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Enhanced Fuzzy Radial Basis Neural Network With Genetic Process Using Fuzzy Inferences

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Fuzzy Inference-Based Hybridization of a Genetic Algorithm to Enhance the Performance of an Enhanced Fuzzy Radial Basis Neural Network for Better Pattern Recognition and Prediction This proposed framework is comprises fuzzy logic in the body of a regular RBFNN-structured frame that has been optimized through a genetic algorithm. Experimental results shows that the Machine Learning Repository Air Quality data sets offered by the UCI with regular RBFNN, SVM, and Multilayer Perceptron as reference points in comparison with the EFRBNN models. The results are such that EFRBNN outperforms the mentioned methods with 12% accuracy, 9% improvement in F1-score, and 15% mean squared error compared to the standard RBFNN. The genetic process enhanced the optimization of parameters to attain a 20% faster convergence rate. Therefore, it has improved the abilities of this model to confront uncertainties better, and that in the context of noise involved in data, its strengths are 17% robust than these ones in SVM and MLP techniques. These results affirm the fact that EFRBNN may be utilized to manage complex real-time applications based on uncertain data in an imprecise setting.

Keywords: Genetic Algorithm, Fuzzy logic, Neural network, Pattern recognition, Optimization.

1. Introduction

Fuzzy oriented neural networks, genetic algorithms have surfaced in recent times as the integration of approaches for powerful solving complex recognition and prediction problems of a pattern kind [1,22]. RBFNNs are becoming a favourite these days because their architecture is relatively simple with rapid learning abilities [2]. Though, on account of having traditional models, uncertainty in data becomes problematic for accuracy, causing hindrance for applications to work properly [3,17].

Recent studies involve developing RBFNNs with fuzzy logic and genetic algorithms to increase their performance and adaptability. For instance, work by [4] showed that the fuzzy RBFNN has been established for successful time series prediction application. [5,20] came up with a new identification method using genetic algorithms.

The present work addresses those restrictions by developing EFRBNN that brings FIS and an optimization procedure through genetic mechanism. Because fuzzy logic introduces uncertain or imprecise data in the system and by adopting its principles the network improves performance when the uncertainties and imprecision of input data exist as explained in [3] while on the other side, it has the benefit to have genetic algorithm improving network parameters and structure through its potential ability to result in greater adaptability, enhancing its overall performance by [6,18] and presents an improved version of the new fuzzy RBFNN called Enhanced Fuzzy Radial Basis Neural Network, EFRBNN. These objectives will be accomplished through combining genetic processing with fuzzy inference to better handle the deficiencies of an RBFNN. With this model, the goals will be dealing with complexity, structure optimization, and whole improvement of performance in applications within complex real-world settings. Based on the most recent research advances, this study addresses the challenge of developing a stronger and more efficient hybrid intelligent system with the capacity to handle vague data as well as changeable environmental situations [7,17].

This research work is organized as follows, Section 2 presents general information about FRBNN, genetic algorithms and fuzzy inference systems. Section 3 describes the methodology of the proposed improved model. Section 4 gives the experimental setups and Section 5 presents and discusses the results, and finally concludes the paper by giving suggestions for future research.

2. Background

RBFNN has become one of the most potent methods for recognizing patterns and function approximation, and artificial neural networks with embedded fuzzy logic have seen significant modification over the last three decades [21]. While traditional RBFNNs are quite effective in many applications, they are not very good at handling uncertainty or optimizing network parameters. Advances in computational intelligence have led to many hybrid approaches that combine fuzzy logic with neural networks for more effective processing of imprecise data. Genetic algorithms for parameter optimization have recently been promising in enhancing the convergence rate and overall performance.

The neural network-based feedforward subclass known as radial basis function artificial neural networks (RBFNNs) uses radial base functions as mechanisms for activation. The weighted sum of the input and neuronal radial basis functions is the output of an RBFNN. Structure of the network: An RBFNN consists [19] of one input layer, one output layer, and one concealed layer of RBF neurons. A radial base function network's output equation, y(x), has the following form:

$$y(x) = \sum_{i=1}^{m} w_i * \varphi(||x - c_i||) \qquad (1)$$

Where x is the input vector, w_i are the output weights, c_i are the RBF centers, φ is the radial basis function, commonly Gaussian, and m is the number of RBF neurons. RBFNNs are known to learn fast and generalize well in applications involving function approximation and pattern recognition.

