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Original Article

A Data-Driven Approach in Predicting Scholarship Grants of a Local Government Unit in the Philippines Using Machine Learning

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Abstract *- Inefficient, tedious, and outdated processes in resource allocation are some of the common hurdles educational institutions and agencies face in managing scholarship grants and selecting potential grantees. In response to the challenge, this study developed a predictive model utilizing a range of machine learning algorithms; by leveraging algorithms like Naïve Bayes, Random Forest, Logistic Regression, Support Vector Machine, and Multilayer Perceptron, the study aimed to enhance the selection process for scholarship programs to match applicants with the most suitable scholarship based on their individual backgrounds and qualifications. A number of measures, including accuracy, precision, recall, and F1-score, were used to assess the performance of the models. Results revealed Logistic Regression as the best-performing model in terms of overall accuracy and balance between precision and recall. Moreover, the Support Vector Machine, Naive Bayes, and Random Forest models demonstrated competitive performance, while the Multilayer Perceptron exhibited the lowest performance among others.*

Keywords *- Education, Scholarship, Machine learning, Prediction, Resource allocation.*

1. Introduction

Traditional methodologies for managing educational resources and addressing student needs have become increasingly outdated and ineffective, failing to accommodate the diverse and evolving requirements of learners [1], [2]. Moreover, the exponential growth of data generated within educational institutions has overwhelmed existing systems, leading to inefficiencies in data management and hindrances in informed decision-making processes [3]. These limitations highlight the urgent necessity for more agile and data-driven approaches to confront the complexities inherent in modern educational systems. In the realm of education and big data, these changes have highlighted the need for more agile and data-driven approaches to meet the evolving needs of students and ensure efficient allocation of resources [4], [5]. As organizations navigate through these multifaceted changes, the traditional methods of managing scholarship grants in higher education institutions have become tedious, increasingly outdated, and inefficient. As such, longstanding issues such as biases in decision-making, lack of transparency, and inefficiencies in resource allocation are some of the common hurdles educational institutions deal with [6], [7], [8]. The complexity of modern challenges requires a more sophisticated approach, such as digitalization, that can effectively leverage data and technology to optimize decision-making processes [9], [10]. Today, educational institutions are increasingly turning to analytics technology to enhance their decision-making processes [11], [12], particularly in areas like scholarship allocation, where precision and fairness are paramount. One notable advancement is the integration of machine learning algorithms into scholarship management systems [13].

By leveraging vast amounts of data on student demographics, academic performance, and financial needs, institutions can now make more informed and equitable decisions when awarding scholarships. These machine learning models not only streamline the selection process but also help identify deserving candidates who may have been overlooked by traditional methods, ultimately ensuring that financial aid reaches those who need it most. This adoption of technology represents a significant step forward in promoting transparency, efficiency, and equity within educational institutions' scholarship programs. The Local Government Unit (LGU) in the City of Davao, Philippines, emphasizes the importance of education as a fundamental right for all residents, viewing it as vital for societal progress, equity, and economic growth.

Through the City's Executive Order No. 27 series of 2011, the Davao City Educational Benefit System Unit (EBSU) was created to ensure equal educational opportunities, especially for disadvantaged groups, such as the poor and vulnerable, aligning with the city's commitment to social justice and development. However, EBSU is faced with difficulties in efficiently allocating scholarship grants. In the past decade, the EBSU office has seen a surge in applications from incoming tertiary students in Davao City, presenting significant challenges in the ranking and selection of potential scholarship grantees due to the increasing number of applicants. Every year, the EBSU office expects hundreds to thousands of applications. Managing this growing influx poses difficulties and delays, as officers are required to manually review and validate each application and its accompanying requirements, such as the applicant's background and qualifications. Most importantly, applicants must specify the scholarship program they wish to avail of, as this is used as the basis by EBSU officers to evaluate whether applicants would be granted a scholarship or not. This poses a significant challenge for the EBSU office, especially as some applicants are uncertain about which program they should apply to, further complicating the selection process.

