

# Predicting Student's Academic Performance Using Deep Learning

Ms. Gazala Begum <sup>1</sup>, Ms. Bhavana <sup>2</sup>, Dr. Jabeen Sultana <sup>3</sup>, Mohammed Ehtesham Ul Baqui <sup>4</sup>, Nouman Ajmal Khan <sup>5</sup>

<sup>1,2</sup>Department of Computer Science Lords Institute of Engineering & Technology Hyderabad

<sup>3</sup>Department of Computer Science Imam Muhammad Ibn Saud Islamic University (IMSIU) Kingdom of Saudi Arabia

<sup>4,5</sup>Student, Department of Computer Science Lords Institute of Engineering & Technology Hyderabad

DOI: <https://doi.org/10.51583/IJLTEMAS.2025.140500010>

Received: 16 May 2025; Accepted: 21 May 2025; Published: 30 May 2025

**Abstract:** Learning Platforms generate huge data and play a vital role in the field of education as a nation's future is dependent upon the progress of the students. These platforms generate lots of data and, offer valuable opportunities to predict and categorize student performance. Machine Learning (ML) has become a prominent method for analyzing this data, providing meaningful insights into academic outcomes. This research proposes a deep learning-based approach for processing and classifying student performance using ML algorithms. ML classifiers like Support Vector Machines (SVM), Multi-Layer Perceptron (MLP), and Naïve Bayes are applied to preprocessed data. The models' effectiveness is measured using parameters like accuracy, precision, recall, F-score, and the time taken to train each model.

**Keywords**—Educational Data, Hold-out Method, 10-Fold Cross Validation, Support Vector Machine (SVM), Multi-Layer Perceptron (MLP) and Naïve Bayes (NB)

## I. Introduction

Educational data mining (EDM) is in high demand and receiving increased attention due to the rapid growth of data generated by learning management systems. EDM is an advancing field focused on developing techniques to classify and analyze diverse data types from these systems. Simultaneously, EDM identifies meaningful patterns, allowing for targeted recommendations to enhance student learning [1]. Traditional data analysis can help assess students' performance, providing insights into where students may struggle with concepts or underperform on exams across a course's duration in specific learning environments. The main challenge lies in effectively leveraging this data to improve the educational experience.

Advancements in learning systems have refined student performance predicting models to support improved student outcomes. Predicting and classifying student performance has become essential in these systems and a significant area of research, as there is a strong emphasis on enhancing learning experiences and attracting students to new courses. Many researchers are actively applying machine learning methods to assist instructors in supporting student progress more effectively in alignment with each student's interests [2]. In a study on data from Middle Eastern students, various machine learning classifiers were used, with neural networks achieving the best performance for predicting and categorizing student outcomes compared to other classifiers [3]

## Related Work

Key interactive attributes, such as student engagement, difficulties faced, and attendance rates, were highlighted along with other factors in a machine learning model that improved classification accuracy by over 22% when interactive attributes were excluded. Additionally, ensemble classifiers were employed to further boost accuracy, achieving an increase of more than 25% [4]. Sentiment analysis was used to understand how students engaged with their course from beginning to end, providing insight into their scheduling approaches. This analysis helped instructors tailor their teaching strategies to better support students. A comparative study of various machine learning approaches found that the Multi-Layer Perceptron (MLP) model achieved the highest accuracy for classifying student data [5].

Sentiment analysis was also applied to Telugu-language tweets about learning, where ML models were used to evaluate user sentiment. The Passive Aggressive Classifier achieved nearly 80% accuracy, with precision of 0.77, recall of 0.78, and an F1 score of 0.77 [6]. Across different fields, machine learning techniques also showed promising results for processing natural language data [7]. Studies applied ML methods to generate insights from healthcare big data [8,9] and consumer goods data, utilizing association rules in market basket analysis [10] and educational data mining [11], showcasing ML's power in knowledge discovery. Traditional and deep learning classifiers were also applied to data from a Middle Eastern university to classify student records, while Twitter data was analyzed to identify public interest in courses; deep learning classifiers consistently outperformed ML classifiers [12,13]. Furthermore, ML and deep learning methods proved effective for categorizing students based on academic performance [14].

