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# Prediction of Student's Academic Performance through Data Mining Approach

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*Abstract* - The universities and institutes produce a large amount of student data that can be used in a disciplinary way and useful information can be extracted by using an automated approach. Educational Data Mining (EDM) is an emerging discipline used in the educational environment to deal with big student data and extract useful information. The data mining of students' data can help the At-risk students as well as the stakeholders by the early warning. This study aims to predict the performance of the students based on student-related data to increase the overall performance. In existing studies, insufficient attributes and complexity of network models is a problem. The student's current records and grades need to be analyzed. In this approach, the Levenberg Marquardt Algorithm (MLA) deep learning algorithm is used. The data consists of the class test, attendance, assignment and midterm scores. The neural network model consists of four input variables, three hidden and one output layer. The performance of the deep neural network is evaluated by accuracy, precision, recall and F1 score. The proposed model gained a higher accuracy of 88.6% than existing studies. The study successfully predicts the student's final grades using current academic records. This research will be beneficial to the students, educators and educational authorities as a whole.

*Keywords—Data Mining, Levenberg Marquardt Algorithm, Educational Data Mining, Deep Learning, Neural Network*

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## I. INTRODUCTION

The academic accomplishment of the students is the most important standard to evaluate the quality of education. The institutions are contending in this regard due to the competitive educational environment. Therefore, research in educational practices has significant value in increasing the quality of education. A large amount of student data can be assessed and measured in many ways for research objectives. EDM is an emerging discipline used in the educational environment to deal with big student academic data and extract useful information through data mining techniques [1, 2]. Another term is learning analytics which is closely related to educational data mining. Learning analytics refers to the investigation's analysis and data processing which the concerns of the learning aim and propose for those who want to understand, investigate, and optimize learning performance [3]. Students' performance can be evaluated by many influencing features. Academic, Demographic (learning attitude participation, performance grades), behavioral (attendance, study hours) and social (affection, activities) were affecting the student performance [4]. It was helpful to understand weak areas of the learner that cause failure and

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dropout and also essential to improve the quality of education. The authors [5] proposed data attributes of student grade records and attendance as they think these attributes are enough to measure the performance of students. The authors proposed that performance can be predicted by classroom activities, midterm scores and tests that can be held quarterly in a year [6]. The authors revealed that students' previous academic records played an important role in performance prediction while demographic and behavioral variables have less impact [7]. The authors also analyzed the current academic grades, attendance and assignment scores of 44 students but the accuracy of the prediction model was not so high [8]. The authors [9] used the academic record to predict performance using deep learning, but accuracy was not so high as compared to current studies. The prediction was based on academic background. The authors proposed the decision tree algorithm as the best predictor with 83.7% accuracy [10]. The information gathered from data and prediction enables educators, facilitators, managers, and policymakers to make necessary decisions and measures to increase learning quality and decrease academic failure.

The existing studies predicted students' performance well but have many limitations as insufficient attributes and the complexity of the network model. To cope with such margins, a modified network model with more current data attributes is used in this research to gain more accuracy and results. The authors revealed that insufficient and irrelevant attributes can minimize the prediction result [11]. This study predicts the performance of the students based on student-related data to increase the overall performance.

The main contribution of this research is developing a framework to predict academic performance using deep learning and a decision-making system for students, educators and other stakeholders.

The rest of the paper is organized as follows: The literature review has been discussed in section II. Research methodology with its research framework, dataset, and evaluation parameters including tools and technology have been discussed in section III. Section IV consists of the proposed work and section V concludes the research and provides the suggestion for future work.

## II. LITERATURE REVIEW

The authors used both NN and conventional statistical methods to predict the CGPA of the students. The authors [12] used socioeconomic data and the entrance exam results of undergraduate students to analyze performance. The conventional statistical method was used to identify affecting factors. An Artificial Neural network was used to predict performance and CGPA. The performance of ANN was evaluated through accuracy, error, sensitivity, specificity and precision. Levenberg Marquardt algorithm was used as a training rule. The results showed that ANN had achieved 84.8% accuracy. The study revealed that the performance of female students was better than male students. There was no effect of the locality; urban or rural, on performance prediction. The performance of non-repeating students was much better than repeating students. Parents, especially mothers can play a better role than fathers in the performance of the student.

The authors [13] proposed an improved version of the Deep Support Vector Machine (DSVM) based on an Improved Conditional Generative Adversarial Network (ICGAN). The proposed DSVM had hidden multiple layers and an output layer of SVM. The proposed methodology was used to predict students' performance under encouraging learning. The prediction was made along with school and family tutoring. The attributes were used like; parents' inhabitant status, parents' education and job, family relationship, school and family educational support. Results showed the usefulness of ICGAN with the current CGAN. The produced specificity, Area Under Curve (AUC) and sensitivity were 0.967, 0.971 and 0.954 respectively. The authors predicted that this study will help educators, scholars and parents to make decisions regarding supportive learning. The authors also suggested that the integration of both school and parent tutoring into the proposed model could increase performance.

