| MAE | 0.063984 | 0.063984 | 0.0100909 | 0.01009 |
| 30% Testing dataset | | | | |
| ACC | 93.8865 | 93.8865 | 98.3087 | 98.3087 |
| MSE | 0.004971 | 0.004971 | 0.016913 | 0.01691 |
| MAE | 0.06246 | 0.06246 | 0.002618 | 0.00261 |

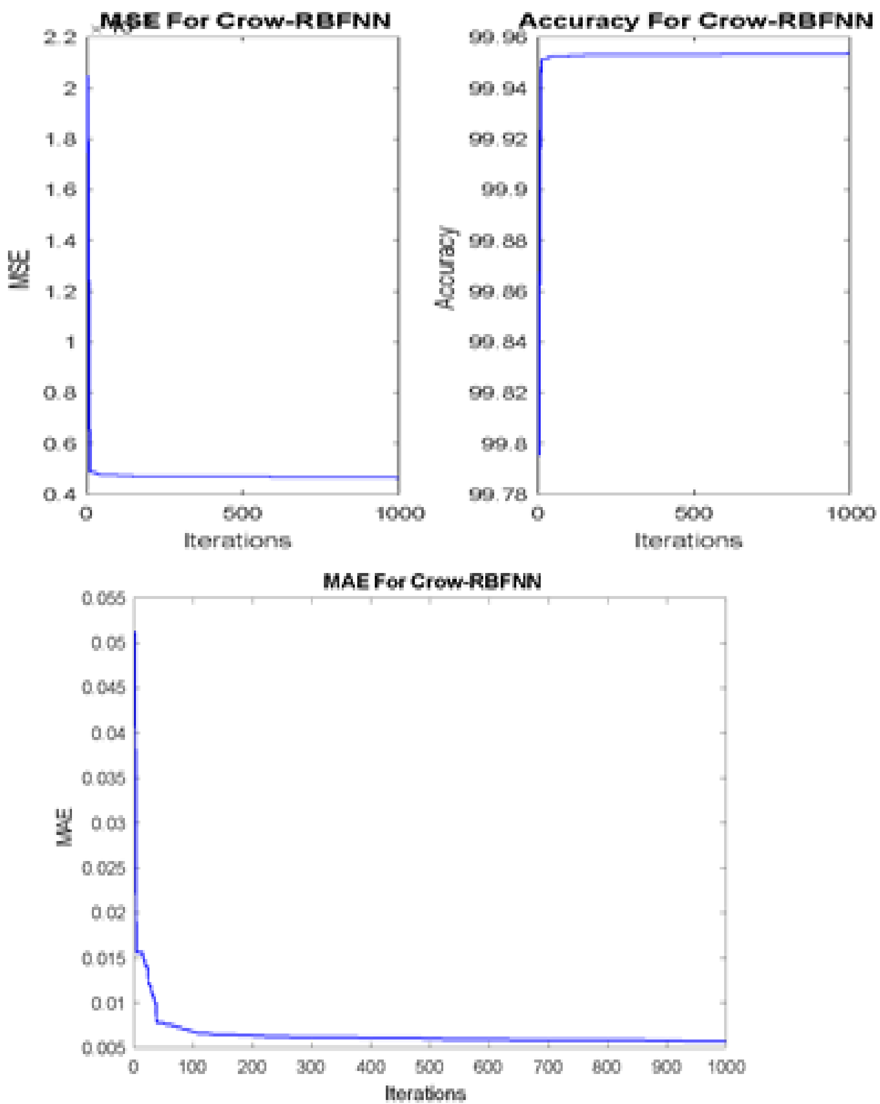


Figure 2. Result of MSE, MAE, and accuracy of 30% Thyroid data of proposed models.