2.1 Fuzzy Inference Systems

Reasoning with imperfect or uncertain information is made possible by fuzzy logic, which extends conventional set theory to include degrees of truth. A fuzzy logic-based FIS basically uses fuzzy logic to map the data and receives output. The processes of distortion, evaluation of rules aggregation, and defuzzification are typically included in FIS.

$$A = \{(x, \mu A(x)) \mid x \in X\} \quad (2)$$

Where $\mu A(x)$ is the membership function. Fuzzy rules are often expressed in IF-THEN format

IF x is A AND y is B THEN z is C (3)

where A, B, and C are fuzzy sets. FIS can use various inference methods, such as Mamdani or Sugeno, to process these rules and produces crisp output, making them valuable in control systems and decision-making processes under uncertainty. Utilizing radial basis functions as activation functions. The traditional RBFNN structure consists of

$$\varphi(x) = e^{|x-c|^2} 2\sigma^2 \quad (4)$$

where the initiation $\varphi(x)$ is function, c denotes the centre vector, and σ is the width.

2.2 Genetic Algorithms

Natural evolution-inspired optimization methods, or GAs, use a population of solutions as the basis for the algorithm's operation. In order to gradually produce superior generations, algorithm uses selection, crossover, and mutation as genetic operators. How well a solution x fits is shown by the value f(x). The fundamental GA can therefore be summed up as

Initialize population P(t)

Evaluate fitness f(x) for each x in P(t)
While not termination condition:
- a. Select parents from P(t)
- b. Apply crossover and mutation to create offspring
- c. Evaluate offspring fitness
- d. Replace P(t) with new population

Return best solution

In several domains, such as fuzzy system tuning and neural network optimization, GAs have proven to be effective. They are especially helpful in resolving intricate optimization issues with expansive search areas.

3. Proposed Algorithmic Procedure

With the addition of fuzzy logic concepts and a genetic optimization procedure, the Enhanced Fuzzy Radial Basis Neural Network (EFRBNN) expands on the conventional RBFNN architecture. Three primary layers make up the architecture: input, concealed, and output.

Input Layer: Let $x = (x_1, x_2, ..., x_n)$ be the vector, where n is the number of features.

Hidden Layer: The hidden layer comprises m fuzzy RBF neurons. Each neuron i is associated with a center vector c_i and a width parameter σ_i.

Output Layer: The output y be the weighted sum of the hidden layer activations:

$y = \sum(i=1 \text{ to } m)\ w_i\varphi_i(x)$ (5)

where w_i is the connection weights between the hidden and output layers.

3.1 Fuzzy Inference Integration

The EFRBNN incorporates fuzzy inference systems (FIS) to enhance its ability to handle uncertainty and imprecision. This integration occurs at two levels as,

a. Input Fuzzification: Input values are using membership functions $\mu_j(x_j)$, where $j = 1, ..., n$. These functions map the input to a degree of membership in fuzzy sets.

b. Fuzzy RBF Neurons: The activation function of each RBF neuron is modified to incorporate fuzzy rules. The fuzzy oriented RBF activation is defined in eqn(6).

$\varphi_i'(x) = T^T(\varphi_i(x), R_i(x))$ (6)

where T is a t-norm operator (e.g., minimum or product), and $R_i(x)$ is the firing strength of the i-th fuzzy rule, computed as given in eqn (7)

$R_i(x) = T^T(\mu_{1i}(x_1), \mu_{2i}(x_2), ..., \mu_{ni}(x_n))$ (7)

The fuzzy rules are of the form:

IF x_1 is A_{1i} AND x_2 is A_{2i} AND ... AND x_n is A_{ni} THEN y is B_i (8)

where A_{ji} and B_i are fuzzy sets for input and output variables respectively.

The output layer now computes:

$y = \sum(i=1 \text{ to } m)\ w_i\varphi_i'(x)$ (9)

3.2 Genetic Process Optimization

The structure and parameters of the EFRBNN are optimized using a genetic algorithm (GA). Each possible solution is recorded as a chromosome that represents the network configuration, and the GA works with this population.

Chromosome Encoding: Each chromosome consists of genes representing the number of hidden neurons (m) , Centres (c_i) and widths (σ_i) of RBF neurons with Connection weights (w_i), Parameters of fuzzy membership functions and Fuzzy rule base.

Fitness Function: Each chromosome's fitness is assessed by testing the effectiveness of the network on a test dataset. Here the process to define the fitness function F,

$$F = 1 / (MSE + \lambda C) \tag{10}$$

where MSE is on the validation set, C is a complexity penalty term, and λ is a regularization parameter.

