# A Deep Learning Approach for Predicting Student Academic Performance Using Artificial Neural Networks and Educational Data Mining

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**Student Academic Performance Using Artificial Neural Networks and Educational Data Mining**

**DOI:** https://doi.org/10.51583/IJLTEMAS.2026.15020000032

**Received: 14 February 2026; Accepted: 19 February 2026; Published: 05 March 2026**

## ABSTRACT

Early prediction of student academic performance is essential for improving learning outcomes and enabling timely educational intervention. Traditional statistical methods often fail to capture the complex and non-linear relationships among academic, behavioral, and engagement-related factors that influence student success. This study proposes a deep learning–based predictive framework using an Artificial Neural Network (ANN) integrated with educational data mining techniques to forecast student academic performance before final examinations.

The model incorporates multidimensional input features, including continuous assessment scores, attendance percentage, assignment performance, midterm marks, and Learning Management System (LMS) engagement indicators. Data preprocessing techniques such as cleaning, normalization, and feature encoding were applied to ensure data quality and model stability. A multilayer feedforward neural network was trained using supervised learning with adaptive optimization to learn hidden relationships within the dataset.

Experimental evaluation on 1,200 student records demonstrated strong predictive performance, achieving a testing $R^2$ value of 0.88 with low prediction errors (MAE = 3.78; RMSE = 4.89). Comparative analysis confirmed that the proposed ANN model outperformed traditional machine learning algorithms, including Decision Tree, K-Nearest Neighbors, and Support Vector Machine. Statistical validation further indicated that there was no significant difference between predicted and actual performance, confirming the reliability of the model.

The proposed framework provides a practical early warning system for identifying academically at-risk students and supports data-driven decision-making in higher education. The findings contribute to the development of intelligent academic monitoring systems that integrate predictive analytics into modern educational environments.

**Keywords:** Artificial Neural Networks, Educational Data Mining, Student Performance Prediction, Deep Learning, Early Warning Systems, Machine Learning in Education

**List of Abbreviations**

| | |
|---|---|
| ANN | Artificial Neural Network |
| DL | Deep Learning |
| EDM | Educational Data Mining |
| ML | Machine Learning |
| LMS | Learning Management System |
| GPA | Grade Point Average |

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue II, February 2026

| | |
|---|---|
| MSE | Mean Squared Error |
| RMSE | Root Mean Squared Error |
| MAE | Mean Absolute Error |
| $R^2$ | Coefficient of Determination |
| SGD | Stochastic Gradient Descent |
| GD | Gradient Descent |
| BP | Backpropagation |
| FFNN | Feed Forward Neural Network |
| CNN | Convolutional Neural Network |
| RNN | Recurrent Neural Network |
| KNN | K-Nearest Neighbors |
| SVM | Support Vector Machine |
| NB | Naïve Bayes |
| DT | Decision Tree |
| RF | Random Forest |

# INTRODUCTION

### Background of the Research

Education systems today generate a massive volume of digital data through examinations, assignments, attendance monitoring, online learning platforms, and student information systems. This rapid growth of educational data has created new opportunities for institutions to analyze student learning behavior and predict academic outcomes using intelligent computational techniques. Traditionally, educators evaluate student performance based on final examination marks or periodic assessments. However, such approaches identify struggling students only after academic failure has already occurred, limiting the possibility of timely intervention.

With the advancement of Artificial Intelligence (AI) and Machine Learning (ML), predictive analytics has emerged as a powerful tool for understanding learning patterns and forecasting student achievement. Educational Data Mining (EDM) focuses on extracting meaningful knowledge from educational datasets to support decision-making in teaching and learning environments. Among various ML techniques, Artificial Neural Networks (ANN) have demonstrated superior capability in modeling complex and non-linear relationships within large datasets.

Student academic performance is influenced by multiple interconnected factors including attendance, continuous assessment results, assignment completion, engagement level, socio-economic background, and learning behavior. These variables interact in complicated ways that traditional statistical methods cannot adequately capture. Deep learning–based ANN models can automatically learn hidden relationships among these factors and provide accurate performance predictions.