The researchers [14] categorized the performance of the students into high, average and low. The proposed support vector machine was used to predict performance by using psychological factors and the academic grades of the students. Comparison algorithms were Decision Tree, KNN and Naive Bayes. Sensitivity, specificity and accuracy were used as evaluation parameters. The linear and radial-based kernel was used in prediction and a confusion matrix was used to compare the results of both. The result of previous studies showed an accuracy of 89%. The existing study overwrote the results. Results showed that the Radial Basis Function kernel indicated a more accurate value, which was 90%.

The authors [15] introduced admission criteria to assess the performance of the students at the early stages of the degree program. The authors proposed four data mining classifiers; Artificial Neural Network, Decision Tree, Support Vector Machine and Naive Bayes. Attributes of previous grade average, Scholastic Achievement Admission Test and GAT test scores were used. Accuracy, precision, recall and F-measure were used as evaluation parameters. Results showed that ANN had the highest accuracy of 79.22% while other classifiers were; DT (75.91%), SVM (75.82%) and NB (73.61%). Results also showed that attribute SAAT had the highest correlation at the value of 40% while HSDA and GAT had 30% each. SAAT was the criteria that can predict students' academic performance more correctly. The study helped the institute to change admission criteria according to the proposed model aiming for high performance of students at the early stages. The impact of new admission criteria was good as performance increased by 31% and the percentage of poor students decreased by 18%.

The researchers [16] used deep learning to predict the academic performance of at-risk students through regression analysis. Academic data of Bachelor of Arts (B.A.) students were collected. The authors used nine academic variables such as results of one to six semesters, total marks in six semesters, overall percentage, percentage and theory plus internal assessment marks. The authors used 80% training and 20% testing data. The authors focused on four research questions; the role of major subjects, performance-based on major subjects, the efficiency of deep learning on smaller data sets, and performance comparison of deep learning with a regression model. Results showed that the role of major subjects was crucial in SAPP. Results also showed that deep learning can perform better on small data sets. The performance of deep learning models was also better than the regression model. The results showed that Mean Absolute Error (MAE) and Mean Square Error (MSE) were 1.61 and 4.7 respectively while the regression model had MAE (1.97) and MSE (6.7). The authors conclude that deep learning models can be applied to both small and big data sets and outperform the linear regression model.

The authors [17] proposed a deep Artificial Neural Network (ANN) to predict the performance of at-risk students. Logistic regression and Support Vector Machine were comparison algorithms. The data set accessed from OULA provides the demographic behavior of the students. Virtual Learning Environment data was also retrieved. The authors used four class label categories such as pass-fail, withdrawn-pass, withdrawn-fail, and distinction pass. Accuracy, precision, recall, and MSE of all four categories were measured. The results showed that the proposed model gave an accuracy of 84%-93% and outperformed the comparison algorithms. The SVM and logistic regression have accuracies between 79.95%-89.14% and 79.82%-85.60% respectively. The accuracy of each model was measured in quartiles. The authors concluded that demographic features and student activity had a remarkable impact on SAPP. Such studies required formulation to provide a supportive and facilitative environment to the students and institutional authorities in the decision-making process.

The authors [18] used academic records such as assignments, quizzes, mid-term results, final-year research project results and behavioral data to forecast the performance of the student. The authors used MOODLE log files data to asses more features. The authors used a decision tree classifier. The proposed model showed 84% accuracy as compared to existing studies. The study concludes that students' behavior during sessions plays an important role in performance.

The authors [19] used a decision tree (j48) classifier to determine the key features of students' performance. In COVID-19, almost every institute changed the way of learning due to the pandemic therefore the authors used four different datasets having different attributes but the main focus was the mid-term exam results. The results showed that two main features i.e. mid-term and final-term have a strong impact on student performance while other behavioral and demographic features like age and attendance have less effect on performance.

The authors [20] proposed a method to predict the performance of enrolled students who had not completed their study program within the session. Early prediction helped at-risk students to adopt necessary measures and new learning attributes to avoid failure. Students' attributes were quizzes, repeating and enrolled courses, B-Board and initial tests were examined through a tree-based classification model. Decisions were made through evaluation parameters of accuracy, precision and recall. The proposed model was straightforward and was easily controlled by educators and practitioners. Students' performance can be assessed and controlled to improve the quality of education.

The authors [21] used 7 different techniques including Naive Bayes, Random Forest, Support Vector Machine, K-Nearest Neighbour, Logistic Regression, Artificial Neural Network and Deep Learning to examine learning management system data of distance learning programs. The authors used a prediction model based on three categories low, medium and high. The Deep Learning, Random Forest and Support Vector Machine provide better performance.