Additionally, many applicants submit their applications to multiple scholarship programs in hopes of improving their chances of being granted one, even if they are not eligible. The whole process is deemed inefficient, laborious, and time-consuming, with the bulk of documents the office needs to review thoroughly. For applicants to qualify and not be rejected, they must ensure that their applications are accurate and that they have chosen the suitable scholarship program based on their background, qualifications, and intended scholarship program to apply to.

This necessity arises from the discrepancy between the number of available grants to be awarded by the LGU and the number of applications EBSU receives. Due to the limited availability of resources, not all students may be able to access these scholarships. In light of all of these challenges, the EBSU office seeks to implement a stringent selection process to ensure that grants are allocated to the most deserving applicants efficiently; thus, this study.

This study endeavors to develop a machine learning model using a variety of machine learning algorithms. Specifically, this study aims to:

1. Develop a model to predict the best scholarship grant for applicants using Logistic Regression (LR), Support Vector Machine (SVM), Multilayer Perceptron (MLP), Naïve Bayes (NB), and Random Forest (RF) algorithms; and
2. Evaluate the performance of these machine learning models according to their average accuracy, precision, recall, and F1 score.

By leveraging algorithms like MLP, SVM, NB, LR, and RF, the study hopes to enhance the selection process for scholarship programs. These advanced computational tools will enable a more data-driven approach to match applicants with the most suitable scholarship opportunities based on their individual backgrounds, qualifications, and academic aspirations. The implementation of machine learning algorithms in predicting the optimal scholarship program for grantees holds the potential to revolutionize how scholarships are allocated. By harnessing the power of predictive modeling, institutions and agencies like EBSU can streamline decision-making processes, improve the accuracy of grant distribution, and ensure that financial aid reaches those who would benefit most. This novel method improves efficiency while also fostering fairness and transparency in the distribution of scholarships. Consequently, it contributes to a more equitable and effective system of educational support.

2. Related Studies and Literature

The use of machine learning in predicting scholarship grants has been a subject of significant research interest [14]. In one study, a Decision Support System (DSS) for scholarship eligibility was developed [15]. The system utilized various features, including academic performance, non-academic accomplishments, major area of study, parental income, and number of dependents, to make its predictions. These attributes were used as inputs to the C4.5 algorithm, which achieved a model accuracy of 94.7%. A comparison of algorithms using a decision tree, J48 and J48graft, was also presented in [16] to determine student scholarship grants. This study utilized 2,549 student documents to train and test models in 10-folds. The results of the study revealed an overall performance of 77.35% accuracy. Meanwhile, the paper [17] used Decision Tree and Naïve Bayes algorithms to identify which is better in predicting scholarship awards to students. The study considered the students' GPA, retake status, number of retake times, and demerit status. The outcomes of the study showed that Naïve Bayes is better in the given task.

Aside from eligibility to scholarship programs, some studies describe the process of predicting the number of scholarship grants, such as in [18], where K-means clustering was used to predict the possible scholarship grants to be awarded by an institution in the future. Similar to this study, machine learning algorithms were used in the literature to eliminate biases and ensure fairness in the distribution or allocation of resources. One example is the study of Lupyani and Phiri [19], which presented the use of machine learning algorithms in allocating research funds of an institution fairly and efficiently.The field of machine learning is rich with opportunities for exploration. Thus, this research is conducted to make meaningful contributions to the expanding knowledge base of machine learning and its practical implementations in the areas of education and resource allocation.

Table 1. Dataset description

Attribute	Type	Description
id	Nominal	ID Number of Applicant
Preferred program	Nominal	The preferred program of the applicant to be enrolled in
Average grade	Numerical	The General Weighted Average of the applicant
isIndigent	Nominal	If the applicant comes from indigenous background (1 – Yes or 0 – No)
isPWD	Nominal	If the applicant has a disability (1 – Yes or 0 – No)
Preferred scholarship	Nominal	The preferred scholarship grant to be availed by the applicant
Actual scholarship granted	Nominal	The actual scholarship program awarded to the applicant