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue II, February 2026

Therefore, this research aims to design and implement a predictive framework using Artificial Neural Networks to forecast student academic performance at an early stage. The model enables educators to identify at-risk students and apply timely academic support strategies, improving learning outcomes and reducing dropout rates.

**Research Problem**

Educational institutions often rely on conventional evaluation methods such as midterm and final examination results to measure student achievement. These methods present several limitations:

- They detect weak performance too late for effective intervention.
- They fail to analyze behavioral and engagement-related factors.
- They cannot model non-linear relationships among academic variables.
- They depend heavily on human judgment and experience.

As a result, students who require academic assistance are often identified only after failure has occurred. This leads to poor academic progression, increased dropout rates, and inefficient allocation of educational resources.

The main problem addressed in this research is:

"How to accurately predict student academic performance at an early stage using historical and behavioral educational data through an intelligent deep learning model?"

This study attempts to develop a data-driven predictive system capable of identifying academically at-risk students before final examinations.

**Objectives of this Research**

The main purpose of this research is to design a predictive analytical model capable of forecasting student academic performance using Artificial Neural Networks and educational data mining techniques.

**Research Objective**

1. To identify the most influential attributes affecting student performance.
2. To design and implement an Artificial Neural Network predictive model.
3. To evaluate prediction accuracy using performance metrics such as MSE, RMSE, MAE, and $R^2$.
4. To compare predicted performance with actual student results.
5. To develop an early warning system for identifying academically at-risk students.

**Research Outcomes**

This research is expected to produce the following outcomes:

- A trained ANN-based prediction model for student academic performance
- Identification of key factors influencing learning success
- Early detection mechanism for weak students
- A decision-support framework for educators and administrators
- Improved academic monitoring and intervention strategies

- Contribution to the application of deep learning in education analytics

**Overview of the Chapters in This Report**

**Introduction**

Provides the background, research problem, objectives, and structure of the study.

**Literature Review**

Discusses previous research related to educational data mining, machine learning approaches, and neural network models used in academic performance prediction.

**Methodology**

Describes data collection, preprocessing techniques, feature selection, model architecture, training procedures, and evaluation metrics used in the study.

**Results and Discussion**

Presents experimental results, model performance analysis, and comparison with existing methods.

**Conclusions, Recommendations, and Limitations**

Summarizes findings, discusses limitations, and proposes improvements and future research directions.

**References**

Lists all academic sources, research papers, and materials referenced throughout the study.

## LITERATURE REVIEW

This chapter reviews previous studies related to student academic performance prediction using Educational Data Mining (EDM), Machine Learning (ML), and Deep Learning techniques. The review highlights existing methods, their advantages, limitations, and the research gap addressed in this study.

**Educational Data Mining in Academic Performance Prediction**

Educational Data Mining (EDM) is an interdisciplinary research area that focuses on extracting meaningful patterns from educational datasets in order to improve teaching and learning processes. With the growth of digital learning environments such as Learning Management Systems (LMS), institutions collect large volumes of student data including attendance, assessments, interaction logs, and demographic details. Researchers have used this data to identify learning behaviors, predict outcomes, and support academic decision-making.

Early studies in EDM mainly relied on statistical analysis techniques such as regression and correlation analysis to understand the relationship between study habits and performance. These approaches were useful in identifying basic trends but lacked the ability to model complex relationships between multiple factors affecting academic success.

Recent research shows that academic performance is influenced by a combination of academic, behavioral, and socio-demographic attributes. EDM techniques help discover hidden patterns such as low engagement, irregular attendance, and incomplete coursework that often lead to poor academic results. Therefore, EDM has become an essential tool for building early warning systems that can identify at-risk students before final examinations.

**Machine Learning Techniques for Student Performance Prediction**

Machine Learning (ML) algorithms have been widely applied in predicting student academic achievement. These algorithms learn patterns from historical educational data and make predictions about future performance.

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Several commonly used ML algorithms include:

**Decision Tree and Random Forest**

Decision Tree models classify students based on attribute rules such as attendance percentage or assignment marks. They are easy to interpret and useful for academic advisors. Random Forest improves prediction accuracy by combining multiple decision trees. However, these models may struggle when relationships between variables become highly non-linear.

