Modified Fuzzy Neural Network Approach for Academic Performance Prediction of Students in Early Childhood Education

Marwah Hameed

Abstract--- *Modern education relies heavily on educational technology, which provides students with unique learning opportunities and enhances their ability to learn. For many years now, computers and other technological tools have been an integral part of education. However, compared to other educational levels, the incorporation of educational technology in early childhood education is a more recent trend. It is because of this that materials and procedures tailored to young children must be created, implemented, and studied. The use of artificial intelligence techniques in educational technology resources has resulted in better engagement for students. Early childhood special education students' academic achievement is predicted using a Modified Fuzzy Neural Network (MFNN). Before constructing the classifier, the dataset had to be preprocessed to remove any extraneous information. As a follow-up, this study will put to the test an organized approach to the implementation of customized fuzzy neural networks for the prediction of academic achievement in early childhood settings. Considerations for the analysis of academic achievement in early childhood education are discussed in this article, including recommendations for the implementation of proposed modified fuzzy neural networks. In terms of evaluation metrics such as Precision, recall, accuracy, and the F1 coefficient, the proposed model outperforms conventional machine-learning (ML) techniques.*

Keywords--- *Early Childhood Special Education, Computer-based Learning System, Artificial Intelligence, Modified Fuzzy Neural Network.*

I. Introduction

EDUCATIONAL technology includes computer-based learning. Computers have been used in education since the 1950s, and students and teachers can utilize them independently or in teams (Wolery, M., et al., 2002). However, educational technology generally combines resources other than computers to maximize each resource's unique traits and benefits. Particularly in early childhood education (McConnell, S. R. (2000)). Besides computers, interactive whiteboards and programmable toys are commonly employed in early childhood education. Using instructional technology has several benefits. Educational technology may motivate pupils to learn by attracting their attention and encouraging innovative actions (Lifter, K., et al., (2011)). The utilization of technology allows for unique instructional characteristics such as multimedia-based engagement and problem-solving process visualization. Technology also fosters collaborative learning and constructivism (Odom, S. L., & Wolery, M. (2003)). Teaching pupils about educational technology helps them understand the Information Society. Finally, technology may help schools connect with their communities.

Artificial Intelligence (AI) is used in many fields. Educational technology is an interesting topic for AI (Warren, S.F. (2000)). Since the 1970s, Artificial Intelligence has been used in instructional technologies. E-learning is a broad phrase [6]. It is the use of instructional technology to meet specific educational needs. The emphasis on new resources in educational technology often ignores older but still important tools (Warren, S.F., & Walker, D. (2005)). The major goal is to assist students and teachers over traditional techniques. Using instructional technology in the classroom might be difficult. The integration process should address concerns specific to a student group (Schwartz, I. S. (2000)). Technology can help solve specific educational issues or offer the infrastructure for activities that would not be possible without it. Creating a good prediction model improves the forecast range. Predicting academic performance in early childhood special education using MFNN.

Section 2 describes the recommended technique for the rest of the research. Section 3 presents the findings. Section 4 concludes and plans future work.

II. Proposed Methodology

For predicting academic success in early childhood special education, an MFNN is presented. Primarily, preprocessing eliminates unnecessary data from the dataset, increasing the classifier's prediction performance. Another goal of this research is to apply modified fuzzy neural networks to predict academic achievement in early childhood education. Considerations for analyzing academic success in early childhood education are discussed in this article. Figure 1 depicts the suggested methodology's overall procedure.