One study presented a Multi-Layer Perceptron (MLP) framework for student performance classification, which demonstrated its effectiveness in educational data mining by using supervised learning to predict academic outcomes. This Student Performance Prediction MLP (SPPML) framework reached an impressive classification accuracy of 93.25%, surpassing other methods such as

Naïve Bayes, SVM, and Decision Trees with accuracies of 91.01%, 89.88%, and 86.72%, respectively [15]. Another approach focused on applying Support Vector Machines (SVM) to predict student performance, based on academic and demographic factors, revealing SVM as the most accurate model with a classification accuracy of 93%, followed by MLP at 86%, RF at 78%, DT at 76%, NB at 75%, and KNN at 67%. SVM also performed strongly in true positive rates and ROC curves [16].

Based on these studies, we suggest a method to classify student performance using real-time data from a Middle Eastern university database.

## II. Proposed Methodology

Data was gathered from a learning management system (LMS) from a Middle Eastern university to predict student performance. The dataset includes 1,300 student records, each with 11 features. After preprocessing, students were classified into three performance levels: those scoring above 85% were categorized as "High Level," those scoring between 70% and 85% as "Middle Level," and those scoring below 70% as "Low Level." This real-time dataset, therefore, contains three distinct classes based on students' total marks or internal scores.

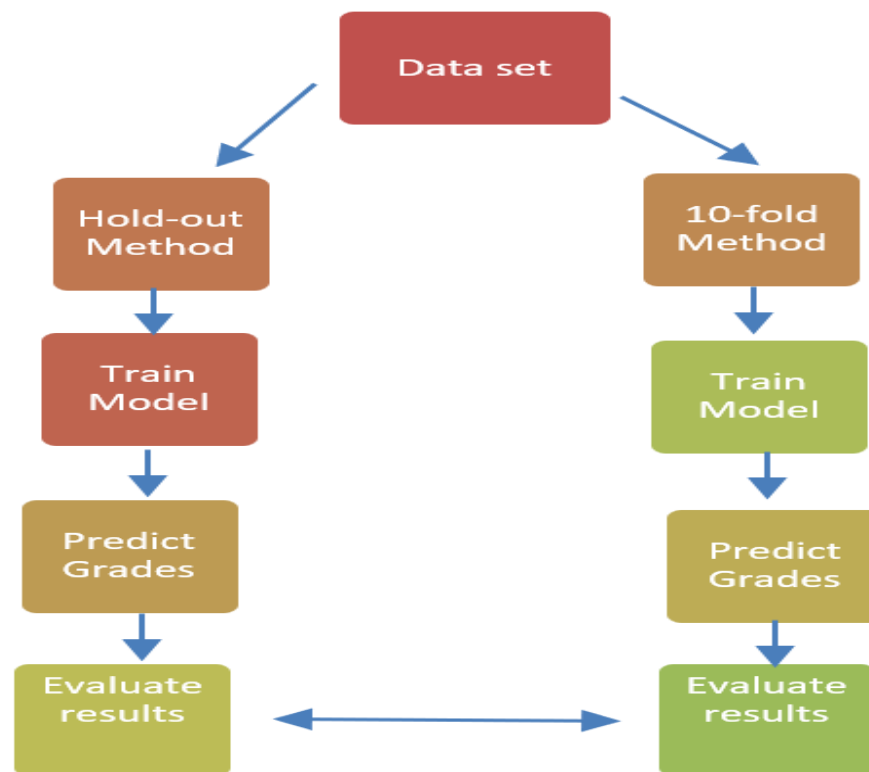


Fig. 1. Steps in student's academic performance

**Figure 1** presents the framework for the proposed methodology, which classifies real-time data using machine learning classifiers.

**Support Vector Machine (SVM):** SVM is a supervised learning model used primarily for classification. It creates an optimal hyperplane from training data to classify samples. Test data is then evaluated based on this hyperplane using the Sequential Minimal Optimization (SMO) classifier [17].

**Multi-Layer Perceptron (MLP) - Deep Learning Technique:** Using the backpropagation algorithm, MLP trains perceptrons and constructs a model with activation functions like logistic and hyperbolic tangent sigmoid functions. In this classifier, inputs pass through multiple layers where they are weighted and summed to produce the activation function, which then flows through subsequent layers until results are generated [18].

**Naïve Bayes (NB):** This probabilistic classifier is based on Bayes' theorem and constructs a model from training data to predict the classes of new data. It assumes that each attribute is independent of the others within a feature set, allowing for simple yet effective classification [19].