**Support Vector Machine**

Support Vector Machine (SVM) is effective in classification problems and works well with high-dimensional datasets. It has been used to classify students into pass/fail categories. Although accurate, SVM requires careful parameter tuning and may not perform well on extremely large datasets.

**K-Nearest Neighbors**

K-Nearest Neighbors (KNN) predicts student results by comparing similar student records. It is simple to implement but becomes computationally expensive with large educational datasets and is sensitive to noisy data.

**Naïve Bayes**

Naïve Bayes classifiers have been applied to predict student grades using probability distributions. They perform well on smaller datasets but assume independence among variables, which is unrealistic in education where factors are highly related.

Overall, traditional machine learning algorithms can achieve moderate prediction accuracy but often fail to capture complex interactions among multiple academic and behavioral attributes.

**Deep Learning Approaches in Education Analytics**

Deep Learning is a subset of machine learning that uses multi-layer neural networks to learn complex patterns from large datasets. Unlike traditional algorithms, deep learning automatically extracts important features without manual selection.

**In education, deep learning models have been applied to:**

- Predict final exam performance
- Detect dropout risk
- Analyze learning behavior
- Recommend personalized learning paths

Research findings indicate that deep learning models outperform traditional ML methods because student learning behavior contains hidden relationships that cannot be modeled using simple linear techniques.

Deep learning is particularly useful when educational datasets include multiple types of attributes such as numeric marks, categorical demographic information, and temporal activity logs.

**Artificial Neural Networks for Academic Performance Prediction**

Artificial Neural Networks (ANN) are one of the most widely used deep learning techniques in educational prediction systems. ANN models simulate the human brain's learning process by adjusting connection weights during training. Researchers have used multilayer feedforward neural networks to predict student performance based on:

- Attendance records

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue II, February 2026

- Continuous assessment marks
- Assignment completion
- Classroom participation
- Learning behavior
- Socio-economic background

ANN models learn non-linear relationships between these attributes and academic outcomes. Studies report that ANN produces higher accuracy compared to Decision Trees, SVM, and Naïve Bayes classifiers.

Another advantage of ANN is its ability to generalize from incomplete or noisy educational data. This makes it suitable for real-world academic datasets where missing values and irregular patterns frequently occur.

**Early Warning Systems for At-Risk Students**

One major application of predictive analytics in education is early identification of academically weak students. Early warning systems analyze ongoing student activities and provide alerts to educators.

Previous research indicates that students who:

- Miss classes frequently
- Submit assignments late
- Show low LMS interaction
- Perform poorly in early assessments are highly likely to fail final examinations.

Predictive models allow instructors to intervene early through counseling, extra classes, or personalized learning materials. Institutions using predictive systems report improved retention rates and reduced dropout levels.

**Research Gap**

Although many studies have used machine learning techniques for student performance prediction, several limitations remain:

1. Traditional ML algorithms cannot effectively model complex non-linear relationships.
2. Some studies only use academic marks and ignore behavioral factors.
3. Many systems classify only pass/fail instead of predicting actual performance levels.
4. Early prediction accuracy remains insufficient for reliable intervention.

Therefore, there is a need for a more accurate predictive model that integrates academic, behavioral, and demographic attributes using deep learning techniques.

This research proposes an Artificial Neural Network-based predictive framework capable of identifying atrisk students at an early stage with higher prediction accuracy.

## METHODOLOGY

This chapter presents the methodological framework adopted to design, implement, and evaluate the proposed Artificial Neural Network (ANN)-based predictive model for student academic performance. The methodology integrates principles from educational data mining, machine learning, and statistical validation to ensure that the

ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue II, February 2026

developed model is both technically sound and scientifically reliable. Each stage of the research process is described in detail to ensure transparency, reproducibility, and academic rigor.

**Research Design and Overall Framework**

This research follows a **quantitative experimental research design** grounded in predictive analytics and supervised machine learning. The primary objective is to develop a data-driven model capable of forecasting student academic performance before final examinations, thereby enabling early academic intervention.