*B. Cancer Dataset*

The table 2, presents a comparative evaluation of four different algorithms, namely Artificial Neural Network (ANN), Radial Basis Function Neural Network (RBFNN), FP_ RFBNN, and Crow Search-based RBFNN (CROW S_RBFNN). The assessment is conducted on cancer dataset that is split into a 70% training subset and a 30% testing subset, using three performance metrics: accuracy (ACC), mean squared error (MSE), and mean absolute error (MAE). In the context of the 70% training dataset, CROW S_RBFNN stands out with the highest accuracy of 99.9753%, indicating its ability to correctly classify data within the training set. FP_ RFBNN also shows strong performance with 97.0503% accuracy. Although ANN and RBFNN achieve slightly lower accuracy, they offer competitive results at 95.0795% and 93.6353%, respectively. MSE, which assesses the precision of predictions, demonstrates that CROW S_RBFNN and ANN have the lowest error rates in the training dataset, with exceptionally low values of 0.000246761 and 0.0044186, respectively. On the other hand, FP_RFBNN and RBFNN show higher MSE values. As for the 30% testing data, CROW S_RBFNN and FP_RFBNN maintain their strong performance, achieving accuracy scores of

99.9693% and 99.9165, respectively. Once again, CROW S_RBFNN show its remarkable accuracy with the lowest MSE value, underlining its precision in predicting testing data. FP_RFBNN also performs well, yielding a low MSE value of 0.00855229. When it comes to MAE, it's worth noting that FP_RFBNN outperforms the other algorithms for both training and testing datasets, demonstrating its consistency in generating predictions with minimal absolute errors. To summarize, the table indicates that CROW S_RBFNN and FP_RFBNN offer impressive accuracy and precision, positioning them as strong contenders for various applications, particularly in classification tasks. Nevertheless, the choice of the most suitable algorithm should take into account the specific requirements and trade-offs of the application. Figure 3 illustrates the convergence of the proposed model in terms of MSE, MAE, and accuracy.

Table 2. Performance Evaluation on Cancer Dataset

| Algorithm | ANN | RBFNN | FP_RFBNN | CROW S_RBFNN |
|---|---|---|---|---|
| 70% Training dataset | | | | |
| ACC | 95.0795 | 93.6353 | 97.0503 | 99.9753 |
| MSE | 0.0044186 | 0.0063992 | 0.0294975 | 0.000246761 |
| MAE | 0.0044186 | 0.0063992 | 0.00503396 | 0.00801612 |
| 30% Testing data | | | | |
| ACC | 94.9176 | 93.7843 | 99.9165 | 99.9693 |
| MSE | 0.00445224 | 0.0072786 | 0.00855229 | 0.000307024 |
| MAE | 0.0509128 | 0.044244 | 0.00613213 | 0.00789449 |

