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Designing and Implementing ANN Model for Predicting Academic Performance of Students

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Abstract: *Proactive planning, resource optimization, and improving the general quality and relevance of education all depend on forecasting in the educational field. It makes it possible for institutions to foresee and react to opportunities and difficulties in the future, ensuring that they can continue to effectively educate future generations. Students who are expected to struggle or fail early in the academic term can be identified with the use of forecasting. This increases the likelihood of success for these students by enabling educators and administrators to offer prompt support and interventions. In complex student data scenarios, both non-linear and linear mapping must be accomplished. Consequently, the goal of our research is to present a novel, effective ANN-based CFFBPNN model for forecasting student performance. Result shows that CFFBPNN outperform in terms of MSE and NRMSE in all the three cases and demonstrates potential for the method to be utilized for student performance prediction in universities.*

Keywords: *EDM, ANN, prediction, student performance, MSE ,CFFBPNN.*

1. Introduction

For educational institutes, student's performance prediction is always considered as a challenging problem due to the large amount of data and its dependence on a variety of factors such as demographic attributes, past academic records, personnel attributes, behavioral attributes etc [1]. We consider finals grades/marks as a parameter to evaluate the students performance. Accurately predicting student performance in the early stages of learning helps in identifying weak students and enables management to take corrective actions to prevent student failure [2].

In response to concerns about student performance prediction, the University of Aberdeen established a commission in 1963 to investigate issues related to student failures. Their committee developed an "early warning system" to identify students that would possibly fail in a course. One way to predict students performance is to analyze the data using Data Mining (DM) techniques. DM technology can help bridging knowledge gaps in educational system via finding hidden patterns, association and anomalies, which can be used to analyze large sets of data in order to discover meaningful patterns and relationships. There are many prediction models available with a difference of approach. [3 - 6]

The increasing attention towards data mining within the educational sector has given rise to a new and evolving research field referred to as Educational Data Mining (EDM). This field primarily focuses on analyzing data generated within educational environments. Several researchers have looked into using EDM approaches to measure student performance based on previous data. These studies primarily focus on early performance prediction of students in terms of grades, marks, and pass/fail status. However, because of the following significant shortcomings with the prior research, predicting student academic performance from huge and complex datasets is a difficult task: i) The student performance was not well predicted due to the poor selection of algorithms, ii) Earlier researchers estimate the linear relationship between input and output using a variety of machine learning models.

In the field of machine learning, there have been achievements in predicting students' performance, this is due to the fact that there are various algorithms that have been developed to make predictions more accurate and identify important factors that are crucial for performance [7 - 11]. Classification and regression are two mostly used prediction methods that usually dealt with in data mining and machine learning . Classification is to predict discrete target variables like whether a student is pass or fail, it will rain or not. Instead regression is used to predict the continuous variables such as prediction of Market Trends, prediction of House prices, prediction of students final grades etc. Linear Regression, Multiple Linear Regression and their extensions have been used to predict the linear relationship among input and output[12, 13].
However, the actual system is complex, because of its dependence on a variety of factors such as demographic attributes, past academic records, personnel attributes, etc. Typical statistical prediction models have difficulty to accurately represent this underlying process [14]. There is a need to include nonlinearity to achieve nonlinear mappings in this complex data. Artificial Neural Networks (ANNs) are effective at modeling complex relationships between input and output variables without requiring prior knowledge [15]. They provide a general and widely applicable tool for making predictions. Using Artificial Neural Networks (ANNs) for forecasting is not a new idea, as Hu used a basic adaptive system called k-Adaline for weather predictions back in 1964. Various ANN based models have been used for forecasting students performance[16, 17].