Unlike traditional descriptive research, this study adopts a predictive modeling approach where historical student data are used to train a computational model that learns hidden patterns and relationships among academic variables. The study is structured as a sequential process consisting of five major phases:

1. Data acquisition and consolidation
2. Data preprocessing and transformation
3. Feature analysis and selection
4. ANN model construction and training
5. Model evaluation and statistical validation

The independent variables include measurable academic and behavioral attributes, while the dependent variable represents final academic performance. The model learns a mapping function between input variables and output performance through iterative optimization.

**This research design ensures:**

- Objectivity in model development
- Reproducibility of results
- Empirical validation of findings
- Minimization of researcher bias

The experimental nature of the study allows for comparison between predicted and actual performance, thereby validating the effectiveness of the proposed framework.

**Data Collection and Preparation**

**Data Sources and Sampling Strategy**

The dataset used in this research was obtained from institutional academic management systems and Learning Management System (LMS) platforms. These systems record structured student data throughout the semester.

The collected data represent multiple cohorts across different academic periods to improve generalizability and reduce sample bias. Each student record constitutes a single observation containing academic and engagement-related variables.

The selected attributes include:

- Attendance percentage
- Continuous assessment results

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- Assignment submission scores
- Midterm examination marks
- LMS login frequency
- Classroom participation indicators
- Final examination marks (target variable)

The inclusion of both academic and behavioral indicators ensures that the model captures multidimensional aspects of student performance rather than relying solely on examination marks.

The sampling strategy was based on availability and completeness of records. Only students with sufficiently complete data were included to maintain dataset reliability.

**Data Cleaning and Quality Assurance**

Raw educational data often contain inconsistencies, missing values, typographical errors, and redundant records. Therefore, systematic data cleaning was conducted.

The cleaning process involved:

- Identifying and removing duplicate entries
- Detecting missing values across variables
- Applying appropriate imputation methods (mean or median replacement)
- Identifying extreme outliers using statistical thresholds
- Verifying logical consistency (e.g., attendance cannot exceed 100%)

Outliers were carefully examined before removal to ensure that legitimate extreme performers were not excluded without justification.

Data consistency checks were also conducted to confirm alignment between LMS logs and assessment records.

**Data Transformation and Normalization**

Since neural networks are sensitive to scale differences among input variables, all numerical attributes were normalized to a consistent range. This prevents large-valued features (such as total marks) from dominating smaller-scale variables (such as participation counts).

Categorical variables, if present, were encoded into numerical form using appropriate encoding techniques.

Normalization contributes to:

- Faster convergence during training
- Improved gradient stability
- Reduced computational imbalance

Following preprocessing, the dataset was partitioned into training, validation, and testing subsets. This separation ensures that model performance is evaluated on previously unseen data, which enhances external validity.

**Development of the Artificial Neural Network Model**

**Model Architecture Design**

A Multilayer Feedforward Artificial Neural Network was designed to capture non-linear relationships among academic variables.

The network consists of:

- An input layer representing selected features
- One or more hidden layers responsible for pattern extraction
- A single output layer producing predicted academic performance

Hidden layers use non-linear activation functions to enable the model to learn complex interactions between attendance, assessments, and engagement patterns.

The number of neurons and hidden layers was determined experimentally. Multiple configurations were tested to identify an optimal balance between model complexity and generalization ability.

An excessively simple network may underfit the data, while an overly complex network may overfit and lose predictive reliability. Therefore, architecture selection was guided by validation performance.

**Training Procedure and Optimization**

The ANN model was trained using supervised learning. During each training iteration:

1. Student data were passed through the network to generate predictions.
2. Prediction error was computed by comparing predicted values with actual results.
3. The error was propagated backward through the network.
4. Connection weights were updated to reduce prediction error.

The Adam optimization algorithm was used due to its adaptive learning rate mechanism and computational efficiency.

Training was conducted over multiple epochs until convergence criteria were met. Early stopping techniques were applied to prevent overfitting when validation error began to increase.

Hyperparameters optimized during experimentation included:

- Learning rate
- Number of hidden neurons • Batch size
- Number of training epochs

This iterative tuning process ensured stable and reliable model performance.

**Model Evaluation and Performance Measurement**

To comprehensively assess predictive capability, multiple evaluation metrics were applied.

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Mean Absolute Error (MAE) was used to measure the average magnitude of prediction errors, providing intuitive interpretation of deviation in marks.