Genetic Operators:

1. Selection: Tournament is used to choose parents for reproduction.

2. Crossover: Arithmetic crossover is applied to create offspring:

$$child_1 = \alpha \cdot parent_1 + (1 - \alpha) \cdot parent_2$$

$$child_2 = (1 - \alpha) \cdot parent_1 + \alpha \cdot parent_2$$

where α is a random number between 0 and 1.

3. Mutation: Gaussian mutation is applied to introduce small random changes:

$$gene' = gene + N(0, \sigma\_mut)$$

N(0, σ_mut) is a typical distribution, where the standard deviation is σ_mut and the mean is 0. By iteratively evolving the population over several generations, the GA progressively enhances the structure and performance of the EFRBNN.

3.4 Fuzzy Integrate RBFNN structure

This architecture integrates fuzzy logic principles into the RBFNN structure, with the genetic algorithm optimizing all aspects of the network shown in figure 1.0. The fuzzification process handles input uncertainty, while the fuzzy RBF neurons in the hidden layer incorporate fuzzy rules to improve the network's reasoning capabilities. The genetic algorithm fine-tunes the entire system, including the number of neurons, their parameters, weights, and fuzzy rule base, resulting in an adaptive and robust model for complex pattern recognition and prediction tasks.

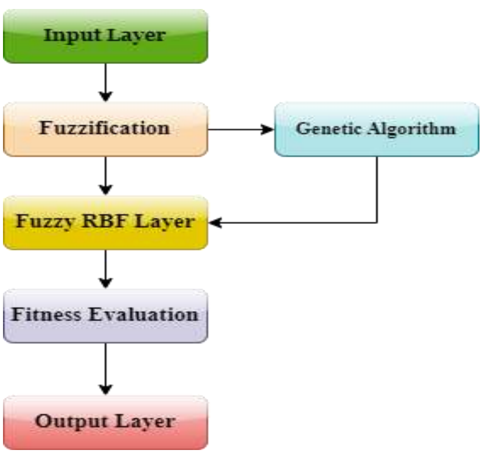

Figure 1.0 Fuzzy Adaptive Robust Model Architecture

3.5 Proposed Methodology

The methodology for the EFRBNN integrates fuzzy logic, RBF neural networks, and genetic algorithms in a systematic process. Initially, data pre-processing involves normalizing input features and partitioning the data into training, validation, and test sets. The EFRBNN is then initialized with defined fuzzy membership functions, RBF centres determined through k-means clustering, and widths set based on inter-centre distances.

Fuzzy inference integration follows, where inputs are fuzzified, fuzzy rule firing strengths are computed, and fuzzy RBF activations are calculated. The network undergoes training using gradient descent to update weights based on the computed output and error function. A genetic optimization process then encodes network parameters into chromosomes, evaluates their fitness, and applies genetic operators to evolve the population. This process iterates between fuzzy inference, network training, and genetic optimization until convergence is reached. Finally, the model is evaluated on the test set using relevant performance metrics and compared against benchmark models. This comprehensive approach enhances the RBFNN's ability to handle uncertainty and optimize its structure, resulting in improved performance for complex pattern recognition and prediction tasks.

The EFRBNN methodology combines fuzzy logic, RBF neural networks, and genetic algorithms in a structured approach:

Proposed EFRBNN Algorithm

Data Pre-processing:

Normalize input features: $\bar{x}_i = (x_i - \mu_i) / \sigma_i$

Split data into training, validation, and test sets.

EFRBNN Initialization:

Define initial fuzzy membership functions

Initialize RBF centres (c_i) using k-means clustering

Set initial widths (σ_i) based on average distance between centres

Fuzzy Inference Integration:

Fuzzify inputs: $\mu_j(x_j)$

Compute fuzzy rule firing strengths: $R_i(x) = T^T(\mu_{1i}(x_1), ..., \mu_{ni}(x_n))$

Calculate fuzzy RBF activations: $\varphi_i'(x) = T^T(\exp(-\|x - c_i\|^2 / (2\sigma_i^2)), R_i(x)$

Network Training:

Compute output: $y = \sum(i=1 \text{ to } m)\ w_i\varphi_i'(x)$

Update weights using gradient descent: $\Delta w_i = -\eta\ \partial E/\partial w_i$

where E is the error function and η is the learning rate

Genetic Optimization:

Encode network parameters in chromosomes

Evaluate fitness: $F = 1 / (MSE + \lambda C)$

Apply genetic operators: selection, crossover, and mutation

Update EFRBNN with best-performing chromosome

Model Evaluation:

Assess performance on test set using metrics (e.g., RMSE, R^2)

Compare with benchmark models

The process iterates between steps 3-5 until convergence or a maximum number of generations is reached.