2. Literature Review

The primary goal of studying literature is to determine to what extent the problem has been solved and what are the future alternatives for improvement exist. A researcher in response will improve the efficiency of the system via decreasing or getting rid of its constraints.
Artificial Neural Networks (ANNs) have been applied to various domains for forecasting and have demonstrated their effectiveness and superiority. G. Shrivastava et al claim that ANN technique can achieve high accuracy and reliability in recognizing and predicting patterns of precipitation.
A. Chaturvedi in 2015, applied artificial neural network (ANN) methods employing backpropagation for rainfall prediction in Delhi, India, achieving minimal Mean Square Error (MSE) [19].
Popescu and Leon (2018) introduced a methodology that utilizes an advanced regression technique called "Large Margin Nearest Neighbor Regression" (LMNNR) to forecast grades based on students' interactions with wiki, forum, and microblogging platforms. The results show strong correlation coefficients and indicate that 85% of the predictions fall within one point of the actual grade, surpassing the performance of conventional regression algorithms[20].
In 2019, Lau and colleagues introduced a method that merges conventional statistical analysis with neural network prediction to forecast student outcomes. Conventional statistical assessments are employed to identify the potential variables impacting students' results. The neural network model has demonstrated a commendable prediction accuracy of 84.8%, albeit with accompanying limitations[21].
In 2014, Mohd Arsad introduced Neural Network and Linear Regression models to forecast students' performance across various entry levels. Both prediction models yielded comparable results in terms of Mean Square Error[22].
Satish Saini in 2015 The breast cancer detection utilized Feed-forward Backpropagation and Cascade-forward backpropagation networks. The evaluation of performance relied on Mean Square Error (MSE). Comparatively, Feed-forward Backpropagation network exhibited higher accuracy than Cascade-forward Backpropagation network and outperformed the latter[23].
Karthikeyan et al.in 2020, explored student performance using a hybrid educational data mining model (HEDM). This model integrates the J48 classifier and Naive Bayes classification techniques. Their findings demonstrate that HEDM delivers superior results compared to traditional educational data mining (EDM) methods[25].
Bravo-Agapito et al. in 2020, conducted a study on predicting the academic performance of 802 undergraduate students in a fully online learning environment. They utilized exploratory factor analysis, cluster analysis, and multiple linear regression. Their findings indicated that "age" is a negative predictor of student performance, suggesting that as age increases, student performance tends to decrease[24].
In 2021, Pranav Dabhade asserted that students' performance hinges on various factors encompassing personal, academic, and behavioral dimensions. Their research focused on forecasting academic achievements within a technical institution in India. Utilizing multiple linear regression and support vector machine algorithms, data from training sets were modeled, and subsequent predictions were generated for test data. Notably, the support vector regression_linear algorithm demonstrated superior predictive capability[26].

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Inssaf El Guabassi et al. (2021) conducted numerous experiments following a seven-step procedure, employing various regression methods including ANCOVA, Logistic Regression (Logit-R), Support Vector Regression (SVR), Log-linear Regression (Log-LR), Decision Tree Regression (DTR), Random Forest Regression (RFR), and Partial Least Squares Regression (PLS-R). Based on the experimental findings, Log-linear Regression (Log-LR) emerged as the preferred model due to its lower Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and higher R-squared (R2) score[27].
Odesanya Ituabhor and colleagues in 2022 propose the adaptive learning of a real-time stochastic phenomenon monitored over an operational LTE broadband radio network interface, employing a cascade forward neural network (CFNN) model. Comparisons between the performance of the adaptive learning model and a benchmark feedforward neural network model (FFNN) were conducted. The results demonstrated that the proposed CFNN model exhibited superior adaptive learning performance with RMSE: 0.9310 and MSE: 0.8669[28].
The paper aims to develop ANN based model using back propagation for predicting the performance of students of Portuguese. Performance evaluation is fundamental not only for students but also for educators, so it is necessary and challenging for researchers to predict student performance in different regions of the country.

3. Proposed Model/ Methodology

To predict student performance we implement Neural networks (ANNs) based model as they are used to efficiently perform complex logic operations and dynamically generate nonlinear mappings [27, 28]. Cascade feed forward neural network provide an extra connection between input and output layer which can learns nonlinear interactions along with linear mappings between inputs and outputs. So, a cascade Feed forward neural network with Back propagation is proposed in our work to efficiently predict the students performance having academic, personnel and socio economic attributes.
For the study firstly, the database was taken from UCI repository and via preprocessing we clean the data for analyzing. This process is explained in Data Preprocessing section [29-32]. Next, we divided our data into two parts: training and testing as explained in splitter section. The model was then build using CFFNN with some functions as explained in build model section to evaluate the student performance. For Prediction some parameters were used as explained in Prediction performance parameters section. Then performance analysis was evaluated using MSE, RMSE and NRMSE as given in Performance Analysis section. Fig 1 shows the Process Diagram of Proposed ANN approach.

3.1. Dataset

The dataset used to forecast student performance was gathered from two Portuguese secondary schools (Gabriel Pereira (GP) and Mousinho da Silveira (MS)) from the UCI Machine Learning Repository. The student dataset consists of 33 attributes and 1044 records, compiled from two Portuguese secondary schools. These attributes encompass a range of information, including student grades and various social, personal, and educational related characteristics. Out of 33, 30 are the demographic attributes consisting personnel and socio economical Information about student and remaining 3 attributes are academic attributes.