Root Mean Squared Error (RMSE) was calculated to penalize larger prediction errors more heavily.

The Coefficient of Determination ($R^2$) was used to measure how much variance in student performance is explained by the model.

Additionally, k-fold cross-validation was performed to enhance robustness. The dataset was divided into multiple folds, and the model was trained and tested repeatedly using different partitions. The average performance across folds was reported as the final accuracy.

Cross-validation ensures:

- Reduced variance in performance estimation
- Greater model stability
- Improved generalization capability

Comparative analysis with traditional machine learning algorithms was also conducted to demonstrate the relative effectiveness of the ANN model.

**Statistical Validation and Hypothesis Testing**

To ensure scientific credibility, formal statistical tests were conducted to validate predictive performance.

**Paired Sample t-Test**

A paired sample t-test was conducted to determine whether differences between actual and predicted marks were statistically significant.

The null hypothesis stated that there is no significant difference between predicted and actual performance. If the p-value exceeded the chosen significance level (0.05), the null hypothesis was not rejected, indicating that predictions were statistically consistent with observed outcomes.

This test confirms whether prediction errors are random fluctuations rather than systematic bias.

**Analysis of Variance (ANOVA)**

ANOVA was applied to compare prediction accuracy among multiple models, including ANN and selected traditional machine learning algorithms.

The null hypothesis assumed equal predictive performance across models. A statistically significant ANOVA result indicates that at least one model differs significantly in accuracy.

Post-hoc comparisons were conducted when necessary to identify the best-performing model.

**Confidence Interval Estimation**

A 95% confidence interval was calculated for the mean prediction error to estimate the range within which the true error lies.

If the confidence interval included zero, this suggested that prediction error was not statistically significant at the 95% confidence level.

Confidence interval analysis provides additional evidence of model reliability beyond hypothesis testing.

**Ethical and Practical Considerations**

All student data were anonymized prior to analysis to protect privacy and confidentiality. Institutional approval was obtained before data access. Data were used exclusively for research purposes and were not shared externally.

The predictive model is designed as a decision-support tool rather than an automated grading system. Final academic decisions remain under human supervision to prevent algorithmic bias.

**Summary**

This chapter presented a comprehensive methodological framework for developing and validating an ANNbased student performance prediction system. The research combined structured data preprocessing, neural network modeling, cross-validation, and statistical hypothesis testing to ensure methodological rigor. The integration of machine learning and statistical validation strengthens the credibility and applicability of the proposed predictive framework.

## RESULTS AND DISCUSSION

This chapter presents the experimental results obtained from the implementation of the proposed Artificial Neural Network (ANN) model for predicting student academic performance. The results are evaluated using multiple performance metrics, cross-validation analysis, and statistical hypothesis testing. A comparative analysis with traditional machine learning models is also conducted to demonstrate the effectiveness of the proposed approach.

**Dataset Overview and Experimental Configuration**

After preprocessing and cleaning, the final dataset consisted of 1,200 complete student records collected across multiple academic semesters. The dataset was partitioned into training, validation, and testing subsets to ensure unbiased model evaluation.

**Table 4.1: Dataset Distribution After Preprocessing**

| Dataset Split | Number of Records | Percentage (%) |
|---|---|---|
| Training Set | 840 | 70% |
| Validation Set | 180 | 15% |
| Testing Set | 180 | 15% |
| **Total** | **1200** | **100%** |

The majority of records were allocated to the training set to enable effective learning of patterns. The validation and testing sets were reserved to assess generalization performance.

Multiple experimental trials were conducted, and the final ANN configuration was selected based on optimal validation performance and stability across epochs.

**Performance Evaluation of the Proposed ANN Model**

The predictive performance of the ANN model was evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Coefficient of Determination ($R^2$).

**Table 4.2: Performance Metrics of the Proposed ANN Model**

| Metric | Training Set | Testing Set |
|---|---|---|
| MAE | 3.42 | 3.78 |
| RMSE | 4.56 | 4.89 |
| $R^2$ | 0.91 | 0.88 |

The model achieved low prediction errors on both training and testing datasets. The small difference between training and testing performance indicates strong generalization capability and minimal overfitting. An $R^2$ value of 0.88 on the testing dataset demonstrates that approximately 88% of the variance in final academic performance is explained by the model.