The researchers [22] used data mining techniques and the Markov Chains Model to examine future performance. The model used students' average previous semester CGPA as input data. The decision tree algorithm gained an accuracy of 41.67%.

The authors [23] forecast the student's performance based on their talents using UCI machine learning data. The authors used 33 different attributes The machine learning algorithms like SVM, DT, ID3 and NB were used but

SVM gained higher accuracy of nearly 85%. The authors concluded that student's talent and involvement play important roles in improving their performance in academics.

The authors [24] used seven different data mining algorithms to predict performance. The comparison algorithms were NB, SVM, KNN, NN, Random Forest and Logistic regression. The authors used midterm exam results as input. The performance of these algorithms was between 69-75% but random forest outperformed among these algorithms. The authors concluded that midterm exam result is the best attribute to predict performance.

## III. RESEARCH METHODOLOGY

### *A. Datasets*

The dataset is obtained from the Government Post Graduate College Safdarabad district Sheikhupura, Pakistan. The data contains students' academic scores for the BS program 1st semester, such as class tests, attendance, assignments and midterm scores as shown in Figure 1. These scores are taken as training data and the final score is target data.

Data pre-processing and cleaning methods are used to deal with incomplete data to make it ready for training and a normal probability distribution function is used for the supplementary analysis. This processed data is provided to a neural network model for the prediction. The data is divided into 70% training and 30% for testing. Accuracy, precision and recall are used as evaluation parameters to compare the performance of the predicted model. These evaluation parameters were also used in the studies based on prediction [25, 26]. The dataset used in this study is different from the literature review in terms of size and attributes (partially).

The data set was obtained and stored in an Excel file. The data was analyzed and only related attributes were selected. Students' personal and registration-related records were eliminated from the dataset. Figure 1 shows the selected attributes with their description.

| 1 | ClassTest | Assignment | Attendance | Midterm | Final |
|---|---|---|---|---|---|
| 2 | 10 | 8 | 10 | 25 | 34 |
| 3 | 10 | 8 | 8 | 27 | 35 |
| 4 | 10 | 9 | 8 | 26 | 31 |
| 5 | 9 | 8 | 7 | 25 | 29 |
| 6 | 9 | 7 | 7 | 24 | 30 |
| 7 | 8 | 6 | 7 | 26 | 24 |
| 8 | 7 | 8 | 7 | 21 | 26 |
| 9 | 7 | 6 | 7 | 22 | 24 |
| 10 | 6 | 7 | 7 | 18 | 28 |
| 11 | 6 | 6 | 7 | 18 | 21 |
| 12 | 6 | 5 | 7 | 17 | 20 |
| 13 | 6 | 6 | 7 | 16 | 23 |
| 14 | 6 | 6 | 7 | 14 | 24 |
| 15 | 6 | 6 | 7 | 15 | 20 |
| 16 | 6 | 6 | 7 | 14 | 21 |
| 17 | 6 | 5 | 7 | 13 | 20 |
| 18 | 6 | 5 | 6 | 14 | 19 |
| 19 | 6 | 5 | 6 | 15 | 19 |
| 20 | 6 | 5 | 6 | 16 | 18 |
| 21 | 6 | 7 | 6 | 10 | 20 |
| 22 | 6 | 5 | 6 | 9 | 17 |
| 23 | 6 | 5 | 6 | 10 | 16 |
| 24 | 6 | 7 | 6 | 11 | 15 |
| 25 | 6 | 5 | 6 | 14 | 14 |
| 26 | 6 | 7 | 6 | 15 | 16 |
| 27 | 5 | 5 | 7 | 17 | 17 |
| 28 | 5 | 4 | 6 | 15 | 16 |
| 29 | 5 | 5 | 6 | 18 | 14 |
| 30 | 5 | 2 | 6 | 9 | 15 |
| 31 | 2 | 7 | 6 | 10 | 15 |
| 32 | 2 | 5 | 6 | 8 | 16 |
| 33 | 1 | 6 | 9 | 9 | 14 |
| 34 | 1 | 4 | 9 | 7 | 17 |
| 35 | 0 | 7 | 6 | 7 | 15 |
| 36 | 0 | 6 | 7 | 7 | 10 |

Figure 1. Snippet of Dataset

The data set was obtained and stored in an Excel file. The data was analyzed and only related attributes were selected. Students' personal and registration-related records were eliminated from the dataset. Table 1 shows the selected attributes with their description.