## III. Results Discussion

Student's educational records were gathered from a learning management system, preprocessed, and then classified using machine learning methods. Initially, the data was used to train the classifiers, resulting in the creation of a model. A test set was subsequently applied to evaluate the model's performance. The classifiers assessed include Support Vector Machine (SVM), Naive Bayes (NB), and Multi-Layer Perceptron (MLP). The evaluation was based on metrics such as accuracy, precision, recall, F-score, and the time required to build the model.

Table I. Classification Results Analysis-10 Fold

| Methods    | Accuracy     | Precision   | Recall      | F-Score     | Time taken to build the Model |
|------------|--------------|-------------|-------------|-------------|-------------------------------|
| <b>MLP</b> | <b>98.45</b> | <b>0.98</b> | <b>0.98</b> | <b>0.98</b> | <b>0.02</b>                   |
| NB         | 97.45        | 0.97        | 0.97        | 0.97        | 0.03                          |
| SVM        | 93.90        | 0.93        | 0.93        | 0.93        | 0.06                          |

Table II. Classification Results Analysis-Hold Out Method

| Methods    | Accuracy     | Precision   | Recall      | F-Score     | Time taken to build the Model |
|------------|--------------|-------------|-------------|-------------|-------------------------------|
| <b>MLP</b> | <b>99.54</b> | <b>0.99</b> | <b>0.99</b> | <b>0.99</b> | <b>0.01</b>                   |
| NB         | 97.72        | 0.97        | 0.97        | 0.97        | 0.03                          |
| SVM        | 94.54        | 0.94        | 0.94        | 0.94        | 0.06                          |

The results reveal that **MLP** outperformed the other classifiers, achieving the best classification results. MLP demonstrated high accuracy, with 99.54% using the hold-out method and 98.45% using the 10-fold method. It also showed superior precision, reaching 0.99 with the hold-out method and 0.98 with the 10-fold method. Additionally, MLP achieved high recall and F-scores of 0.99 for the hold-out method and 0.98 for the 10-fold method. **Naive Bayes** attained accuracy scores of 97.72% (hold-out) and 97.45% (10-fold), while **SVM** had accuracy scores of 94.54% (hold-out) and 93.90% (10-fold).

Furthermore, MLP required the least time to build the model, taking only 0.1 seconds with the hold-out method and 0.2 seconds with the 10-fold method, followed by Naive Bayes and SVM.

The following graphs display a comparison of the MLP, Naive Bayes, and SVM classifiers using both the hold-out and 10-fold methods.

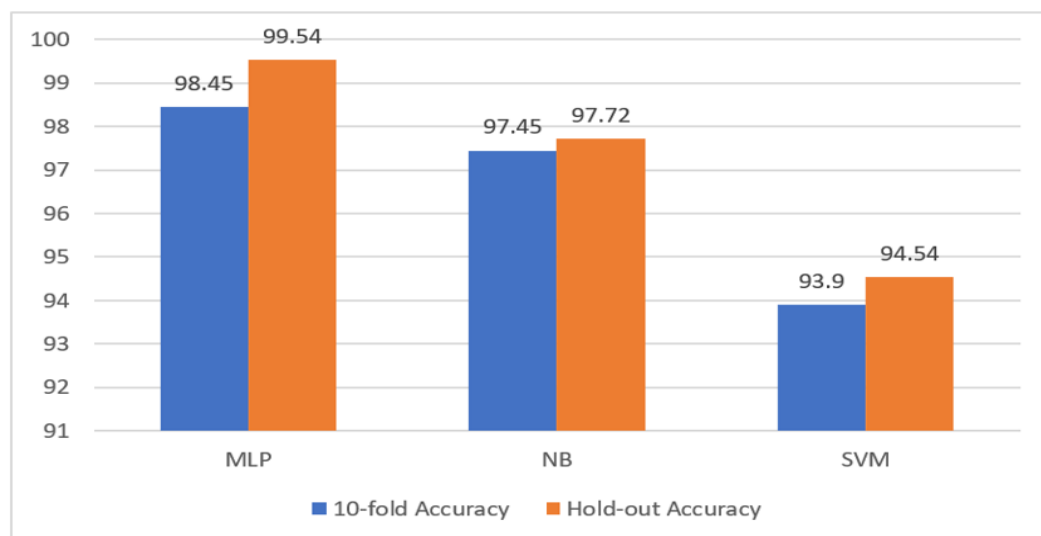


Fig. 2. shows classification accuracy obtained by MLP, NB, and SVM.