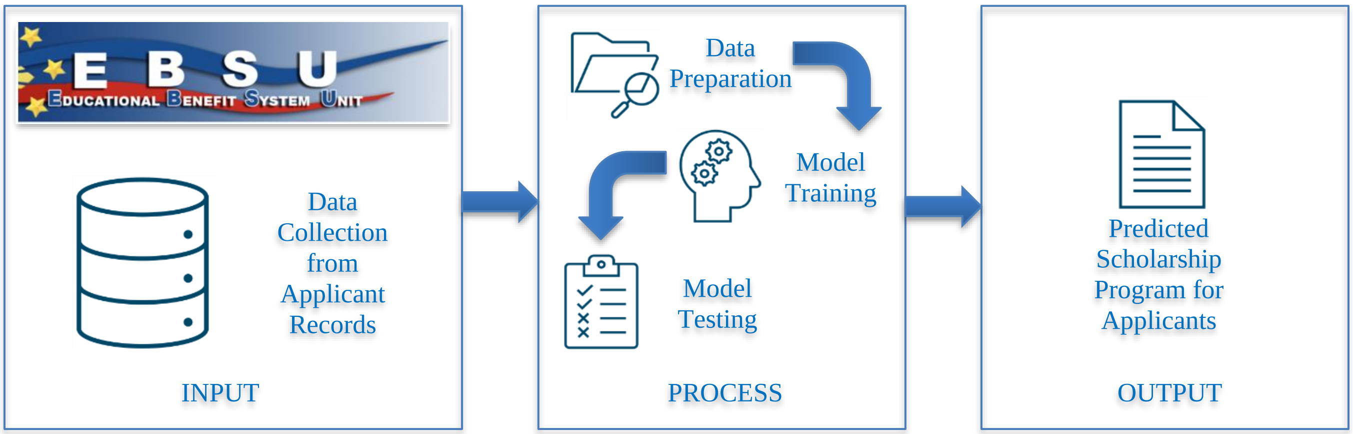

Fig. 1 Conceptual framework

3. Methods

This study presents four important stages in the development of machine learning models for scholarship grant prediction. The process involves data collection, data preparation, model training, and model testing, as presented in the conceptual framework in Figure 1.

3.1. Data Collection

The data used in this study was collected from the EBSU office. A total of 5,604 records from 2014 to 2022 were retrieved and stored in a CSV file. The dataset is characterized by seven (7) diverse features, as presented in Table 1.

3.2. Ethical Considerations

Prior to data collection, the EBSU office was clearly informed about the purpose of the research, the types of data to be collected, how their data would be used, and the measures in place to protect the privacy of their data. All personal information collected was anonymized to prevent identification. It is suggested that regular audits and validation of the model should be conducted to identify and mitigate any biases that could unfairly influence the prediction of scholarship grants.

3.3. Data Preparation

To facilitate the preparation of data for modeling, the CSV file was imported into WEKA version 3.8.6. Upon closer examination, it was determined that the dataset consists exclusively of nominal values, except for one (1) numerical feature – average grade.

Further analysis confirmed that there were no missing values. This is crucial as missing data can lead to inaccurate and biased models. Moreover, the “id” attribute was removed as it does not provide any meaningful information to the model.

3.4. Model Construction

Five (5) distinct algorithms were used to categorize the dataset and predict the class label in the test set. These algorithms, namely MLP, SVM, NB, LR, and RF, were selected due to their proven effectiveness and popularity in the machine learning domain. The training of the models was conducted using WEKA version 3.8.6.

3.5. Model Testing

To evaluate the accuracy of the models, the predicted labels were compared to the actual labels. Various measures, such as the average precision, recall, and F1 score, were also used to evaluate the performance of the models.

3.5.1. Classification Accuracy

Classification accuracy, a fundamental metric in machine learning, represents the ratio of correctly classified instances to the total number of classified objects. It serves as a key indicator of a model's performance, signifying better predictive capabilities with higher accuracy values [20], [21]. To obtain the classification accuracy of a model, the following equation is used:

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

Where TP represents True Positives, FP denotes False Positives, TN stands for True Negatives, and FN indicates False Negatives. This formula represents the fraction of correct predictions our model made out of all predictions. For instance, when a model correctly predicts 91 out of 100 examples, the overall accuracy would be 91%.