Table 1. Attributes of Student Data with Description

| **Sr. #** | **Data Attributes** | **Description** |
|---|---|---|
| **1** | Class_Test_Score | Class test score of the student |
| **2** | Assignment_Score | Assignment scores for the current semester |
| **3** | Attendance_Score | Attendance of the current semester |
| **4** | Midterm_Score | Midterm result score of the current semester |

The importance of predictors is trustworthy in performance prediction. Some predictors like student age and study grades are common predictors and have a high correlation to performance while social relationships and parents' behavior, etc are uncommon predictors that have less influence [4]. The researchers showed that the most influential predictor is students' current and current grades and attendance can provide promising results [27, 28].

*B. Proposed Method*

The proposed methodology consists of 5 layers. In the first layer, the student's academic and behavioral data is obtained, in the second layer; data processing is done including data preprocessing and cleaning. The data obtained is cleaned as there may be incorrect, missing, or duplicate entities. The data is prepared according to the research aim and only desired variables are included. The third layer consists of the analysis prediction model. Levenberg Marquardt Algorithm (MLA) deep learning algorithm is used to train Multi-Layer Perceptron. The optimized MLA is used by changing the network and removing complexities. The current academic scores (see Equation (1)) are taken as input neurons that are denoted by Xi where 'i' can be increased depending on the number of input variables, such as,

$$Xi = \{X1, X2, X3 \ldots.\} \quad (1)$$

The fourth layer is a data analytics layer that consists of knowledge extraction and ranking in academics. The results are visualized according to the study's aim. Layer five is an application layer. The obtained results can be applied according to the research aim. The prediction helps not only at-risk students but also other stakeholders like parents and institutions. It can also help the policymakers. The application will help to apply the proposed model in educational institutes. Figure 2 shows the complete design of the proposed model.

The experiments for the proposed computational method were implemented using MATLAB R2020a running on Microsoft Windows 10 64-bit OS. The desktop PC was built with 4 GM Random Access Memory (RAM) and an Intel Core i3 2.30 GHz Central Processing Unit (CPU).

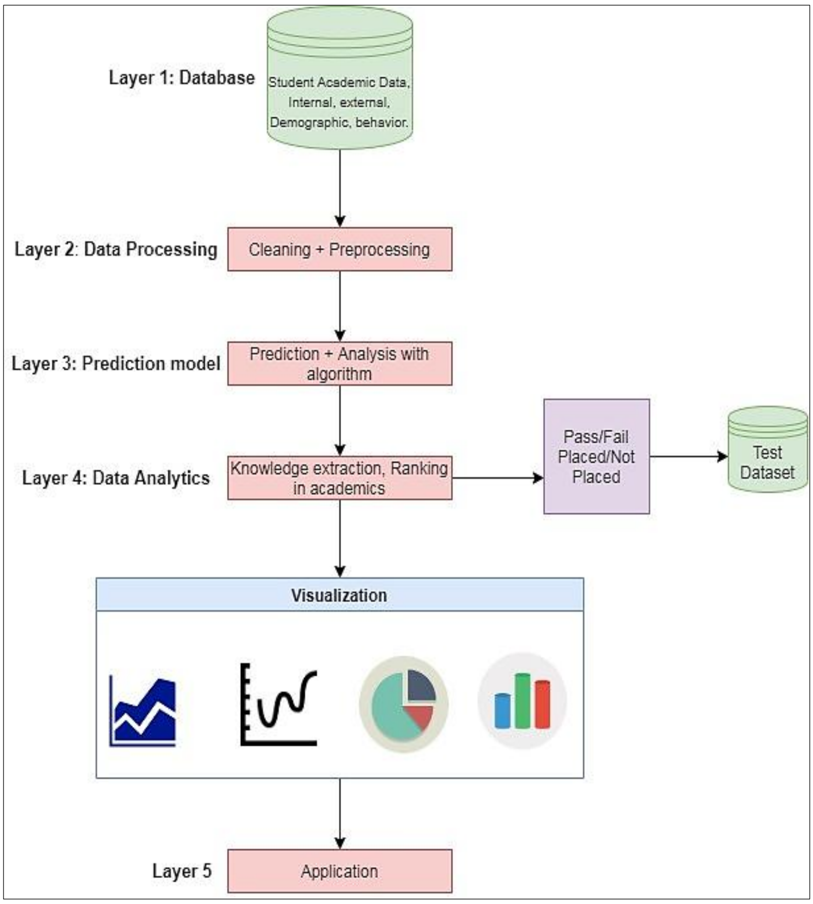


Figure 2. Workflow of Proposed Methodology

## IV. RESULTS AND DISCUSSIONS

This study focuses on the prediction of students' final scores using a deep neural network. The student's current academic and behavioral data is assessed for the prediction of students' performance as final grades by selecting a neural network model using the MATLAB fitting tool.