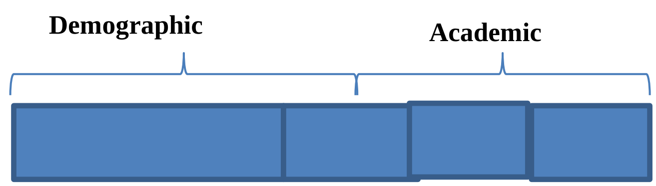

Fig 1. Types of attributes in dataset

3.2. Data Preprocessing

In order to create a successful predictive model, applying data preprocessing steps is crucial to enhance the performance of machine learning classifiers, as raw data can negatively impact their effectiveness. The dataset we obtained is in raw format with skewed data, so we conducted the following preprocessing steps: The dataset initially had 8 missing values spread across different features out of 403 records. After eliminating the missing values records, the cleaned dataset was reduced to 395 records. Converting textual data into numerical format: During this preprocessing stage, textual data is converted into numeric form. We convert this by the use of Microsoft excel. The Portuguese education system employs a 20-point grading scale, where 0 represents the lowest score and 20 signifies maximum score. To discretize continuous data into bins with approximately equal frequencies, we utilize the scikit-learn package's KBinsDiscretizer in Python for this purpose.

3.3. Splitter

The dataset is divided into training and testing subsets based on a predetermined ratio. Various combinations of training and test dataset splits are considered to ensure consistent data division. In our analysis, we experimented with data splits ranging from 10% for training and 90% for testing to 90% for training and 10% for testing, with a 10% variation in each split.

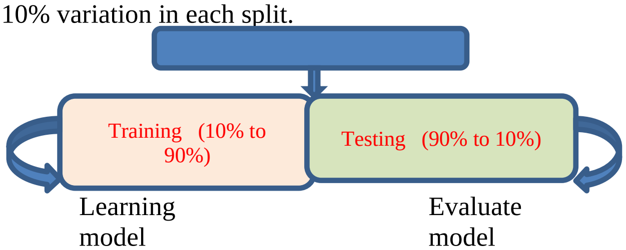

Fig. 2. Data Splitter into Training and Testing

3.4. Build Model

For constructing the model, we employ a CFFNNBP (Cascade Feedforward Neural Network with Backpropagation) to assess student performance. We utilize two learning functions, known as trainlm and traingdx, for training the model. Consequently, we have developed two models: CFFNNBP with traingdx and CFFNNBP with trainlm. Below Fig shows the flow diagram of proposed CFFNNBP model.

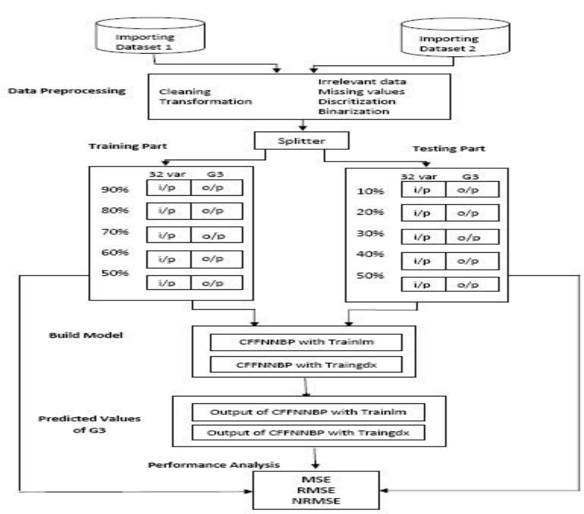

Fig. 3. Work Flow of Proposed CFFBPNN model

3.5. Performance Analysis

The primary parameter used to assess the performance of the prediction model is Mean Squared Error (MSE), which measures the network's effectiveness by averaging the squared errors.

$$MSE = \left[\left[\sum_1^N \left(\frac{Y_{exp} - Y_{cal}}{n}\right)^2\right]\right] \quad .... \quad (1)$$

where, Y_{exp} = Observed value; Y_{cal} = Predicted value; n is the number of observations in dataset.