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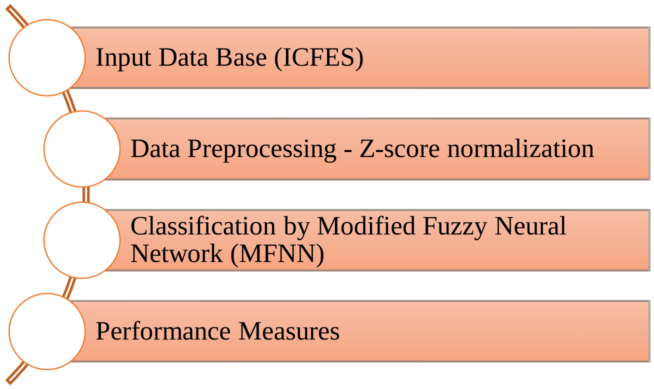

Figure 1: The Overall Process of the Proposed Methodology

1. Data Preprocessing Using Z-Score Normalization

Each experiment's basic intensity data were normalized by computing the average intensity for each dataset, then the average of the averages [9]. This grand average was used to compute normalization factors for each experiment. The grand average was then equaled by all normalized data. A z-normal score's distribution curve. There is a -3 standard deviation (far left of the normal distribution curve) to a +3 standard deviation range (fall to the far right of the normal distribution curve). In order to use a z-score, you need to know the mean μ and also the population standard deviation σ.

Esp, let xi (i = 1, 2, · · ·, D) represents the i-th component of each feature vector x ∈ R D. The mean and the standard deviation of these D components are evaluated as:

$$\mu_x = \frac{1}{D}\sum_{i=1}^{D} x_i, \sigma_x = \sqrt{\frac{1}{D}\sum_{i=1}^{D}(x_i - \mu_x)^2} \qquad (1)$$

Z-score normalization is then applied as,

$$x^{(zn)} = ZN(x) = \frac{x-\mu_x 1}{\sigma_x} \qquad (2)$$

Based on these calculations, z-score normalization extends the original feature vectors along the 1 vector to a hyperplane including the origin and being perpendicular to √ 1. These vectors are then adjusted to have a similar length as D, resulting in final normalized vectors that lie on a hypersphere of radius √D. Next the preprocessing of the given data, the feature selection procedure is carried out, as explained in the following section.

2. Classification Using MFNN

Neuronal networks and fuzzy logic are emerging technologies that could be used in pharmaceutical formulation and processing (Yang, B., et al., (2007)). ANNs and evolutionary algorithms work well together to forecast and optimize formulation conditions. Fuzzy-neural systems seem to have flourished more than other methods of symbolic connectionism. A fuzzy neural network has three layers: an input layer (fuzzification), a hidden layer (fuzzy rules), and an output layer (fuzzification) (defuzzification). Sometimes a five-layer network containing sets in the second and fourth layers can be found. In practice, the criteria are connected. The linear evaluation function cannot capture inter-criteria relationships. To solve the SBP algorithm's disadvantage. This paper proposes a Fuzzy Backpropagation (FBP) technique. It calculates the net value using an LR type fuzzy number and so does not presume criteria independence. The FBP algorithm also avoids oscillations and falls into local minima. The convergence of the FBP algorithm for single-output networks with single and multiple training patterns is proven.

3. Fuzzy Backpropagation Algorithm (FBP Algorithm)

Different neuro-fuzzy approaches have recently been presented for calculating the net value of the ith neuron's inputs. The mapping is mathematically represented by Sugeno's fuzzy integral, which is based on a psychological foundation.

Step 1: Randomly create the initial weight sets w for the input hidden layer in which each $w_{ji} = (w_{mji}, w_{\alpha ji}, w_{\beta ji})$ is an LR-type fuzzy number. And create the weight set w' for the hidden output layer

Here $w'_{kj} = (w'_{mkj}, w'_{\alpha kj}, w'_{\beta kj})$

$$w_{ji} = (w_{mji}, w_{\alpha ji}, w_{\beta ji})$$

$$w'_{kj} = (w'_{mkj}, w'_{\alpha kj}, w'_{\beta kj})$$

Step 2: Consider (I_p, D_p) $p = 1, 20 \ldots N$ input-output pattern set. In which $I_p = (I_{p0}, I_{p1}, I_{p1})$ also every I_{pi} is an LR-type fuzzy number.