The dataset is divided into two portions such as (70:30) using the MATLAB tool. 70% data is selected as training, and 30% data is taken as testing and validation. The input variables are assigned weighs and brought up with a bias. Then a transfer function conceded this data to the hidden layer. The sigmoid function between the input and the hidden layer was used. The final output is customized to attain minimal error. The data can also be used for comparison purposes.

### *A. Training Datasets*

First, the dataset is loaded into the MATLAB workspace. Two variables were created named Training_Datasets and Training_Datasets_Options and used DetectImportOptions to detect the options we have to import the dataset. Another variable Training_Datasets used and readtable function to read the dataset. The dataset is read as a file, not as an exile. The training and target functions are now ready to load the dataset. As we have the dataset ready, we can design and train the network. To train the network, a variable Train_Network took the Training Datasets and target dataset as input arguments. Levenberg Marquardt Algorithm (MLA) backpropagation is used which has three hidden layers and 10 nodes in each layer. Then used set_random_stream and arbitrary values to make sure the network generated the same results every time. The network has been designed. We used fitnet function to construct the network. The first argument is Network_architecture and the second is LearningAlgorithms and it returned the network we need. The dataset was divided randomly and considered as the sample while dividing. 70% of the data is selected as training, and 30% data is taken as testing data. The performance is evaluated as Mean square Error (MSE) and we want to plot the performance, training_state, and error histogram and regression graph. Finally, use the train function to train the network. After training, the function will return the predictor which is the trained network and training records. The training is completed with 18 iterations. The error histogram shows good results as most of the errors occurred near zero point and gradually decreased when moving away from zero point. The results in the regression plot showed good results with an overall R=0.97633 value. The error histogram and regression plot are in Figure 3 and Figure 4 respectively.