The second measure used is Root Mean Square Error (RMSE). RMSE quantifies the difference between the observed (actual) array A and the predicted (forecast) array F by taking the square root of the average of the squared differences.

$$RMSE = ` \sqrt{\frac{1}{n}\left[\sum_1^n \left(\frac{Y_{exp} - Y_{cal}}{Y_{exp}}\right)^2\right]} \quad .... \quad (2)$$

The third parameter is Normalized RMSE (NRMSE), which assesses the goodness of fit of a regression model based on a specified target and output value matrix or vector. Normalization is performed by dividing the error by the difference between the maximum and minimum values:

NRMSE=RMSE/(MAX(XA)-MIN(XA)) .... (3)

where MAX denotes the maximum and MIN denotes the minimum

The prediction performance of the developed models was assessed using Mean Squared Error (MSE) (1), Root Mean Square Error (RMSE) (2), and Normalized RMSE (NRMSE) (3) for comparison.

4. Experimental Setup

The dataset used to predict student performances was sourced from the publicly available datasets (two datasets) from the UCI Machine Learning Repository. This dataset includes information from two courses: Portuguese and Mathematics. We have focused exclusively on the Portuguese lesson data for our analysis, as Portuguese dataset is giving more accurate results as compared to Mathematics lesson dataset. The training dataset is employed to implement learning techniques and construct models. We are utilizing an ANN-based CFFNNBP model for forecasting student performance in our study.

4.1. Environmental Setting

We use MATLAB to implement the proposed CFFNN algorithms. The model is developed on a system equipped with an i3 processor running the Windows 11 operating system, featuring a 256GB SSD and 8GB of RAM. The model development process involves leveraging specific MATLAB user-defined functions, including:
load_data() : Load the database file of Portuguese language having 33 attributes.
lag_ratio_fixation(): Set training and testing data percentage randomly.
split_data(): Split the data in two parts (training and testing) as per lag ratio defined above
build_model():To construct a model using predefined initial parameter values described in the below section.
train_model(): Using trainlm and traingdx functions, train the model as per the lag ratio.
performance_analysis(): For performance analysis, Parameters used are RMSE, MSE and NRMSE.

4.2. Configuration Settings

The following Table 1 describes various configuration settings for the parameters of the proposed model. Their initial values are also described :

Table 1: Configuration Parameters

S.No.	Parameters	Initial values
1	Learning function	Trainlm, Traingdx
2	No. of Hidden layers	
3	No. of neurons in hidden layer	30
4	Learning Rate	0.0002
5	No. of epochs	1000
6	Activation Function used	Sigmoid
7	Stopping criteria	When MSE is optimum

The literature review and professional judgment are used to set the parameters.

5. Result Analysis

The MSE, Covariance, RMSE, and NRMSE results of the CFFBPNN model's training and testing using the provided dataset are displayed in the figure below. The provided dataset is divided into 10% interval sections for testing and training, with the training data set ranging from 10% to 90%. The CFFBPNN was developed using three situations to predict the value of G3: At first, we predicted G3 only on the basis of demographic traits. Secondly, in order to forecast G3, we additionally include G1 with demographic attributes. Third, in order to predict G3, we incorporate both G1 and G2 with demographic attributes. Next, we forecast the G3 values, or final grade values, by dividing the data into nine delays. As a result, we get three tables for the traingdx and trainlm functions, each with nine outputs. Unfortunately, only four training ratios—in which the training lags were greater than the testing lags—were considered by the research work's authors. As a result, this research only includes four lags: training ratios of 60%, 70%, 80%, and 90%.
With the exception of G1 and G2, Table 2 below presents the findings of the Traingdx and Trainlm functions for each of the four train-test split ratios of the CFFBPNN model, accounting for 30 demographic input variables and G3 as an output attribute. The table below demonstrates that we may obtain the lowest Mean Squared Error (MSE) of 0.250401 among all by using the Trainlm function with a 60% train-test ratio. Having a 60% train-test ratio and reduced RMSE (0.500401) and NRMSE (0.250201) values of the trainlm function is the result.

Table 2: CFFBPNN Model (Predict G3 on demo) (Portugueuse database)

Model	Train Test Ratio	Training Perf in terms of MSE	Testing Perf in terms of MSE	Covar	RMSE	NRMSE
Traingdx	60% Train Data	0.118899	0.416068	0.243814	0.645033	0.322517
	70% Train Data	0.10035	0.488485	0.055919	0.698917	0.349458
	80% Train Data	0.120084	0.389744	0.223006	0.624295	0.312148
	90% Train Data	0.097918	0.430412	0.128521	0.656058	0.328029
Trainlm	60% Train Data	0.033601	0.250401	0.257113	0.500401	0.250201
	70% Train Data	0.079538	0.33852	0.073266	0.581825	0.290912
	80% Train Data	0.055924	0.386771	0.260264	0.621909	0.310955
	90% Train Data	0.060184	0.364951	0.317653	0.604112	0.302056