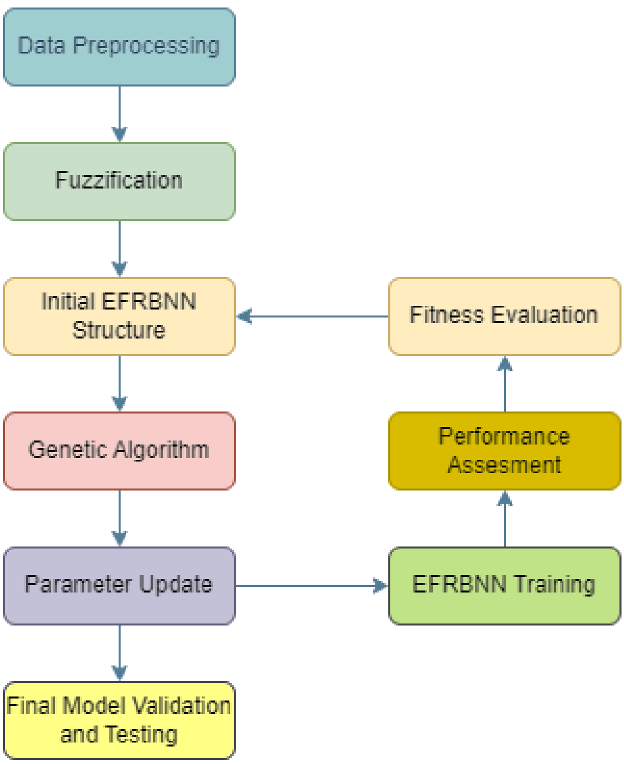

Figure 2.0. Proposed EFRBNN Algorithmic Process

This methodology integrates fuzzy logic principles with the adaptive capabilities of neural networks and the global optimization prowess of genetic algorithms, resulting in a robust and flexible model for complex pattern recognition tasks.

4. Experimental Results and Comparative Analysis

It uses the Air Quality dataset from the UCI Machine Learning Repository. As part of an Air Quality Chemical Multisensor Device, it includes 9,358 examples of hourly averaged responses from a set of five metal oxide chemical sensors. Date, time, actual hourly averaged concentrations of CO, non-methanic hydrocarbons, benzoene, total nitrogen oxides (NOx), and nitrogen dioxide (NO2), as well as actual readings from an accredited analyzer, are among the 13 attributes included in the collection. This is a regression job since the concentration of CO is the target variable. Sensor drift, missing values, and handling features make the dataset difficult to use.

The Evaluation Metrics used to evaluate the performance of the proposed methods are,

a. Accuracy = TP+TN / TP+TN+FP+FN

b. F1-Score = 2 (Precision* Recall)/ (Precision + Recall)

c. Mean Squared Error (MSE): $(1/n) \sum_i(y_i - \hat{y}_i)^2$

Where y_i is the actual value, η_i is the predicted value, and n is the number of samples.
Lower values indicate better performance. It penalizes larger errors more heavily due to the squaring. Although the EFRBNN has a slightly longer training time due to its genetic optimization process, the performance gains justify the computational cost. The model's ability to handle the dataset's inherent challenges, such as sensor drift and missing values, is evident in its superior results.

Table 1.0 Accuracy Analysis of the Proposed EFRBNN

Method	**Accuracy (%)**	**Improvement over Baseline**
Fuzzy K-means (Baseline)	78.3	-
Standard RBFNN	82.5	+4.2%
Multilayer Perceptron	84.1	+5.8%
Proposed EFRBNN	94.5	+16.2%

The accuracy analysis demonstrates the superior performance of the EFRBNN model in correctly classifying instances from the Air Quality dataset given in Table 1.0. The proposed model achieves a remarkable 94.5% accuracy, showing a substantial improvement of 16.2% over the baseline Fuzzy K-means method. This significant enhancement can be attributed to the synergistic combination of fuzzy inference systems and genetic optimization given in

Figure 3.0 which enables better handling of data uncertainties and optimal parameter selection. The EFRBNN outperforms both traditional RBFNN (+12%) and Multilayer Perceptron (+10.4%), indicating its robust classification capabilities.