However, despite its widespread applicability, accuracy may not consistently serve as the most reliable performance metric, especially in cases where the classes of the target variable in the dataset are imbalanced. For this reason, the precision, recall, and F1 score metrics are introduced to accompany classification accuracy as an evaluation method.

3.5.2. Precision

In machine learning, precision is a metric that assesses how accurately a model makes positive predictions. It is also defined as the ratio of true positives to the total number of positive predictions [22]. A model with high precision indicates that it correctly predicts positive outcomes more often. The precision in machine learning is calculated as follows:

$$Precision = \frac{TP}{TP + FP}$$

3.5.3. Recall

In machine learning, recall is a metric that measures how often a model correctly identifies positive instances, also known as true positives [23]. The formula for recall in machine learning is calculated as:

$$Recall = \frac{TP}{TP + FN}$$

This equation calculates the ratio of correctly identified positive instances to the total number of positive examples, including both true positives and false negatives. A higher recall value indicates better performance, with perfect recall achieved when the model can identify all instances of the target class in the dataset. In scenarios with imbalanced datasets, where one class significantly outnumbers the other, recall plays a critical role in evaluating model effectiveness alongside metrics like precision and the F1 score.

3.5.4. F1 Score

In machine learning, the F1 score is a key metric used to evaluate a model's performance. By calculating the harmonic mean between the precision and recall, it effectively combines these two measures into a single value, ensuring a balanced assessment of the model's accuracy and ability to identify relevant instances [24], [25]. This metric is especially valuable for imbalanced datasets, where accuracy alone might be misleading. The F1 score varies from 0 to 1, with higher values reflecting superior model performance. The formula for the F1 score is:

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

4. Results and Discussion

The following section showcases the results acquired after training and testing the various predictive models generated using Random Forest, Multilayer Perceptron, Support Vector Machine, Logistic Regression, and Naïve Bayes algorithms in WEKA version 3.8.6.

The performance of these models was then evaluated based on four key metrics: Classification Accuracy, F1 Score, Precision, and Recall. Results in Table 2 show that the Logistic Regression model correctly predicted the class label for 78.00% of the instances. The F1 score was 74.50%, suggesting that the model achieved a balance between precision (76.00%) and recall (78.00%). This suggests that although the model's overall accuracy was satisfactory, there is potential for enhancement in capturing more true positives and decreasing false negatives.

Based on the results, SVM, or Support Vector Machine, exhibited slightly lower performance compared to Logistic Regression, with a classification accuracy of 76.44%, as presented in Table 3. The F1 score, precision, and recall were also lower than those of Logistic Regression, indicating that SVM may have struggled with correctly classifying instances and maintaining a balance between precision and recall.

Despite this, SVM still offered competitive performance. Naive Bayes demonstrated performance similar to Logistic Regression, with a classification accuracy of 77.63% and comparable F1 score, precision, and recall rates shown in Table 4. This suggests that Naive Bayes performed similarly to Logistic Regression in terms of correctly classifying instances and balancing precision and recall. Despite its simplicity, Naive Bayes performed admirably well across all metrics, making it a viable option for classification tasks.

Table 2. Logistic regression model performance

Metrics	Result
Classification Accuracy	78.00%
F1 Score	74.50%
Precision	76.00%
Recall	78.00%

Table 3. SVM model performance

Metrics	Result
Classification Accuracy	76.44%
F1 Score	71.90%
Precision	75.30%
Recall	76.40%

Table 4. Naive Bayes model performance

Metrics	Result
Classification Accuracy	77.63%
F1 Score	74.50%
Precision	75.20%
Recall	77.60%

Table 5. Random forest model performance

Metrics	Result
Classification Accuracy	76.45%
F1 Score	74.80%
Precision	74.50%
Recall	76.50%

Table 6. Multilayer perceptron model performance

Metrics	Result
Classification Accuracy	70.7%
F1 Score	70.7%
Precision	70.7%
Recall	70.7%