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The second scenario is examined in Table 3 below, where G1 attribute and demographic attribute are taken into consideration, resulting in 31 input variables and G3 as an output variable. For each of the four train-test split ratio combinations of the CFFBPNN model, it shows the results of the Traingdx and Trainlm functions. The table below demonstrates that we may obtain the lowest Mean Squared Error (MSE) of 0.138812 out of all by using the Trainlm function with an 80% train-test ratio. This MSE (0.138812) is smaller than the previous MSE (0.250401), which we calculated only by factoring in demographic data. Consequently, the trainlm function with an 80% train-test ratio had lower RMSE (0.372574) and NRMSE (0.186287) values than in the preceding scenario.

Table 3: CFFBPNN Model (Predict G3 on demo and G1) (Port-Database)

Model	Train Test Ratio	Training Perf in terms of MSE	Testing Perf in terms of MSE	Covar	RMSE	NRMSE
Traingdx	60% Train Data	4.971299	6.315577	0.145047	2.513081	1.256541
	70% Train Data	0.087729	0.385757	0.336962	0.621094	0.310547
	80% Train Data	0.089313	0.299646	0.390363	0.547399	0.2737
	90% Train Data	0.077325	0.325859	0.701117	0.570841	0.28542
Trainlm	60% Train Data	0.034593	0.139248	0.56812	0.373159	0.18658
	70% Train Data	0.039954	0.15637	0.494806	0.395436	0.197718
	80% Train Data	0.022666	0.138812	0.668729	0.372574	0.186287
	90% Train Data	0.029073	0.20291	0.579996	0.450456	0.225228

The third case is examined in Table 4 below, where G3 is the output characteristic and 32 input variables total since G1 and G2 attributes are combined with demographic attributes. The results of the Traingdx and Trainlm functions are also shown for each of the four train test split ratio configurations that the CFFBPNN model offers. This table shows that when we use the Trainlm function with an 80% train-test split ratio and add both the 'G1' and 'G2' features along with demographic characteristics, we receive a decreased Mean Squared Error (MSE) of 0.07324. Again, the MSE decline is discernible from the previous MSE obtained solely with demographic characteristics and 'G1'.

Table 4: CFFBPNN Model (Predict G3 on demo, G1 and G2) (Port-Database)

Model	Train Test Ratio	Training Perf in terms of MSE	Testing Perf in terms of MSE	Covar	RMSE	NRMSE3
Traingdx	60% Train Data	0.064392	0.19206	0.54132	0.438247	0.219123
	70% Train Data	0.084521	0.295094	0.537142	0.543225	0.271613
	80% Train Data	7.06994	13.3795	0.068366	3.6578	1.8289
	90% Train Data	0.060042	0.114033	0.789447	0.337688	0.168844
Trainlm	60% Train Data	0.012271	0.077757	0.757021	0.27885	0.139425
	70% Train Data	0.01412	0.078787	0.763412	0.28069	0.140345
	80% Train Data	0.016579	0.07324	0.830119	0.270628	0.135314
	90% Train Data	0.014424	0.114034	0.832968	0.337689	0.168845

Figure 2 below displays a bar graph of all the evaluation parameters for the CFFBPNN model along with the traingdx function and the four possible train test split ratio combinations. The CFFBPNN model's graph below

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displays the MSE values for each of the three scenarios we looked at forecasting G3, along with each of the four train test split percentages. The graph indicates that the MSE of CFFBPNN with demographic inputs, G1 and G2, yields the lowest MSE value in each of the three scenarios.

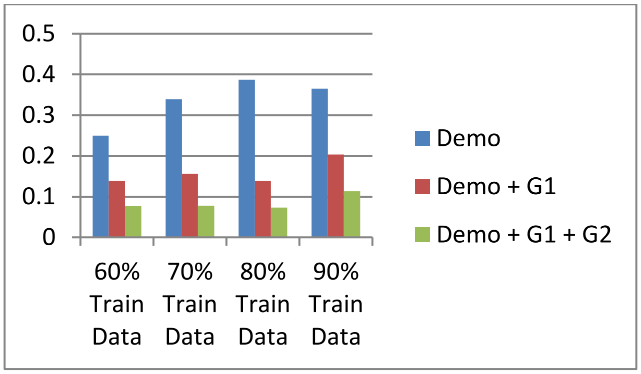

Fig 4: Comparison of MSE using Trainlm function in CFFBPNN

6. Comparative Analysis

This analysis compares the performance of CFFNNBP, using various training data ratios and feature combinations. The models were evaluated using three feature sets: Demo, Demo + G1, and Demo + G1 + G2. The following analysis examines the performance metrics (MSE, RMSE and NRMSE) for each configuration.