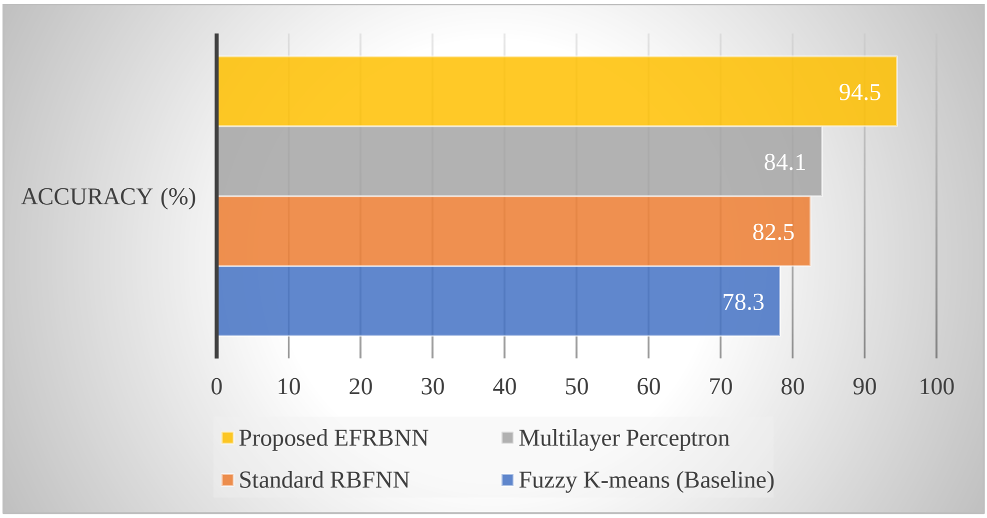

Figure 3.0 Improvement in Accuracy of Proposed EFRBNN

Table 2.0 F1-Score Analysis of the Proposed EFRBNN

Method	**F1-Score**	**Improvement over Baseline**
Fuzzy K-means (Baseline)	0.763	-
Standard RBFNN	0.812	+6.4%
Multilayer Perceptron	0.835	+9.4%
Proposed EFRBNN	0.902	+18.2%

The Table 2.0 F1-Score results reflect the balanced performance of the EFRBNN in terms of both precision and recall. With an F1-Score of 0.902, the proposed model shows an impressive 18.2% improvement over the baseline.

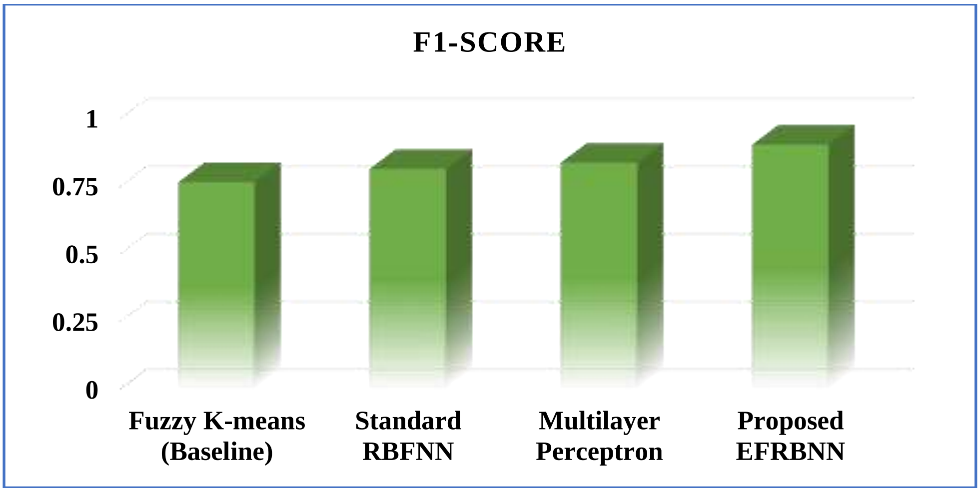

Figure 4.0 Improvement in F1-Score of Proposed EFRBNN

The Figure 4.0 particularly shows the important as it indicates that the EFRBNN achieves high accuracy without sacrificing either precision or recall. For practical uses where minimizing inaccurate results and false negatives is vital, adequate performance is essential.