Step 3: Allocate values for α and η; Alpha=0.1 Neta =0.9

Step 4: Acquire next pattern set (I_p, D_p) Assign $(O_{pi} = I_{pi}$, i=1,2,3..1

Step 5: Calculate the input to hidden neurons

$$O'_{pj} = f\left(NET_{pj}\right), j = 1,2 \ldots., m; O'_{p0} = 1$$

Where $NET_{pj} = CE\ (\sum W_{ji} O_{pi})$

Step 6: Evaluate the hidden to output neurons

$$O''_{pk} = f\ (NET'_{pk}), k = 1,2, .. n;$$

Where $NET'_{pk} = CE\ (\sum W_{ji} O'_{pj})$

Step 7: Evaluate modification of weights Δ w'(t) for the hidden output layer as below

Evaluate

$$\Delta E_p(t) = (\partial E_p/\partial w'_{mkj}, \partial E_p/\partial w\alpha kj, \partial Ep/\partial w'_{\beta kj})$$

Evaluate

$$\Delta w'(t) = -\eta \Delta E_p(t) + \alpha \Delta w'(t-1)$$

The modified weight i of hidden to output neuron is

$$W'(t) = W'(t-1) + \Delta W'(t)$$

Step 8: Calculate modification of the weights Δ w'(t) for the input hidden layer as follows

Let

$$\delta_{pmk} = -\left(D_{pk} - O''_{pk}\right)O''_{pk}\left(1 - O''_{pk}\right).1$$

$$\delta_{pmk} = -\left(D_{pk} - O''_{pk}\right)O''_{pk}\left(1 - O''_{pk}\right).\left(-\frac{1}{3}\right)$$

$$\delta_{pmk} = -\left(D_{pk} - O''_{pk}\right)O''_{pk}\left(1 - O''_{pk}\right).\left(\frac{1}{3}\right)$$

Evaluate

$$\Delta E_p(t) = (\partial E_p/\partial w'_{mji}, \partial E_p/\partial w\alpha_{ji}, \partial Ep/\partial w'_{\beta ji})$$

Calculate

$$\Delta w'(t) = -\eta \Delta E_p(t) + \alpha \Delta w'(t-1)$$

Step 9: Modify weight for the input-hidden-output layer as,

$$W(t) = W(t-1) + \Delta W(t)$$

$$W'(t) = W'(t-1) + \Delta W'(t)$$

Step 10: $p = p + 1;$

if (p<=N) go to step 5

Step11: output w' and w'' the final weight sets.

4. Regularity Distribution Factor

To reduce the likelihood of failure in iterations, the regularity distribution factor should select a convex function in the early iterations, allowing the population to find an optimal solution over a large range. In the late phase, a concave function should be chosen so that the regularity distribution factor can gradually change to the minimum for local development to occur. It ensures the algorithm's convergence. The functional regularity distribution factor structuring on the basis of the cosine function is demonstrated in formula (3):

$$K = \frac{\cos((\pi/G_{max}) \times T) + 2.5}{4} \quad (3)$$

In which T is the number of iterations. Assume G_{max}= 40, the changing curve of value K arrived. Formula (3) is described below:

$$v_{id} = \left(\frac{\cos((\pi \times T/G_{max})) \times 2.5}{4}\right) \times [v_{id} + 2 \times rand() \times (p_{id} - x_{id}) + 2 \times Rand() \times (p_{gd} - x_{id})] \quad (4)$$

Here V_{id} is the regularity distribution factor, and the decreasing V_{id} value is dispersed in combination with the rand function. The modified number of leaders per iteration is V_{id}·N and the number of followers is equal to $1 - V_{id}$·N.

III. Results and Discussion

The ICFES collected the information for this research. Approximately 200,000 Colombian university students took the SABER PRO test in 2016. These included data on each student's SABER 11 test results, socioeconomic status, childhood school characteristics, and academic status. The original data set included student gender, age, and academic program. The pupils' identities were kept secret because they were coded in the ICFES data collection. TP, FP, TN, and FN rates are used to determine various performance measures. The first performance metric was precision or the fraction of relevant retrieved occurrences. Remember that recall is defined as the proportion of relevant instances retrieved. The measurements of accuracy and recall are both significant in evaluating a prediction approach's success. So these two metrics can be merged with equal weights to get the F-measure. Accuracy is the proportion of accurately predicted instances to all expected instances.