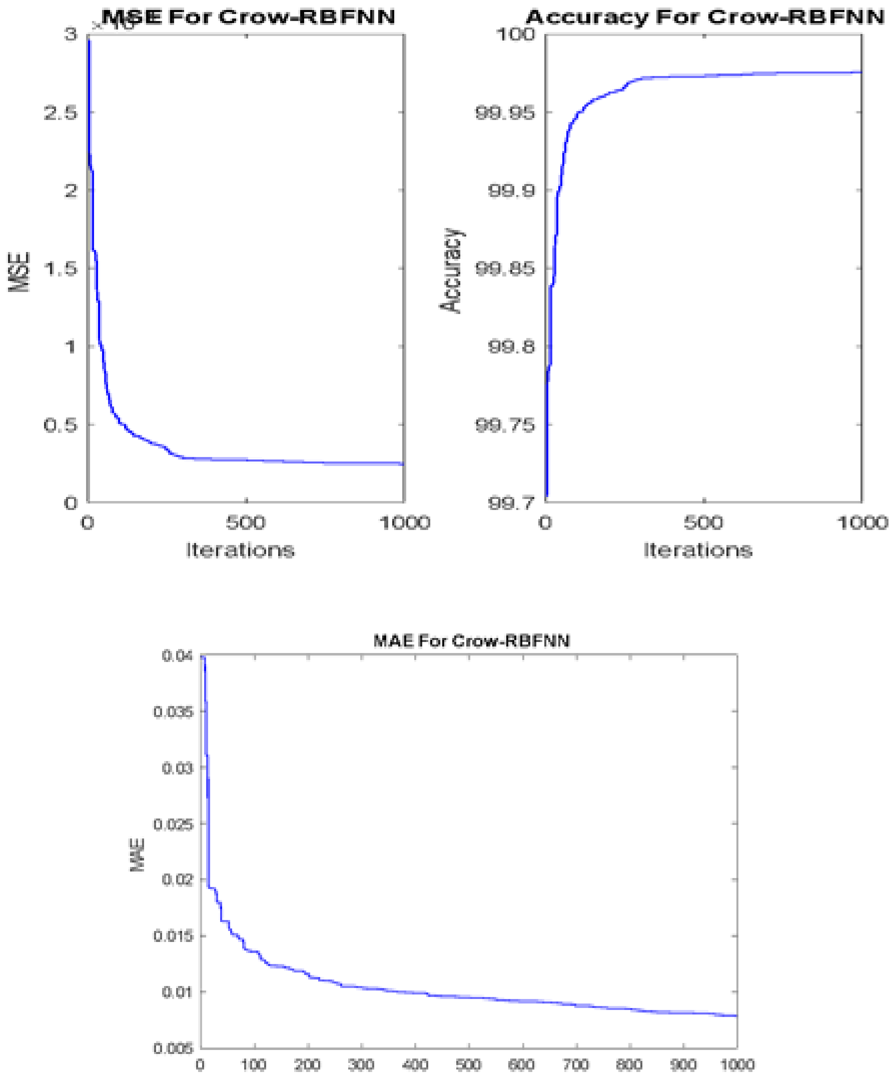


Figure 3. Result of MSE, MAE, and accuracy of 30% Cancer data of proposed models.

*C. Diabetes Dataset*

The Diabetes dataset, obtained from the UCI machine learning repository, is derived from the Pima Indian population's diabetes-related data. It encompasses comprehensive information about chemical changes in the female body, where variations can lead to diabetes. With 768 examples, 8 inputs, and 2 outputs, the feedforward network topology for this dataset is configured as 8-5-2. The designated target error for diabetes classification is set at 0.00001.

Table 3. Performance Evaluation on Diabetes Dataset

| Algorithm | ANN | RBFNN | FP_RFBNN | CROW S_RBFNN |
|---|---|---|---|---|
| 70% Training dataset | | | | |
| ACC | 95.3729 | 94.6252 | 96.0513 | 98.9713 |
| MSE | 0.0243776 | 0.04082 | 0.06012 | 0.006013 |
| MAE | 0.44186 | 0.06391 | 0.05033 | 0.008011 |
| 30% Testing dataset | | | | |
| ACC | 94.8136 | 92.4823 | 97.7125 | 98.8673 |
| MSE | 0.44521 | 0.072176 | 0.08529 | 0.003024 |
| MAE | 0.2128 | 0.04241 | 0.03213 | 0.009449 |

Table 3 provides a comprehensive performance assessment of four different algorithms applied to a Diabetes dataset. The algorithms under examination include the Artificial Neural Network (ANN), Radial Basis Function Neural Network (RBFNN), Flower Pollination Radial Basis Function Neural Network (FP_RFBNN), and CROW Self-organizing Radial Basis Function Neural Network (CROW S_RBFNN). The evaluation is conducted on both a 70% training dataset and a 30% testing dataset, utilizing key metrics such as Accuracy (ACC), Mean Squared Error (MSE), and Mean Absolute Error (MAE). For the 70% training dataset, the ANN achieved an accuracy of 95.37%, with MSE and MAE values of 0.02438 and 0.44186, respectively. The RBFNN exhibited a slightly lower accuracy at 94.63%, with higher MSE and MAE values of 0.04082 and 0.06391. The FP_RFBNN demonstrated an improved accuracy of 96.05%, along with MSE and MAE values of 0.06012 and 0.05033. Notably, the CROW S_RBFNN outperformed the other algorithms with an accuracy of 98.97% and remarkably low MSE and MAE values of 0.00601 and 0.00801.