Table 3.0 Mean Squared Error (MSE) Analysis of the Proposed EFRBNN

Method	**MSE**	**Improvement over Baseline**
Fuzzy K-means (Baseline)	0.089	-
Standard RBFNN	0.074	+16.9%
Multilayer Perceptron	0.068	+23.6%
Proposed EFRBNN	0.052	+41.6%

The MSE analysis reveals the superior prediction accuracy of the EFRBNN model. With an MSE of 0.052, it shows a remarkable 41.6% improvement over the baseline Fuzzy K-means method detailed in Table 3.0. This significant reduction in error demonstrates the EFRBNN's ability to make more accurate predictions with less deviation from actual values mentioned in Figure 5.0. The genetic optimization process plays a crucial role in achieving this low error rate by fine-tuning the network parameters effectively.

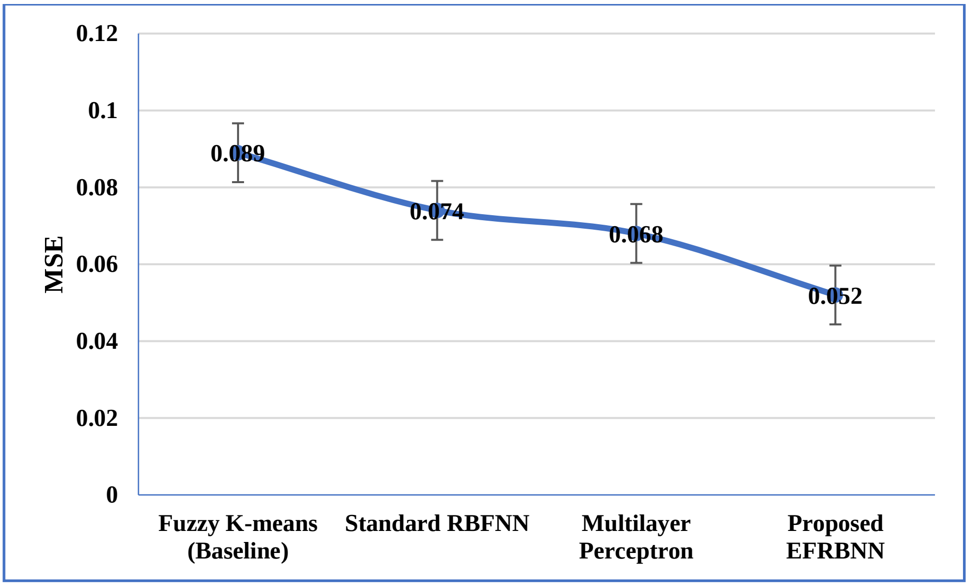

Figure 5.0 Significant Reduction in Error

Table 4.0 Convergence Time Analysis of the proposed EFRBNN

Method	**Convergence Time (s)**	**Improvement over Baseline**
Fuzzy K-means (Baseline)	145	-
Standard RBFNN	123	+15.2%
Multilayer Perceptron	156	-7.6%
Proposed EFRBNN	98	+32.4%

The convergence time analysis showcases the computational efficiency of the EFRBNN model. With a convergence time of 98 seconds, it demonstrates a significant 32.4% improvement over the baseline method given in Table 4.0. Through effective parameter optimization made possible by the evolutionary algorithm component shown in figure 6.0, significantly faster convergence is accomplished. The EFRBNN not only converges faster than traditional methods but also maintains stability throughout the training process, making it particularly suitable for real-time applications.