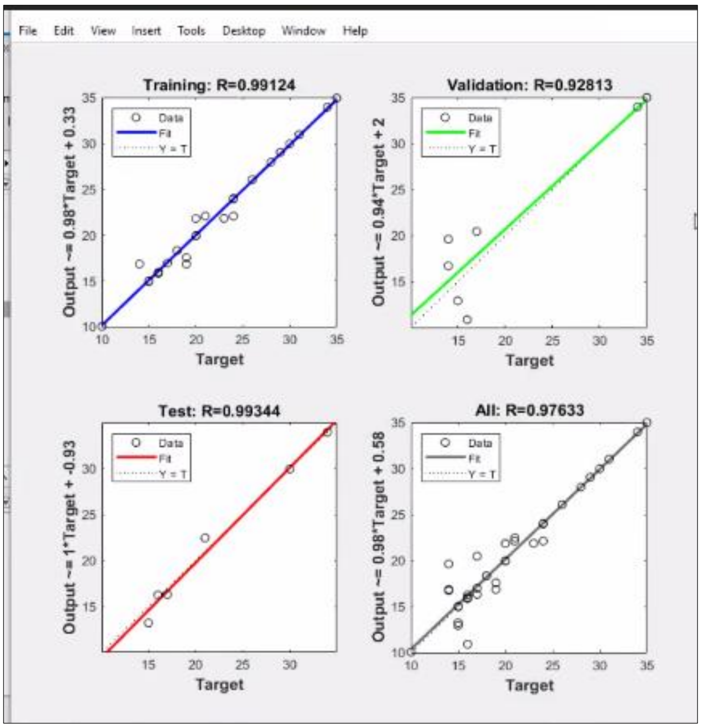


Figure 3. Regression Plot of Datasets

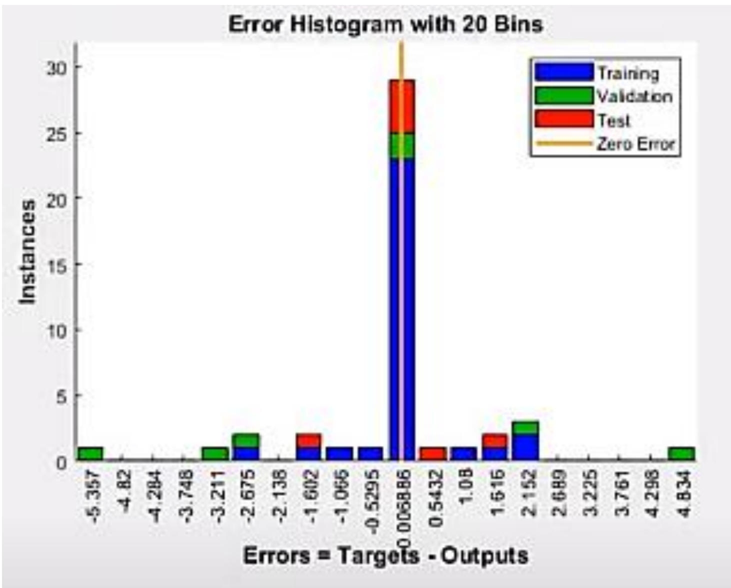


Figure 4. Error Histogram of the Model

*B. Test Network*

The training is completed, now test the network by creating a new stream Test_Network where a function to test the network is to return the predicted score of final exams and the total predicted score. The name of the function is Test_Network, it takes the predictor which is the trained network and the data as arguments. The data means the class tests, attendance, assignments and mid-term scores of the students. Take a variable named final and use the predictor to predict the final score. The arguments have been transposing of the data then the total score is the sum of the data plus the predicted final exam score that is enough for this function. Let's see the performance of the network. Suppose a student gets 9 in-class tests, 10 in attendance, 10 in assignments and 28 in the midterm. Our deep neural network predicts that the student will get 26.53 in the final exams out of 40 and its total score will be 83.35 which means the performance will be good as in Figure 5. Another student gets 5 in-class tests, 7 in attendance, 6 in assignments and 14 in the midterm. According to our deep neural network, the 15.24 score in the final exams and his total score will be 47.24 as in Figure 6. So, our network can predict the performance of the students well.

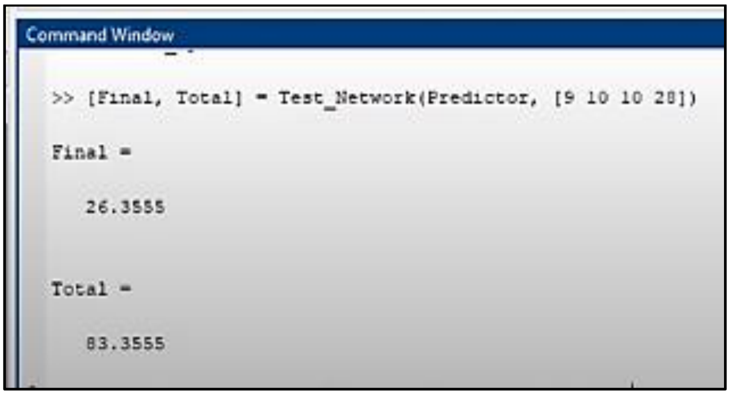


Figure 5. Performance of the Network

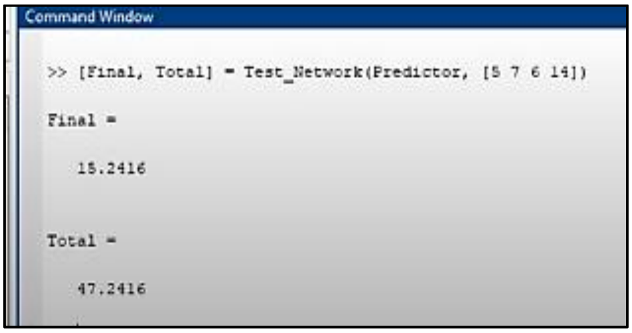


Figure 6. Predicted Results

*C. Confusion Matrix*

To calculate accuracy, precision and recall, a confusionmat function is used that requires two arguments: actual and predicted values. The confusion matrix was generated. To calculate accuracy, precision, recall and F1 score, the confusion matrix is transposed as a variable cmt and transposes the confusion matrix. The desired confusion matrix is ready.

Accuracy tells how a model predicts accurately. In other words, it is a measurement of authenticity. The study showed 88.6% accuracy. The formula of accuracy in terms of true positive TP, true negative TN, false positive FP and false negative FN is as in Equation (2).

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+TN+FP} \tag{2}$$

To calculate precision, need to get diagonal values from the confusion matrix and variable named diagonal along with the diag function. The argument of this diag function is the transposed confusion matrix. Take a variable named sum_of_rows and use the sum function. The first argument of the sum function is the transpose of the confusion matrix and the second argument is a value. The division of diagonal and sum of rows is a precision. The study showed 96.3% precision. The formula of precision in terms of true-positive TP and false-positive FP is as depicted in Equation (3).

$$\text{Precision}= \frac{TP}{TP+FP} \tag{3}$$

To calculate recall, the sum of columns is generated using the sum_of_columms variable along with the sum function. The arguments are cmt and a value. The division between diagonal and sum_of_columns gives recall. The overall recall is generated using a mean function with argument recall. The study showed 89.6% recall. The formula of recall in terms of true positive TP and false negative FN is as in Equation (4).

$$\text{Recall} = \frac{TP}{TP+FN} \tag{4}$$

The F1 score (see Equation (5)) is generated using multiplication and summation of overall precision and recall. The division of both with multiplication with 2 gives a recall value. The study showed a 93.3% F1 score.

$$\text{F1} = \frac{2 \times Precision \times Recall}{Precision+Recall} \tag{5}$$

Table 2 shows the confusion matrix result in terms of accuracy, precision, recall and F1 score.