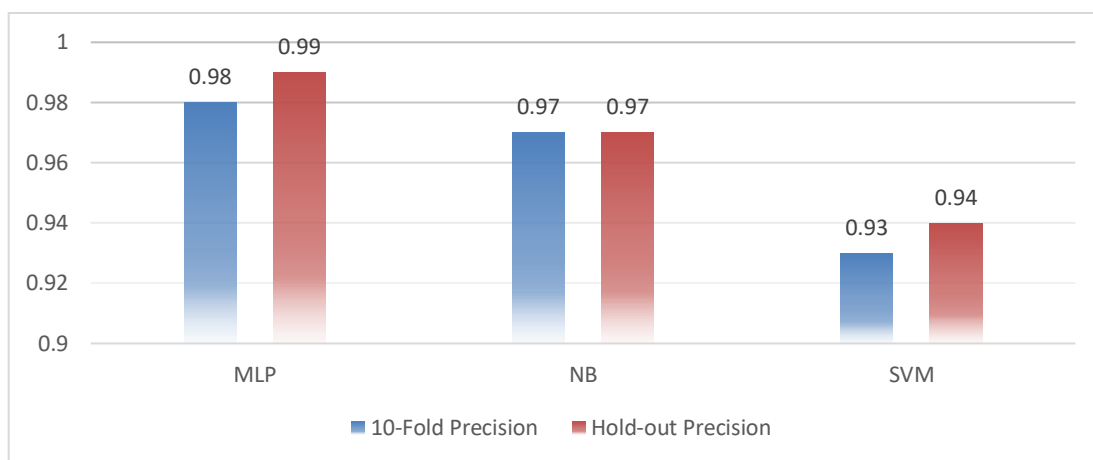


Fig. 3 shows the precision obtained by MLP, NB, and SVM.