As presented in Table 5, the Random Forest model achieved a classification accuracy of 76.45%, with F1 score, precision, and recall rates close to those of Naive Bayes and Logistic Regression. This indicates that Random Forest performed similarly to these models in terms of overall accuracy and balance between precision and recall. Finally, the Multilayer Perceptron exhibited the lowest performance among the models evaluated, with a classification accuracy of 70.7% and identical F1 score, precision, and recall rates, as shown in Table 6. This suggests that the Multilayer Perceptron struggled to achieve high accuracy and precision rates compared to the other models, indicating potential issues with model complexity or training data quality. Figure 2 highlights the performance of the machine learning models in terms of their classification accuracy. It is evident that the Logistic Regression model outperformed all other machine learning models at 78.00%. Close at second is the Naïve Bayes algorithm at 77.63%.

This is followed by the Random Forest and Support Vector Machine. The least accurate model is the multilayer perceptron at 70.70%.

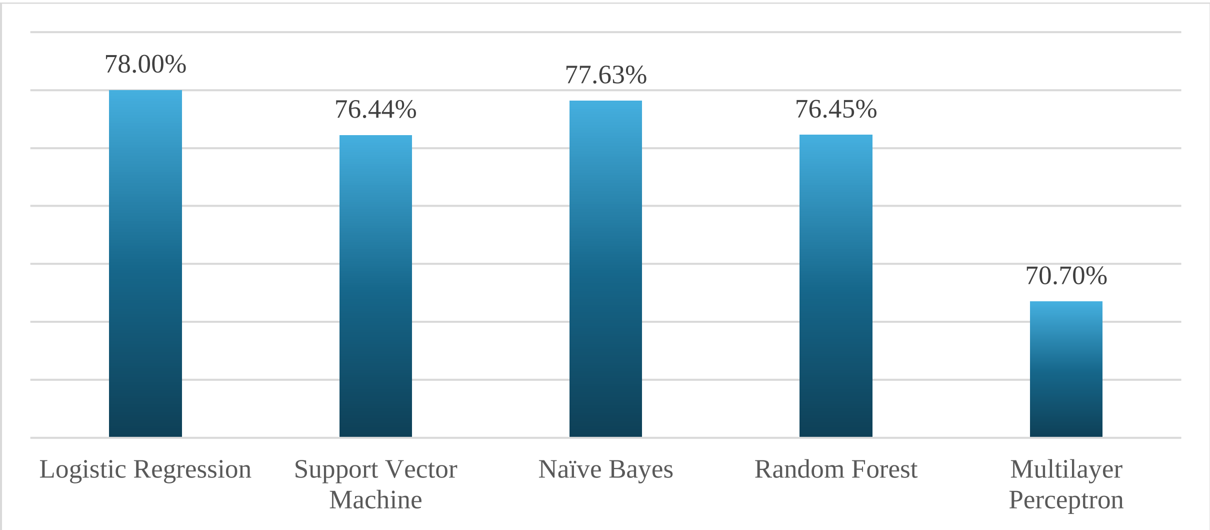

Fig. 2 Classification accuracy comparison

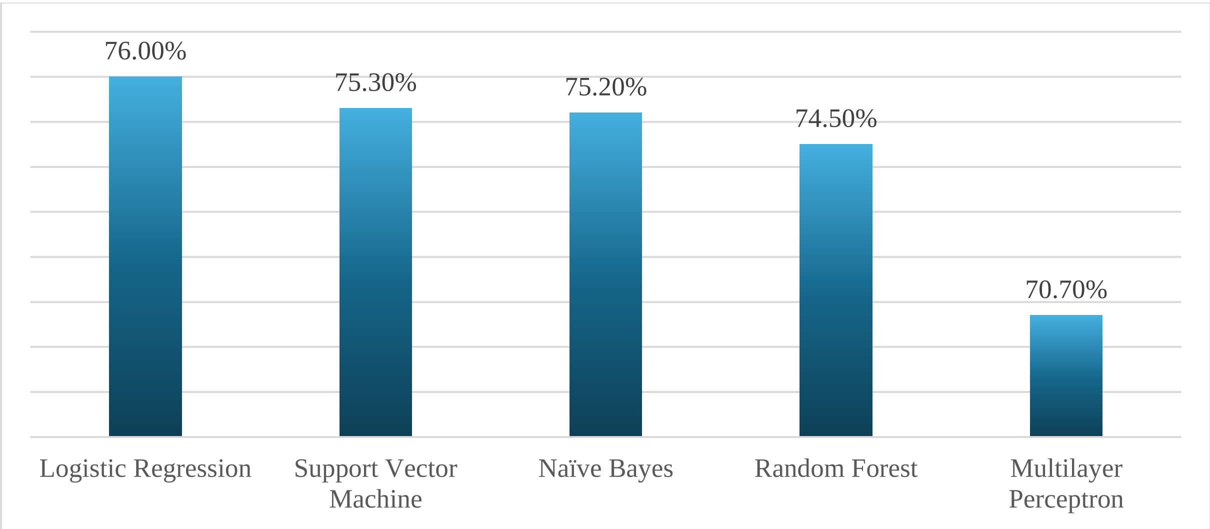

Fig. 3 Precision comparison

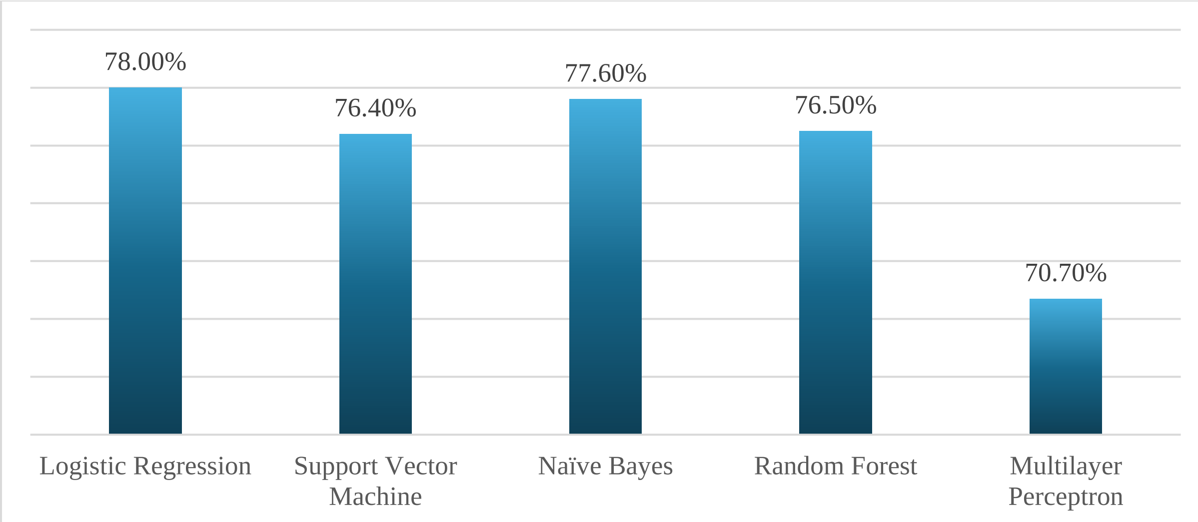

Fig. 4 Recall comparison

Figure 3 presents the performance of the machine learning models based on the obtained precision values. In this metric, the Logistic Regression model is the clear winner at 76.00%. The Support Vector Machine and Naïve Bayes ranked 2nd and 3rd, respectively. On the other hand, Random Forest performed slightly better than the Multilayer Perceptron at 74.50%. Figure 4 shows the performance of the machine learning models relative to their recall values. In this metric, the Random Forest obtained the best recall at 78.00% compared to that of the Naïve Bayes. The Random Forest and Support Vector Machine models attained almost similar recalls, while the Multilayer Perceptron obtained the least recall at 70.70%. Figure 5 highlights the performance of the machine learning models according to their respective F1 scores or the harmony between precision and recall values. In this metric, the Random Forest performed best at 74.80%.