Moving to the 30% testing dataset, the ANN maintained a high accuracy of 94.81%, while the RBFNN showed a slightly lower accuracy at 92.48%. The FP_RFBNN excelled with an accuracy of 97.71%, outperforming both ANN and RBFNN. Once again, the CROW S_RBFNN demonstrated superior performance with the highest accuracy of 98.87%. These findings indicate that the CROW S_RBFNN algorithm consistently delivers exceptional results in both training and testing phases, showcasing its efficacy in handling the complexities of the Diabetes dataset. The additional Figure 4 likely illustrates the results graphically, providing a visual representation of MSE, MAE, and Accuracy for the proposed models on the 30% Diabetes dataset. Overall, this comprehensive analysis offers valuable insights into the comparative strengths and weaknesses of the evaluated algorithms in the context of diabetes classification.

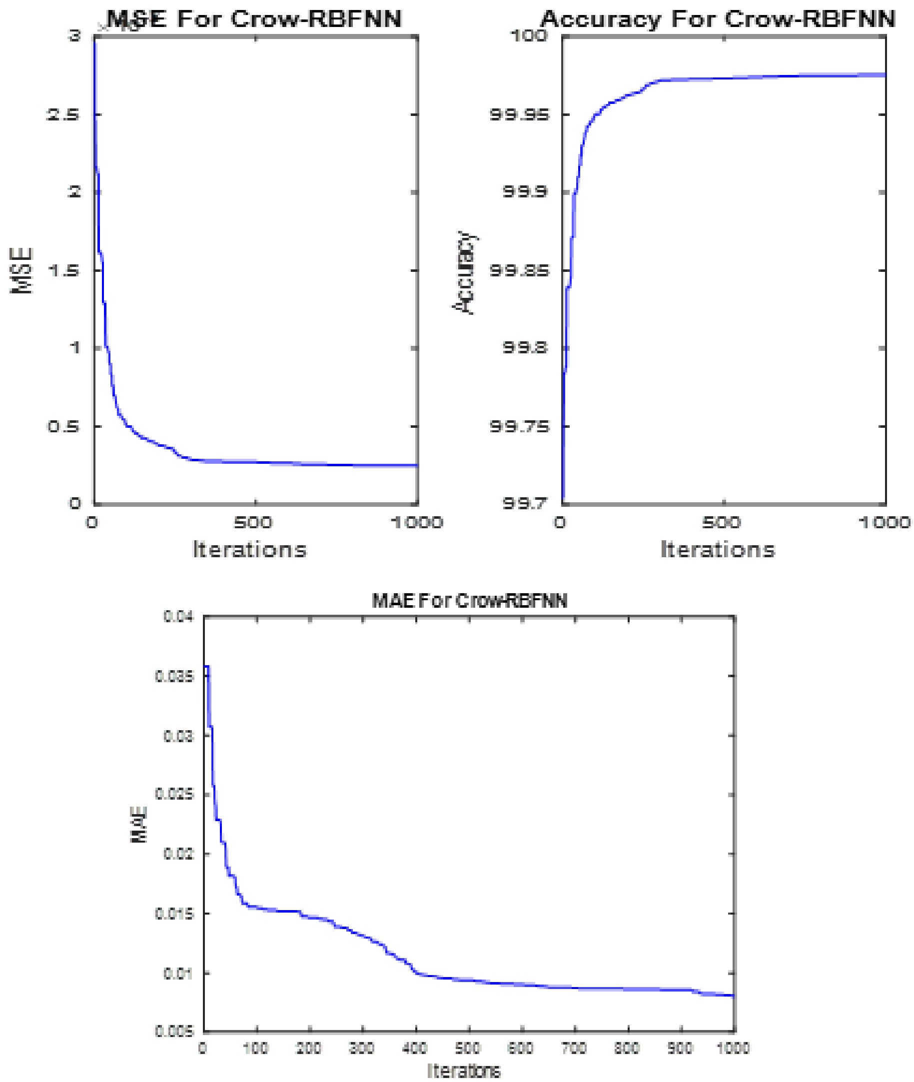


Figure 4. Result of MSE, MAE, and accuracy of 30% Diabetes data of proposed models.