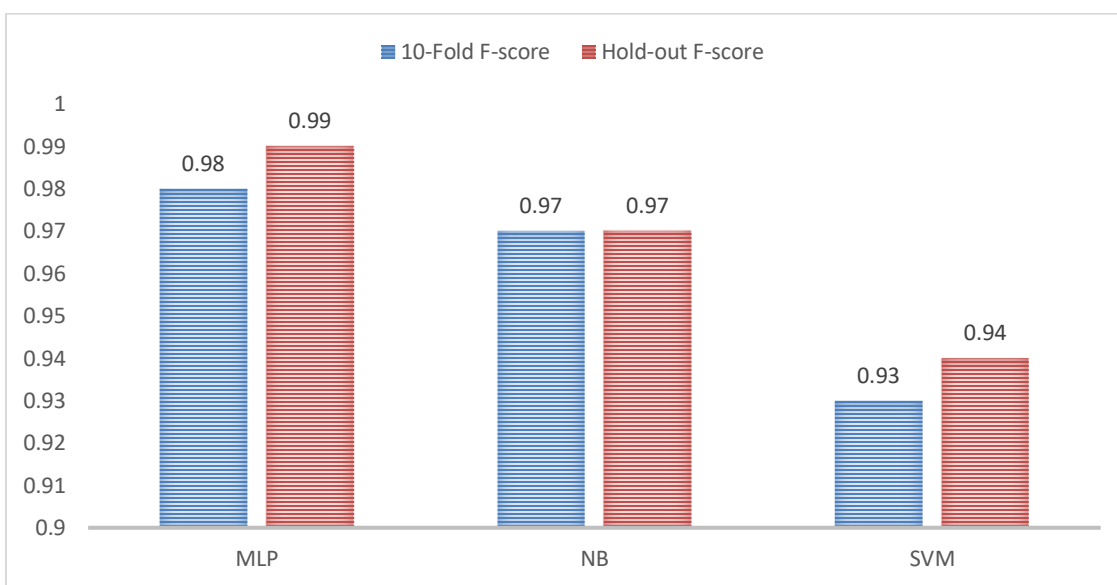


Fig.4. shows recall obtained by MLP, NB, and SVM

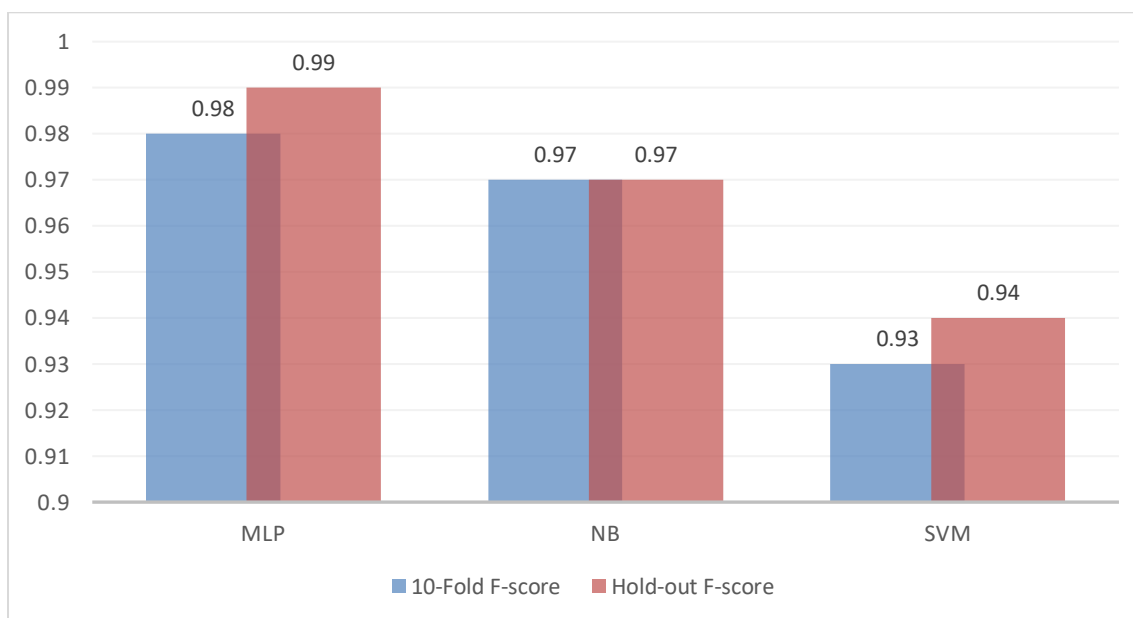


Fig. 5. shows the F-Score obtained by MLP, NB, and SVM.

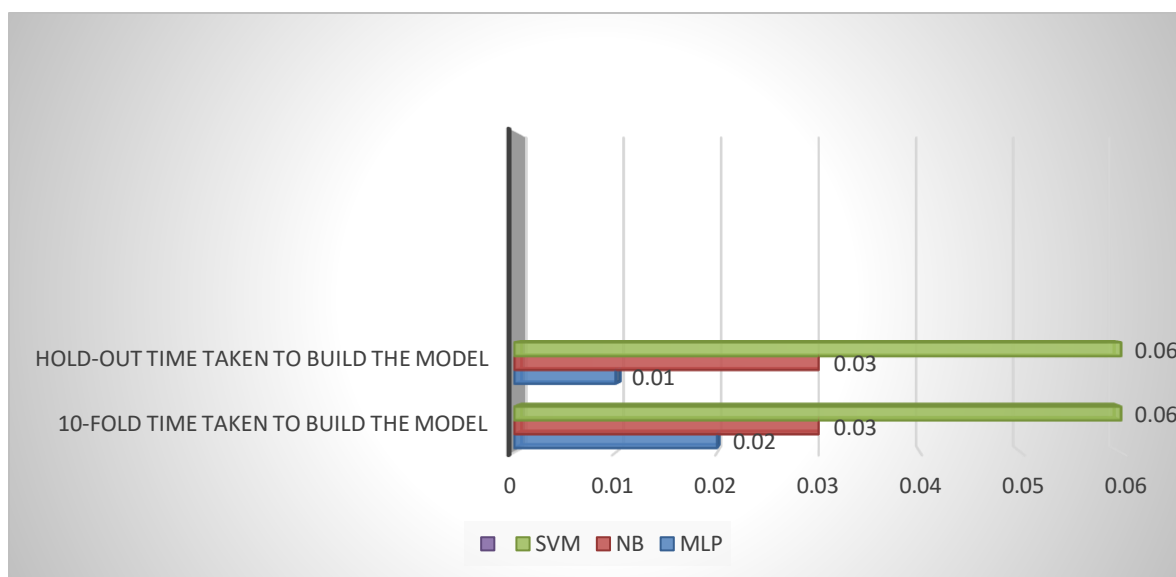


Fig. 6 shows the time taken to build the model obtained by MLP, NB, and SVM

#### IV. Conclusion and Future Work

In this research work, data was chosen from an LMS system, preprocessed, and then the model was built by undergoing training and later validated. Hold-out and 10-fold cross-validation methods were used. It was found that MLP outperforms by producing the outmost classification accuracy with 99.54 when the hold-out method is used and 98.45 when the 10-fold method is used. Also, less time was taken to build the model i.e., 0.2 seconds in 10-fold and 0.1 seconds in the hold-out method followed by NB and SVM. In the future, we plan to work on improving the classification results of SVM and NB.