Table 1: Performance results of the proposed and existing prediction methods

Metrics	SVM	ANN	FNN
Accuracy	91.24	93.58	99.57
Precision	71.45	84.67	91.58
Recall	78.24	86.57	92.51
F-measure	87.24	92.57	98.24

Table 1. tabulate the performance results of the proposed and existing prediction methods.

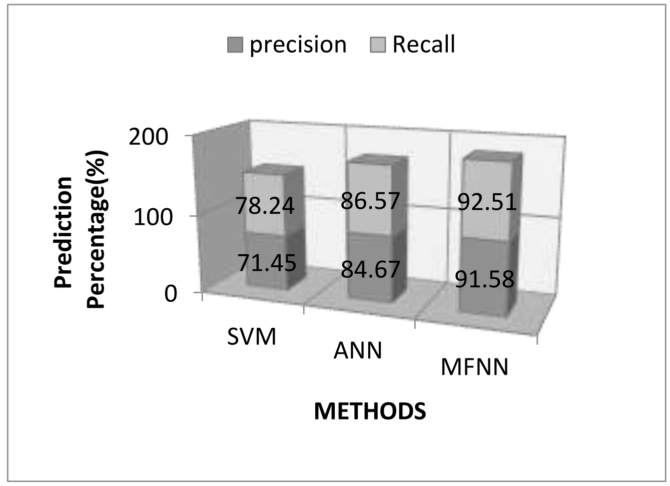

Figure 2: Precision and recall results between the proposed and existing methods

Figure 2. shows the proposed MFNN technique gives high value of Precision and recall than the existing classifier. From the results it is identified that the proposed algorithm is highly effective. So the performance of the proposed model will be higher compared to other classifier built on previously generated model.

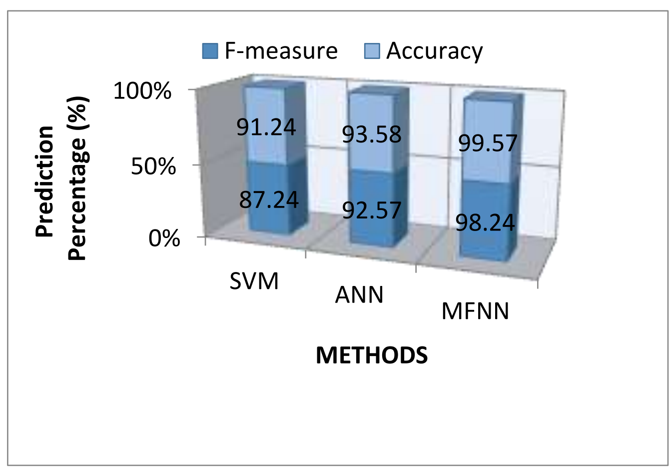

Figure 3: Accuracy results between the proposed and existing methods

Figure.3. show the relationship between the experimental and the MFNN based learning predicted results on the SVM and ANN-based methods. The result indicates that the proposed MFNN based learning can greatly improve the accuracy prediction among the different methods.

IV. Conclusion

This study examines the use of Artificial Intelligence in early childhood education. For predicting academic success in early childhood special education, an MFNN is suggested. It was designed to classify students' academic achievement using numerous MFNNs. This conclusion may be explained by the fact that different academic programs attract students with diverse abilities and interests. The substance of each academic program may also have influenced student preparation and performance. Thus, the predictive efficacy of selected academic performance predictors may vary by discipline. The suggested model outperforms the existing techniques in terms of prediction accuracy. So more topologies with different learning paradigms should be investigated. Furthermore, determining MFNN confidence and prediction intervals requires more research.

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