## IV. DISCUSSIONS

In the context of the thyroid dataset, Table 1 provides a comprehensive overview of the performance of four distinct algorithms ANN, RBFNN, FP_RFBNN, and CROW S_RBFNN. The dataset is partitioned into a 70% training subset and a 30% testing subset, with key metrics such as accuracy (ACC), mean squared error (MSE), and mean absolute error (MAE) used for assessment. Notably, on the training dataset, FP_RFBNN and CROW S_RBFNN exhibit superior accuracy of 99.5591%, outperforming ANN and RBFNN at 93.6018%. The FP_RFBNN and CROW S_RBFNN models also demonstrate the lowest MSE and MAE values, indicating precision in predictions. Transitioning to the testing dataset, FP_RFBNN and CROW S_RBFNN maintain higher accuracy, achieving 98.3087%, compared to ANN and RBFNN at 93.8865%. Although FP_RFBNN and CROW S_RBFNN show slightly higher MSE values, their superiority in terms of MAE and overall accuracy, particularly on the testing dataset, is evident. Figure 2 visually depicts the convergence of the proposed models in terms of MSE, MAE, and accuracy.

Similarly, the evaluation of the cancer dataset in Table 2 involves the same set of used for the thyroid dataset. The dataset is divided into a 70% training subset and a 30% testing subset, with ACC, MSE, and MAE used as performance metrics. In the 70% training dataset, CROW S_RBFNN stands out with the highest accuracy of 99.9753%, surpassing the other algorithms. FP_RFBNN also demonstrates strong performance with 97.0503% accuracy, while ANN and RBFNN achieve competitive results. Additionally, CROW S_RBFNN and ANN exhibit the lowest MSE values in the training dataset. For the 30% testing data, CROW S_RBFNN and FP_RFBNN maintain their strong performance, achieving accuracy scores of 99.9693% and 99.9165%, respectively. CROW S_RBFNN stands out with the lowest MSE, emphasizing its precision in predicting testing data. FP_RFBNN performs well with a low MSE value of 0.00855229. Particularly, FP_RFBNN consistently outperforms other algorithms in terms of MAE for both training and testing datasets. Figure 3 visually illustrates the convergence of the proposed models in terms of MSE, MAE, and accuracy.

Moving to the diabetes dataset, Table 3 evaluates the performance of ANN, RBFNN, FP_RFBNN, and CROW S_RBFNN on a dataset obtained from the UCI machine learning repository, which pertains to diabetes-related data in the Pima Indian population. The dataset comprises 768 examples with an 8-5-2 feedforward network topology, and the target error for diabetes classification is set at 0.00001. In the 70% training dataset, CROW S_RBFNN demonstrates the highest accuracy at 98.9713%, outperforming the other algorithms. Additionally, CROW S_RBFNN exhibits the lowest MSE and MAE values, emphasizing its precision. For the 30% testing data, CROW S_RBFNN maintains its superior accuracy at 98.8673%, with low MSE and MAE values. FP_RFBNN also performs well, showcasing accuracy and precision. The accompanying Figure 4 likely provides a graphical representation of MSE, MAE, and Accuracy for the proposed models on the 30% Diabetes dataset. In summary, the evaluation underscores the consistent performance of CROW S_RBFNN across different datasets, particularly excelling in accuracy and precision metrics.

## V. CONCLUSION

In summary, the assessment of four distinct algorithms RBFNN, FP_RFBNN, and CROW S_RBFNN on thyroid diabetes, and cancer datasets, partitioned into training and testing sets, yields valuable insights into their performance. Notably, CROW S_RBFNN consistently stands out as the top performer in accuracy, achieving exceptional scores of 99.9753% in the training dataset and 99.9693% in the testing dataset. It also betters in minimizing mean squared error (MSE), signifying high precision in its predictions. FP_RFBNN is another strong contender, particularly for applications that require consistently low mean absolute error (MAE) values. It demonstrates competitive accuracy in both datasets and is precise in its predictions. While ANN and RBFNN also show good performance, they fall slightly behind CROW S_RBFNN and FP_RFBNN in terms of accuracy and precision. These findings suggest that CROW S_RBFNN and FP_RFBNN are promising choices for classification tasks, especially when high accuracy and precision are of paramount importance. However, the selection of the most suitable algorithm should ultimately be guided by the specific requirements and trade-offs of the intended application. In future the RBFNN will be integrated with different optimization algorithms. And theses hybrid models will be used for different classification task.

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