### Cross-Validation Analysis

To evaluate robustness, five-fold cross-validation was performed. The model was trained and tested across five different partitions of the dataset.

**Table 4.3: Cross-Validation Results of ANN Model**

| Fold | MAE | RMSE | $R^2$ |
|---|---|---|---|
| Fold 1 | 3.81 | 4.92 | 0.87 |
| Fold 2 | 3.69 | 4.85 | 0.88 |
| Fold 3 | 3.74 | 4.88 | 0.88 |
| Fold 4 | 3.79 | 4.91 | 0.87 |
| Fold 5 | 3.71 | 4.86 | 0.88 |
| **Average** | **3.75** | **4.88** | **0.88** |

The minimal variation across folds confirms the stability of the ANN model. This demonstrates that the predictive performance is not dependent on a specific dataset partition and that the model generalizes effectively.

### Comparative Analysis with Traditional Machine Learning Models

To assess the superiority of the ANN model, a comparative analysis was conducted using Decision Tree, KNearest Neighbors (KNN), and Support Vector Machine (SVM).

**Table 4.4: Comparison of ANN with Traditional Machine Learning Models**

| Model | MAE | RMSE | $R^2$ |
|---|---|---|---|
| Decision Tree | 5.92 | 7.41 | 0.71 |
| KNN | 5.48 | 6.98 | 0.74 |
| SVM | 4.61 | 5.89 | 0.81 |
| **ANN (Proposed)** | **3.78** | **4.89** | **0.88** |

The ANN model outperformed all traditional algorithms across all evaluation metrics. Traditional models struggled to capture complex non-linear interactions between academic and behavioral variables, whereas the ANN model effectively modeled these relationships.

**Statistical Validation of Predictive Performance**

To ensure scientific validity, statistical tests were conducted.

**Paired Sample t-Test**

A paired sample t-test was conducted to determine whether there was a statistically significant difference between actual and predicted marks.

**Table 4.5: Paired Sample t-Test Results**

| Statistic | Value |
|---|---|
| Mean Difference | 0.36 |
| Standard Deviation | 4.21 |
| t-value | 1.27 |
| p-value | 0.21 |

The p-value (0.21) is greater than 0.05. Therefore, there is no significant difference between actual and predicted marks. This means the model predictions are statistically reliable.

**ANOVA for Model Comparison**

ANOVA was conducted to compare the predictive performance of all models.

**Table 4.6: ANOVA Results**

| Source | Sum of Squares | Degrees of Freedom | Mean Square | F-value | p-value |
|---|---|---|---|---|---|
| Between Models | 212.4 | 3 | 70.8 | 9.46 | 0.000 |
| Within Models | 871.6 | 116 | 7.51 | | |
| **Total** | **1084.0** | **119** | | | |

The ANOVA test shows a significant difference between models ($p < 0.05$). This confirms that the ANN model performs better than the other algorithms. This confirms that model selection significantly impacts predictive performance.

**Table 4.7: Post-hoc Comparison Summary**

| Model Comparison | Performance Difference | Significance |
|---|---|---|
| ANN vs Decision Tree | High | Significant |

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| | | |
|---|---|---|
| ANN vs KNN | High | Significant |
| ANN vs SVM | Moderate | Significant |

Post-hoc analysis confirms that the ANN model significantly outperforms traditional models.

**Confidence Interval Analysis**

A 95% confidence interval was calculated for the mean prediction error.

**Table 4.8: Confidence Interval for Mean Prediction Error**

| Statistic | Value |
|---|---|
| Mean Error | 0.36 |
| Lower Bound | -0.18 |
| Upper Bound | 0.90 |

The confidence interval includes zero, indicating that prediction errors are small and not statistically significant.

**Early Warning Risk Classification**

Based on predicted performance, students were categorized into risk levels.

**Table 4.9: Early Warning Risk Classification Results**

| Risk Category | Number of Students | Percentage (%) |
|---|---|---|
| High Risk | 96 | 8% |
| Moderate Risk | 312 | 26% |
| Low Risk | 792 | 66% |
| **Total** | **1200** | **100%** |

The model successfully identified students at high academic risk. This demonstrates the practical applicability of the predictive system in supporting early academic intervention strategies.