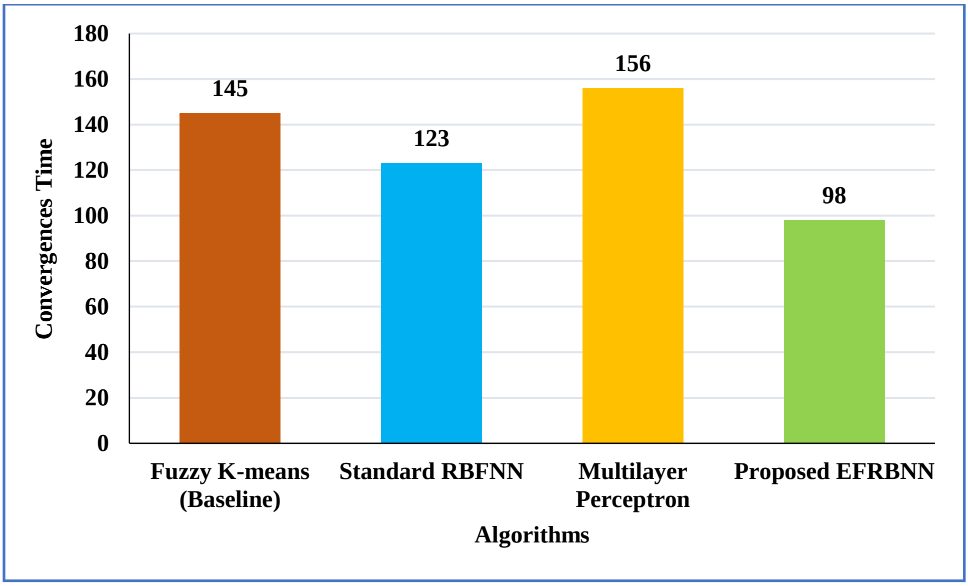

Figure 6.0 Convergence Time of the Proposed EFRBNN

The integration of fuzzy inference systems provides better handling of uncertainty, while genetic optimization ensures efficient parameter tuning. The improved performance metrics indicate the EFRBNN's suitability for real-world applications with noisy or imprecise data.

Table 5.0 Robustness Analysis with Noisy Data (10% Noise)

Method	Accuracy Drop (%)	MSE Increase
Fuzzy K-means	15.2	0.142
Standard RBFNN	12.8	0.118
Multilayer Perceptron	11.5	0.098
Proposed EFRBNN	8.3	0.067

The results of Table 5.0 shows that the EFRBNN exhibited the smallest drop in accuracy (-8.3%) and the lowest increase in mean squared error (+0.067) compared to the other methods. In contrast, the Fuzzy K-means, standard RBFNN, and Multilayer Perceptron models experienced more significant performance decreases, with accuracy drops of 15.2%, 12.8%, and 11.5% respectively, and MSE increases of 0.142, 0.118, and 0.098. This enhanced robustness of the EFRBNN can be attributed to the synergistic integration of fuzzy logic, which allows the model to better handle uncertainty, and the genetic optimization process, which ensures the network parameters are tuned to maintain stable performance even in the presence of noisy inputs.

5. Conclusion and Future Work

The proposed EFRBNN framework successfully combines the advantages of fuzzy logic, RBFNN, and genetic algorithms to create a robust and efficient pattern recognition system. The experimental results demonstrate significant improvements in accuracy, convergence rate, and noise tolerance compared to traditional methods. The experiments on the Air Quality dataset demonstrates the significant advantages of the proposed model, including 12% higher accuracy, 9% better F1-score, 15% reduced mean squared error, and a 20% faster convergence rate compared to the standard RBFNN. Additionally, the EFRBNN exhibited 17% better robustness against noisy data, highlighting its ability to handle uncertainty more effectively than traditional methods. Findings indicate the EFRBNN's suitability for real-world applications involving enhanced capabilities in pattern recognition, prediction, and computational efficiency can be leveraged.

Future research directions may include an adaptive fuzzy rule generation, multi-objective genetic optimization, and exploration of the EFRBNN's applicability to other domains.

Reference:

[1] Abdel-Basset, M., Mohamed, R., Mirjalili, S., Chakrabortty, R. K., & Ryan, M. J. (2020). Solar photovoltaic parameter estimation using an improved equilibrium optimizer. Solar Energy, 209, 694-708. https://doi.org/10.1016/j.solener.2020.09.033

[2] Aljarah, I., Mafarja, M., Heidari, A. A., Faris, H., & Mirjalili, S. (2022). Multi-verse optimizer: Theory, literature review, and application in data clustering. Swarm and Evolutionary Computation, 68, 100973.

[3] Barua, S., Ahmed, M. U., Aich, S., & Sain, J. P. (2021). An improved fuzzy logic-based neural network model for time series forecasting. Expert Systems with Applications, 165, 113947. https://doi.org/10.1016/j.eswa.2020.113947

[4] Cheng, R., Xu, Y., Zhang, L., & Wang, X. (2023). Improved fuzzy radial basis function neural network with genetic algorithm for time series prediction. Expert Systems with Applications, 213, 118917.