#### References

1. C. Scheuer, et al., "Educational data mining," in Encyclopedia of the Sciences of Learning, pp. 1075–1079, Springer, 2012.
2. C. Romero and S. Ventura, "Educational data mining: A review of the state of the art," IEEE Trans. Syst., Man, Cybern., vol. 0, no. 6, pp. 601–618, 2010.
3. J. Sultana, U. Rani, and M. Farquaq, "An efficient deep learning method to predict student's performance," 2019. [Online]. Available: <https://www.researchgate.net/publication>
4. A. Amrieh, et al., "Mining educational data to predict student's academic performance using ensemble methods," Int. J. Database Theory Appl., vol. 9, no. 8, pp. 119-136, 2016.
5. J. Sultana, N. Sultana, K. Yadav, and F. AlFayez, "Prediction of sentiment analysis on educational data based on deep learning approach," in Proc. 2018 Saudi Comput. Soc. Nat. Comput. Conf. (NCC), 2018, pp. 1-5.
6. G. B. K. Priya, J. Sultana, and M. U. Rani, "Telugu news data classification using machine learning approach," in Handbook of Research on Advances in Data Analytics and Complex Communication Networks, IGI Global, 2022.
7. J. Sultana, M. U. Rani, and M. A. H. Farquaq, "An extensive survey on some deep-learning applications," in Emerging Research in Data Engineering Systems and Computer Communications, Springer, Singapore, 2020, pp. 511-519.
8. J. Sultana and A. K. Jilani, "Predicting breast cancer using logistic regression and multi-class classifiers," Int. J. Eng. Technol., vol. 7, no. 4.20, pp. 22-26, 2018.
9. J. Sultana, K. Sadaf, A. K. Jilani, and R. Alabdan, "Diagnosing breast cancer using support vector machine and multi-classifiers," in Proc. 2019 Int. Conf. Comput. Intell. Knowl. Economy (ICCIKE), 2019, pp. 449-451.
10. J. Sultana and G. Nagalaxmi, "How efficient is Apriori: A comparative analysis," Int. J. Curr. Eng. Sci. Res., vol. 2, no. 8, pp. 91-99, 2015.
11. J. Sultana, M. U. Rani, and M. A. H. Farquaq, "Knowledge discovery from recommender systems using deep learning," in Proc. 2019 Int. Conf. Smart Syst. Inventive Technol. (ICSSIT), 2019, pp. 1074-1078.
12. J. Sultana, M. U. Rani, and M. A. H. Farquaq, "Deep learning based recommender system using sentiment analysis to reform Indian education," in Proc. Int. Conf. Comput. Bio Eng., Springer, Cham, 2019, pp. 143-150.
13. M. J. Sultana, M. U. Rani, and M. A. H. Farquaq, "Sentiment analysis based recommender system for reforming Indian education using multi-classifiers," 2020.
14. J. Sultana, M. U. Rani, and M. A. H. Farquaq, "Student's performance prediction using deep learning and data mining methods," Int. J. Recent Technol. Eng. (IJRTE), vol. 8, no. 1S4, 2019.

16. J. Sultana, N. Farhat, S. Kazi, and M. U. Rani, "An SPPML framework to classify students performance using MLP," *Design Eng.*, no. 9, pp. 14235-14244, 2021.
17. J. Sultana, K. Sadaf, and A. K. Jilani, "Classifying student's academic performance using SVM," *J. Eng. Appl. Sci.*, vol. 8, no. 2, pp. 61-68, 2021, DOI: 10.5455/jeas.2021110107.
18. D. Martens, B. Baesens, and T. Van Gestel, "Decompositional rule extraction from support vector machines by active learning," *IEEE Trans.*
19. *Knowl. Data Eng.*, vol. 21, no. 2, pp. 352-358, 2009.
20. W. H. Delashmit and M. T. Manry, "Recent developments in multilayer perceptron neural networks," in *Proc. 7th Annu. Memphis Area Eng. Sci. Conf. (MAESC)*, 2005.
21. R. Kohavi, "Scaling up the accuracy of naïve-Bayes classifiers: A decision tree hybrid," in *Proc. KDD-96*, Portland, USA, pp. 202-207, 1996.