Table 2. Confusion Matrix Results

| Sr. # | Parameters | Results in Percentage |
|---|---|---|
| **1** | Accuracy | 88.6% |
| **2** | Precision | 96.3% |
| **3** | Recall | 89.6% |
| **4** | F1 score | 93.3% |

Table 3 shows the comparison of existing studies with the proposed study.

Table 3. Comparison of Studies

| Reference | Year | Technique | Accuracy |
|---|---|---|---|
| **[12]** | 2019 | Classification using ANN | 84.8% |
| **[18]** | 2022 | Prediction using current academic data | 84% |
| **[7]** | 2023 | Prediction using academic background | 87% |
| **Proposed model** | 2023 | Prediction using current academic data | 88.6% |

Figure 7 shows the distribution of TP, TN, FP and FN in the confusion matrix.

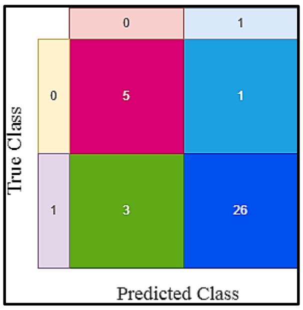


Figure 7. Confusion Matrix

## V. CONCLUSION

Predicting student academic performance is an essential question that arises in educational practices that are important to improve learning capabilities that cause improvements in the quality of education. Previous studies were reviewed based on predicting performance with both technical and non-technical attributes. Researchers used the academic record and behavior of students as the data set. Social and demographic data were also used. The results were made under data mining techniques based on clustering and classification. NB, DT and NN were highly used. The existing studies have drawbacks like the use of insufficient student data attributes and complexity in the NN model. The study analyzes three research questions the first research question is how to predict student academic performance through deep learning. The answer is that deep learning successfully predicts student final grades using the current academic records with the help of the LM Algorithm. The second research question is how do current academic scores play an important role in performance? The current academic scores played an important role in predicting final grades effectively as the proposed model gained a higher accuracy of 88.6%thanthe previous. The third research question was how this study will help students, educators, policymakers and other stakeholders in student academic performance prediction. The early prediction helps the at-risk students at different levels. The early prediction is beneficial to the students, educators and educational authorities as a whole. It can develop a better data-driven decision-making system for all stakeholders. The performance of the deep NN model is evaluated by accuracy, precision, recall and F1 score. A systematic and rational literature review also helps educators and learners to understand study patterns and practices.

This research recommends the use of more attributes like the effects of social affection and media can be added for further effective research. For the future perspective, the large publicly available data sets should be used in performance prediction. Further improvements in the NN model can be made.

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## REFERENCES

[1] E. Aksoy, S. Narli, and M. A. Aksoy, “An Educational Data Mining Application by Using Multiple Intelligences”, in *Examining Multiple Intelligences and Digital Technologies for Enhanced Learning Opportunities*, ed: IGI Global, 2020, pp. 93-110.

[2] A. Tüfekci and E. A. G. Yılmaz, “Educational Data Mining: A Systematic Literature Mapping Study”, *Engineering Education Trends in the Digital Era,* pp. 70-82, 2020.

[3] N. Tomasevic, N. Gvozdenovic, and S. Vranes, “An overview and comparison of supervised data mining techniques for student exam performance prediction”, *Computers & education,* vol. 143, p. 103676, 2020.

[4] I. Issah, O. Appiah, P. Appiahene, and F. Inusah, “A systematic review of the literature on machine learning application of determining the attributes influencing academic performance”, *Decision Analytics Journal,* p. 100204, 2023.

[5] K. S. Bhagavan, J. Thangakumar, and D. V. Subramanian, “Predictive analysis of student academic performance and employability chances using HLVQ algorithm”, *Journal of Ambient Intelligence and Humanized Computing,* vol. 12, pp. 3789-3797, 2021.

[6] A. Abdelmagid and A. Qahmash, “Utilizing the Educational Data Mining Techniques" Orange Technology" for Detecting Patterns and Predicting Academic Performance of University Students”, *Inf. Sci. Lett,* vol. 12, pp. 1415-1431, 2023.

[7] M. H. B. Roslan and C. J. Chen, “Predicting students’ performance in English and Mathematics using data mining techniques”, *Education and Information Technologies,* vol. 28, pp. 1427-1453, 2023.

[8] N. Z. Salih and W. Khalaf, “Prediction of student’s performance through educational data mining techniques”, *Indonesian Journal of Electrical Engineering and Computer Science,* vol. 22, pp. 1708-1715, 2021.

[9] L. Gerritsen and R. Conijn, “Predicting student performance with Neural Networks”, *Tilburg University, Netherlands,* 2017.