Proposed models perform better with more training data. However, the performance does not always improve linearly with the increase in training data ratio. Adding G1 and G2 features consistently improves the model performance across all training data ratios. The addition of G2 has a more significant impact when combined with G1 and demographic attributes, demonstrating the importance of feature combinations.

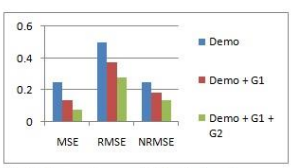

Fig. 5: Comparison at 60% Training data

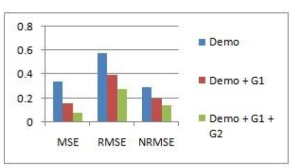

Fig.6: Comparison at 70% Training data

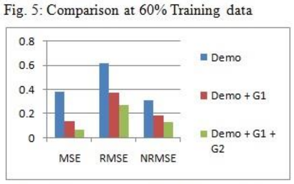

Fig.7: Comparison at 80% Training data

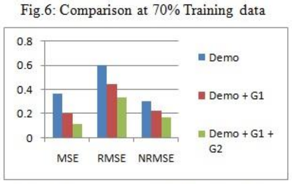

Fig.8: Comparison at 90% Training data

In third case when we consider all 32 attributes as an input and predicting G3 as output, our CFFBPNN model outperforms achieving lowest MSE of 0.07324 at 80% train and 20% test ratio. Thus our suggested CFFBPNN model gives better and efficient results with third case with all input parameters.

First graph shows MSE, RMSE and NRMSE with 60% train data, adding G1 reduces the error significantly, and adding G2 improves the model further. With more training data (70%), the performance improves slightly, though the overall pattern of error reduction stays consistent. With 80% training data, Again performance improves as compared to 60% and 70% and error reduction is consistent. With 90% training data, all models perform better compared to 60%, 70% and 80%. However, the performance hierarchy remains consistent—Demo + G1 + G2 performs the best, followed by Demo + G1, with Demo performing the worst.

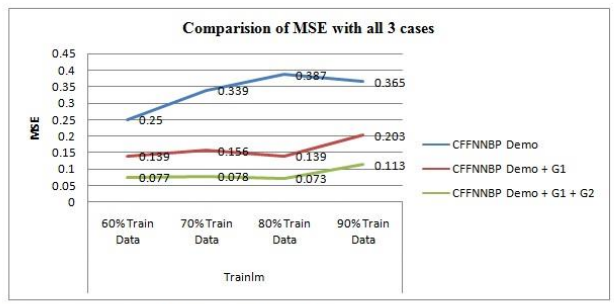

Fig.9: Comparison of MSE values of CFFBPNN

Across all percentages of training data (60%, 70%, and 80%), Demo + G1 + G2 consistently shows the best performance with the lowest MSE, RMSE, and NRMSE values. Increasing the amount of training data improves the performance of all models, as shown by the reduction in error values across the board. The model with only Demo (blue) has the highest error rates across all training data percentages, suggesting that the additional features G1 and G2 are important for improving model performance.

7. Conclusion and Future Scope

The CFFBPNN model was applied to a student performance dataset containing Portuguese language data. Initially, the CFFBPNN model was tested with various train-test split ratios to predict G3 in three different scenarios. The results indicated that, in addition to demographic features, academic attributes significantly impact the prediction of student performance, with the best outcomes achieved using all 32 attributes (including demographics, G1, and G2). Secondly, the Trainlm function consistently produced better results than the Traingdx function. Thirdly, across different data split ratios of 60%, 70%, 80%, and 90%, the CFFBPNN model using the Trainlm function outperformed the one using the Traingdx function, achieving the lowest MSE of 0.07324 in all cases. To develop a model that can produce the most accurate and consistently accurate predictions, each experiment must be repeated. According to experimental findings, the CFFBPNN model that was built has successfully predicted data sets with the lowest Mean Squared Error (MSE). Moreover, this modeling technique can be modified to fit a variety of datasets intended for student performance prediction. For the purpose of predicting student performance, further ANN models can be constructed.

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