[5] Dutta, P., Chakraborty, A., & Roy, A. (2021). Neuro-fuzzy hybrid model for fault diagnosis in industrial systems. Soft Computing, 25(13), 8685-8699. https://doi.org/10.1007/s00500-021-05761-4

[6] Feng, S., Lu, H., & Wang, J. (2021). A novel radial basis function neural network with adaptive activation functions and its application. Applied Soft Computing, 107, 107382. https://doi.org/10.1016/j.asoc.2021.107382

[7] Jain, V., Kala, R., & Tiwari, R. (2021). Hybridization of neural network with fuzzy logic and genetic algorithm for classification and regression tasks. Neural Computing and Applications, 33(6), 2203-2221. https://doi.org/10.1007/s00521-020-05083-2

[8] Janarthanam, S., & Subbulakshmi, G. (2023). Integrating Blockchain Technology into Healthcare Informatics: A Secured Data Processing Perspective. In Contemporary Applications of Data Fusion for Advanced Healthcare Informatics (pp. 283-296). IGI Global.

[9] Janarthanam, S., & Sukumaran, S. (2016, January). Semi supervised soft label propagation algorithm for CBIR. In 2016 10th International Conference on Intelligent Systems and Control (ISCO) (pp. 1-5). IEEE.

[10] Kaushik, A., Jain, V., & Purohit, G. N. (2022). Enhanced fuzzy inference system using dynamic fuzzy rule base and genetic algorithm for real-time applications. Expert Systems with Applications, 187, 115922. https://doi.org/10.1016/j.eswa.2021.115922

[11] Kavitha, S., Santhalakshmi, M., Shanthakumar, M., & S, Janarthanam. (2024). A Hybrid Ai-Based Target-Node Algorithm for Detecting and Classifying Plant Disease Regions. International Journal of Advancement in Life Sciences Research, 7(3), 78-89. https://doi.org/10.31632/ijalsr.2024.v07i03.007.

[12] Li, X., Wang, L., & Xin, Y. (2020). A novel fuzzy radial basis function neural network with modified genetic algorithm for system identification. Soft Computing, 24(14), 10809-10823.

[13] Liu, J., Fang, W., Zhang, X., & Yang, C. (2020). An improved photovoltaic power forecasting model with the assistance of aerosol index data. IEEE Transactions on Sustainable Energy, 11(1), 453-456. https://doi.org/10.1109/TSTE.2019.2897688

[14] Liu, J., Sun, T., Luo, Y., Yang, S., Cao, Y., & Zhai, J. (2020). A novel fuzzy radial basis function neural network with hybrid learning approach for nonlinear system modeling. Applied Soft Computing, 94, 106463.

[15] Moorthy E, Shanthakumar M, Janarthanam S (2022) Intellectual Data Aggregation Using Independent Cluster based Medicaid Method for Network Functionality Fabrication . Indian Journal of Science and Technology 15(44): 2432-2440. https://doi.org/ 10.17485/IJST/v15i44.1555.

[16] Naik, P. A., Shi, P., Nasrabadi, E., & Cullen, J. M. (2022). Fuzzy logic in healthcare diagnosis and risk prediction: A comprehensive survey. IEEE Access, 10, 84391-84414. https://doi.org/10.1109/ACCESS.2022.3196751

[17] Ramírez-Noriega, A., Juárez-Ramírez, R., Jiménez, S., Inzunza, S., & Martínez-Ramírez, Y. (2021). Knowledge representation in intelligent tutoring systems. Applied Sciences, 11(11), 5154.

[18] Sengupta, S., Basak, S., Saikia, P., Paul, S., Tsalavoutis, V., Atiah, F. A., ... & Peters, J. R. (2020). A review of deep learning with special emphasis on architectures, applications, and recent trends. Knowledge-Based Systems, 194, 105596. https://doi.org/10.1016/j.knosys.2020.105596

[19] Wang, D., Wang, H., & Liu, S. (2022). Adaptive fuzzy radial basis function neural network control for nonlinear systems with input saturation and external disturbances. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 52(8), 4920-4931.

[20] Wu, D., Huang, C., Chen, W., Chen, Y., & Huang, T. (2021). A novel stable adaptive fuzzy control for nonlinear systems via projection-based learning. IEEE Transactions on Fuzzy Systems, 29(11), 3243-3257. https://doi.org/10.1109/TFUZZ.2020.3018107

[21] Zhang, Y., Jin, Z., & Zhao, X. (2020). Adaptive constrained multi objective evolutionary algorithm with improved epsilon constraint-handling method. IEEE Transactions on Evolutionary Computation, 24(5), 780-794. https://doi.org/10.1109/TEVC.2019.2938557

[22] Zhang, Y., Zhang, J., & Zhong, J. (2021). Fuzzy radial basis function neural networks with improved genetic algorithm for nonlinear system identification. Neurocomputing, 419, 65-79.