[10] M. Al-Saleem, N. Al-Kathiry, S. Al-Osimi, and G. Badr, “Mining educational data to predict students’ academic performance”, in *Machine Learning and Data Mining in Pattern Recognition: 11th International Conference, MLDM 2015, Hamburg, Germany, July 20-21, 2015, Proceedings 11*, 2015, pp. 403-414.

[11] S. Batool, J. Rashid, M. W. Nisar, J. Kim, H.-Y. Kwon, and A. Hussain, “Educational data mining to predict students' academic performance: A survey study”, *Education and Information Technologies,* vol. 28, pp. 905-971, 2023.

[12] E. Lau, L. Sun, and Q. Yang, “Modelling, prediction and classification of student academic performance using artificial neural networks”, *SN Applied Sciences,* vol. 1, pp. 1-10, 2019.

[13] K. T. Chui, R. W. Liu, M. Zhao, and P. O. De Pablos, “Predicting students’ performance with school and family tutoring using generative adversarial network-based deep support vector machine”, *IEEE Access,* vol. 8, pp. 86745-86752, 2020.

[14] I. Burman and S. Som, “Predicting students academic performance using support vector machine”, in *2019 Amity international conference on artificial intelligence (AICAI)*, 2019, pp. 756-759.

[15] H. A. Mengash, “Using data mining techniques to predict student performance to support decision making in university admission systems”, *Ieee Access,* vol. 8, pp. 55462-55470, 2020.

[16] S. Hussain, S. Gaftandzhieva, M. Maniruzzaman, R. Doneva, and Z. F. Muhsin, “Regression analysis of student academic performance using deep learning”, *Education and Information Technologies,* vol. 26, pp. 783-798, 2021.

[17] H. Waheed, S.-U. Hassan, N. R. Aljohani, J. Hardman, S. Alelyani, and R. Nawaz, “Predicting academic performance of students from VLE big data using deep learning models”, *Computers in Human behavior,* vol. 104, p. 106189, 2020.

[18] J. de Deus Guterres, K. A. Laksitowening, and F. Sthevanie, “PREDICTING STUDENTS’PERFORMANCE IN BASIC ALGORITHMS PROGRAMMING IN AN E-LEARNING ENVIRONMENT USING DECISION TREE APPROACH”, *Journal of Syntax Literate,* vol. 7, 2022.

[19] M. Al Karim, M. Y. Ara, M. M. Masnad, M. Rasel, and D. Nandi, “Student performance classification and prediction in fully online environment using Decision tree”, *AIUB Journal of Science and Engineering (AJSE),* vol. 20, pp. 70-76, 2021.

[20] J. Figueroa-Cañas and T. Sancho-Vinuesa, “Early prediction of dropout and final exam performance in an online statistics course”, *IEEE Revista Iberoamericana de Tecnologias del Aprendizaje,* vol. 15, pp. 86-94, 2020.

[21] R. BÜTÜNER and M. H. Calp, “Estimation of the Academic Performance of Students in Distance Education Using Data Mining Methods”, *International Journal of Assessment Tools in Education,* vol. 9, pp. 410-429, 2022.

[22] S. Mallak, M. Kanan, N. Al-Ramahi, A. Qedan, and H. Khalilia, “Using Markov Chains and Data Mining Techniques to Predict Students’ Academic Performance”, 2023.

[23] H. Pallathadka, A. Wenda, E. Ramirez-Asís, M. Asís-López, J. Flores-Albornoz, and K. Phasinam, “Classification and prediction of student performance data using various machine learning algorithms”, *Materials today: proceedings,* vol. 80, pp. 3782-3785, 2023.

[24] M. Yağcı, “Educational data mining: prediction of students' academic performance using machine learning algorithms”, *Smart Learning Environments,* vol. 9, p. 11, 2022.

[25] S. T. Lim, J. Y. Yuan, K. W. Khaw, and X. Chew, “Predicting Travel Insurance Purchases in an Insurance Firm through Machine Learning Methods after COVID-19”, *Journal of Informatics and Web Engineering,* vol. 2, pp. 43-58, 2023.

[26] Z. Yujiao, L. W. Ang, S. Shaomin, and S. Palaniappan, “Dropout Prediction Model for College Students in MOOCs Based on Weighted Multi-feature and SVM”, *Journal of Informatics and Web Engineering,* vol. 2, pp. 29-42, 2023.

[27] R. Mehdi and M. Nachouki, “A neuro-fuzzy model for predicting and analyzing student graduation performance in computing programs”, *Education and Information Technologies,* vol. 28, pp. 2455-2484, 2023.

[28] M. Abou Naaj, R. Mehdi, E. A. Mohamed, and M. Nachouki, “Analysis of the Factors Affecting Student Performance Using a Neuro-Fuzzy Approach”, *Education Sciences,* vol. 13, p. 313, 2023.