**Feature Importance Analysis**

To better understand the contribution of individual input variables to the predictive performance of the Artificial Neural Network (ANN) model, a feature importance analysis was conducted. The relative importance of each feature was estimated based on its contribution to reducing prediction error during model training. This analysis helps identify the most influential academic and behavioral factors affecting student performance.

**Table 4.10: Relative Importance of Input Features**

| Feature | Importance Score | Rank |
|---|---|---|
| Continuous Assessment | 0.34 | 1 |
| Attendance Percentage | 0.26 | 2 |

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| | | |
|---|---|---|
| LMS Engagement | 0.18 | 3 |
| Assignment Scores | 0.14 | 4 |
| Midterm Marks | 0.08 | 5 |

The results indicate that continuous assessment scores are the most influential predictor of final academic performance, followed by attendance percentage and LMS engagement. These findings highlight the importance of ongoing academic evaluation and student participation throughout the semester. Behavioral engagement indicators, particularly LMS interaction, also play a meaningful role in forecasting outcomes. The relatively lower contribution of midterm marks suggests that continuous performance monitoring provides stronger predictive power than single examination results.

## DISCUSSION OF FINDINGS

The experimental results indicate that the proposed Artificial Neural Network (ANN) model performs effectively in predicting student academic performance. The model achieved high predictive accuracy on both the training and testing datasets, with low error values and an $R^2$ of 0.88 on the testing set.

This demonstrates that the ANN successfully captured complex relationships among academic, behavioral, and engagement-related variables.

The comparison with traditional machine learning models, such as Decision Tree, K-Nearest Neighbors (KNN), and Support Vector Machine (SVM), confirms the superior performance of the ANN. While Decision Trees provided interpretable rules and SVM achieved moderate accuracy, the ANN consistently delivered lower prediction errors and better generalization.

This suggests that nonlinear interactions among variables, such as attendance, assignment completion, and continuous assessment scores, are significant predictors of final academic outcomes and are best modeled with neural networks.

Statistical validation further supports these findings. The paired sample t-test indicates no significant difference between actual and predicted marks, while ANOVA confirms the superiority of the ANN model over other approaches. The confidence interval analysis demonstrates that prediction errors are minimal and reliable, further reinforcing the model’s credibility.

Analysis of feature influence revealed that continuous assessment scores, attendance percentage, and LMS engagement were the most critical factors affecting performance. This emphasizes the importance of monitoring ongoing student engagement and assessment outcomes, rather than relying solely on final examination results.

The early warning classification successfully identified students at high or moderate academic risk, enabling timely intervention strategies. Such predictive insights can guide educators in implementing targeted support programs, improving academic outcomes, and reducing dropout rates.

Overall, the findings confirm that the ANN-based predictive framework is both technically robust and practically applicable for early identification of at-risk students. It demonstrates the advantages of integrating academic, behavioral, and engagement data into a single predictive system.

**Summary**

This chapter presented detailed experimental results and statistical validation of the proposed ANN-based academic performance prediction model. The results confirm high predictive accuracy, strong generalization capability, and statistically validated superiority over traditional machine learning models. The developed framework demonstrates both technical robustness and practical applicability for early identification of academically at-risk students.

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# CONCLUSIONS, RECOMMENDATIONS, AND LIMITATIONS

## Conclusions

This study developed and validated an Artificial Neural Network (ANN)-based predictive framework for forecasting student academic performance at an early stage. The findings confirm that a deep learning approach integrating academic and behavioral indicators can reliably predict final examination outcomes and effectively identify students at academic risk before performance declines.

The results demonstrate that multidimensional data—including continuous assessment scores, attendance patterns, assignment performance, and LMS engagement—provide strong predictive capability when modeled collectively. The feature importance analysis revealed that ongoing assessment and participation indicators are more influential than single examination measures, emphasizing the value of continuous academic monitoring.

From a practical perspective, the proposed framework functions as an early warning system that supports educators in identifying at-risk students and implementing timely interventions. By transforming institutional data into actionable insights, the model assists academic administrators in improving resource allocation, student support strategies, and overall performance management.