The Logistic Regression and Naïve Bayes. It can also be noted that the Multilayer Perceptron obtained the lowest F1-Score among models.

In summary, Logistic Regression, Support Vector Machine, Naive Bayes, and Random Forest demonstrated competitive overall performance, with Logistic Regression slightly outperforming the others in terms of overall accuracy and balance between precision and recall.

The Multilayer Perceptron lagged behind, indicating areas for improvement in its architecture or training approach. As a result of this study, the Logistic Regression model is found to be the best in predicting scholarship grants for the EBSU office.

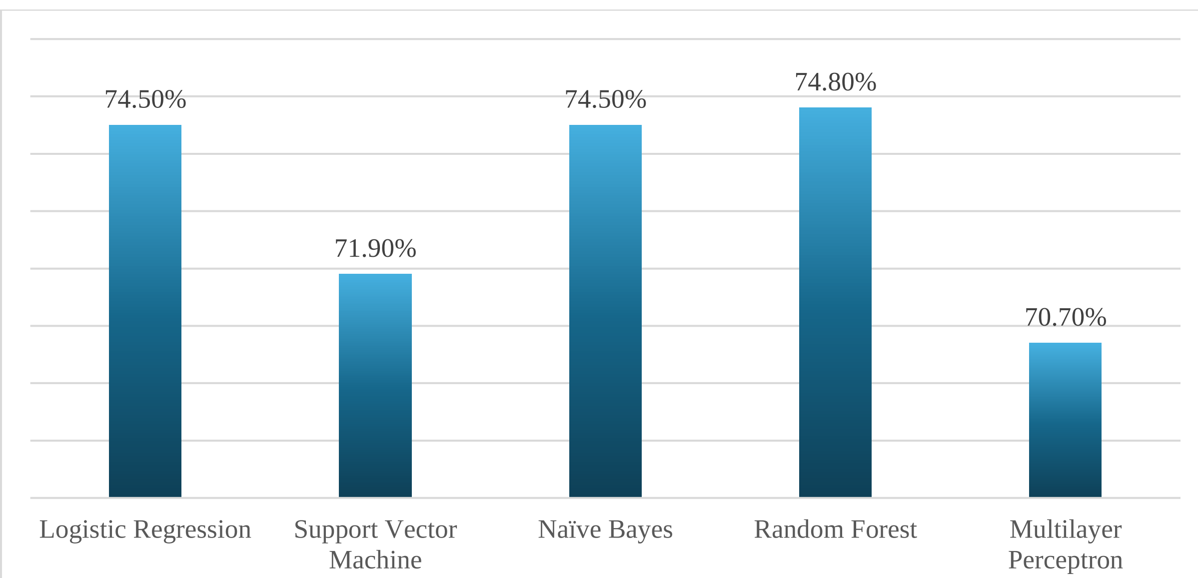

Fig. 5 F1-Score

5. Conclusion

In conclusion, the traditional methods of managing scholarship grants in higher education institutions and agencies, such as EBSU, have proven to be cumbersome, outdated, and inefficient. With a growing number of applicants and limited resources, selecting deserving grantees becomes increasingly challenging. Applicants often face uncertainty about which program to apply for, leading to a complex and convoluted selection process. Moreover, the discrepancy between available grants and the number of students in need further intensifies the issue. To address these challenges, this study focused on developing a predictive model using various machine learning algorithms. By leveraging the algorithms presented in this study, EBSU aims to streamline the selection process and match applicants with the most suitable scholarship opportunities based on their individual backgrounds and qualifications.

The analysis of different machine learning models revealed promising results, with Logistic Regression emerging as the best-performing model in terms of overall accuracy and balance between precision and recall. Support Vector Machine, Random Forest, and Naive Bayes also demonstrated competitive performance, albeit with slight variations in accuracy and precision. However, the Multilayer Perceptron exhibited the lowest performance among the models evaluated, highlighting potential areas for improvement in its architecture or training approach. Overall, the adoption of machine learning algorithms holds immense potential for enhancing the efficiency and effectiveness of the scholarship selection process at EBSU, ultimately ensuring that grants are allocated to the most deserving applicants.

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