Scientifically, this research contributes to the field of educational data mining by demonstrating the effectiveness of ANN-based predictive modeling combined with statistical validation techniques. The study provides a scalable and empirically validated framework that can support the integration of predictive analytics into modern higher education systems.

**High Predictive Accuracy of ANN:**

The ANN model demonstrated superior predictive capability compared to traditional machine learning models such as Decision Tree, K-Nearest Neighbors, and Support Vector Machine. With a testing $R^2$ of 0.88 and low prediction errors (MAE = 3.78, RMSE = 4.89), the model reliably forecasts final academic performance.

**Importance of Multidimensional Data:**

Integrating multiple factors, including continuous assessment scores, attendance, assignment completion, and LMS engagement, significantly improved prediction accuracy. This highlights the importance of considering both academic and behavioral variables rather than relying solely on examination results.

**Effectiveness of Early Warning System:**

The predictive framework successfully classified students into risk categories (high, moderate, low). The system can identify at-risk students before final examinations, enabling timely academic intervention strategies such as counseling, remedial classes, and personalized support.

**Statistical Validation Confirms Reliability:**

Hypothesis testing (paired t-test), ANOVA, and confidence interval analysis confirmed that the ANN predictions are statistically consistent with actual outcomes, reinforcing the robustness and reliability of the model.

**Practical Applicability:**

The framework can serve as a decision-support tool for educators and administrators, assisting in early detection of weak students, resource allocation, and the design of targeted academic support strategies.

Overall, the research demonstrates that ANN-based predictive models can effectively transform raw educational data into actionable insights for improving student academic outcomes.

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**Recommendations**

Based on the findings, the following recommendations are proposed for educational institutions and future research:

**Implementation of Early Intervention Programs:**

Institutions should integrate ANN-based predictive systems into their academic monitoring processes to identify at-risk students and provide timely support.

**Continuous Data Monitoring:**

Regular collection of attendance, assessment, and LMS engagement data will ensure the predictive model remains accurate and relevant over time.

**Incorporation of Additional Variables:**

Future implementations may include socio-economic, psychological, or demographic factors to further enhance prediction accuracy and personalized support.

**Training for Educators:**

Faculty and administrative staff should be trained in interpreting predictive outputs and applying interventions effectively without over-relying on automated predictions.

**Scalability and Multi-Institutional Deployment:**

Expanding the model across multiple courses or institutions can improve generalizability and enable benchmarking of academic performance trends.

**Limitations**

Despite the positive outcomes, several limitations were identified:

**Data Limitations:**

The study relied on institutional datasets, which may contain incomplete or inconsistent records. Missing variables or irregularities could influence prediction accuracy.

**Context-Specific Findings:**

The predictive model was developed based on data from a specific institution. Generalization to other institutions may require additional tuning or retraining.

**Exclusion of Non-Academic Factors:**

Psychological, social, and family-related factors were not included. These may have a significant impact on student performance and could further improve model accuracy if incorporated.

**Temporal Dynamics Not Fully Explored:**

The current model captures static patterns within a semester. Time-series modeling or recurrent neural networks may enhance the ability to capture evolving learning behaviors over time.

**Dependence on Data Quality:**

ANN models require high-quality, consistent input data. Data entry errors or inconsistent engagement logs may affect prediction reliability.

**Future Work**

Building on this research, the following areas are recommended for future studies:

- Integration of **longitudinal data** to model changes in student behavior over multiple semesters.
- Exploration of **advanced deep learning architectures** (e.g., LSTM, GRU) to capture temporal dependencies in student performance.
- Development of **personalized learning recommendation systems** based on early predictions.
- Inclusion of **psychosocial, demographic, and peer influence factors** to enrich prediction accuracy and interpretability.
- Deployment of the system across **multiple institutions** to assess scalability and generalizability.

**Summary**

This chapter summarized the key findings of the study, highlighted practical and theoretical implications, and provided actionable recommendations for educational institutions. While the ANN-based predictive framework demonstrated high accuracy and practical utility, limitations were identified that can guide future research to further enhance predictive performance and intervention strategies.

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ISSN 2278-2540 | DOI: 10.51583/IJLTEMAS | Volume XV, Issue II, February 2026


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