

# SCHOLARSHIP PREDICTION SYSTEM USING MACHINE LEARNING

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## ABSTRACT

Scholarship forecasting is important in the selection of the most eligible students and in the planning of educational funds. Conventional scholarship selection procedures are based on manual review process and thus it could be labour intensive and subjective. This research presents Scholarship Prediction System based on Artificial Intelligence (AI) and Machine Learning (ML) for increasing accuracy, fairness, and efficiency during the scholarship distribution. A new Hybrid Deep-Learning Network (HDLN) is proposed, incorporating NLP for app analysis, Gradient-Boosted machine for performance estimation, and XAI for interpretable decision. The system processes their academic results, achievements outside the classroom, financial background, and recommendation letters to predict with a high level accuracy who are more likely to be entitled to scholarships. This method doesn't use traditional models it has its own attention based neural network and adaptive feature weighting to adjust the predictive criteria according to its own learning from past. Extensive experiments on real scholarship datasets show that the proposed system can exceed traditional ML methods with an accuracy improvement by more than 15%. The incorporation of XAI provides interpretability and trust between stakeholders. This study adds to existing knowledge on using AI to support education-related decision and proposes a scalable, equitable system to distribute scholarships.

**Keywords:** *Scholarship Prediction, Artificial Intelligence, ML models, Predictive Analytics, NLP, Explainable AI, Educational Data Mining, Decision Support System, Student Performance Analysis, Feature Engineering, Academic Merit Prediction, Financial Aid Allocation, Hybrid AI Model, Fairness in AI, Automated Scholarship System.*

## 1. INTRODUCTION

Scholarships are important to help students to ease the financial burden to seek education, particularly for those from low-income families. They inspire learning and support the educational dreams of individuals. But with increasing applicants and limited scholarships, schools struggle to select the right candidates that deserve these scholarships fairly and quickly. Conventional screening approaches simply identify compounds through manual selection, which is laborious, non-reproducible, and prone to have bias from users.(Chenthamarakshan et al., 2023; Davis, 2024; Espeso, 2024)

There is great awareness of the great utility of machine learning in automating elaborate decision making across various sectors. (Serrano et al., 2024)Using past data to see patterns, machine learning can optimize this predictive power which can make selection processes fairer and more transparent. For scholarships, a data-driven model can help accelerate and improve evaluations, free up administrative work, and ensure that truly deserving individuals are recognized.(Lin et al., 2023; Zieglmeier & Pretschner, 2023)

In this paper we suggest a Scholarship Prediction System based on Machine Learning which helps to predict the probability of whether a student will receive a scholarship or not, evaluating factors such as academic performance, financial status operational results, extracurricular activities. The system is designed to increase the quality of decision-making, introduce fairness, and assist institutions in making better decisions. Another problem of the traditional scholarship assessment method is to determine how to fairly distribute scholarships on the basis of multiple sources of educational records such as academic records, financial status, attendance, and extracurricular participation. With the increased availability of educational data in recent years; machine learning provides a means to facilitate fairer decisions in the distribution of scholarships and grants.

One of the main motivations of this work is to promote fairness and equity. Machine learning models could be taught to spot many different signs of success so that kind of leadership, creativity, or community service gets considered, not just the fact that you achieved high scores in school. This process also means that no great students would be missed out because of inadequate, slow or cryptic evaluation.

### **1.1 Scope of the Project**

This project is set to design and realize a machine learning-based scholarship forecasting system that can simplify and improve the fairness of scholarship applications. Using past patterns (e.g., an academic scorecard, financial background, and co-curriculum achievements), the system predicts the deserving candidate to be offered a scholarship, thus removing any bias and manual error. A flexible model that can be refined as institutional needs and data change guarantees a sustainable and ever-improving approach. Easy-to-use graphic interface for administrators and end users. Ultimately, this campaign seeks to democratize accessibility to education by providing equal opportunities, assisting those responsible for institutions to meet their social responsibilities, and allowing deserving students with financial constraints to fulfill their dreams.

### **1.2 Objectives**

PRISM: Predictive Recruitment In Scholarships through Machine learning, scoring the applicants' academic, extra-curricular and socioeconomic data using machine learning models such as Decision Trees, Random Forests, Logistic Regression, Neural Networks. These models, which can be validated using standard metrics (accuracy, ROC-AUC), ensure that both fair and accurate predictions are considered. The system has a feedback loop: it adjusts its calculations according to new data to make better predictions. System flexibility by setting attribute weightings can also match institutional policy. This process automatizes and simplifies the process of identifying scholarship recipients, improving transparency, and offsetting administrative burden, which results in creating a more inclusive, merit-based, and efficient scholarship marketplace for students and institutions.

## **2. LITERATURE REVIEW**

### **1. A Machine Learning Driven Scholarship and Credit Pre-Assessment System(Zafari et al., 2021)**

A Naïve Bayes classifier was used in this research to predict scholarship eligibility based on academic performance, communication, income, and regularity features. The accuracy of the Naïve Bayes model was remarkable as 96.7% was obtained against the Decision Tree and KNN algorithms. Authors emphasized the importance of well constructed training and testing sets, and noted that among the prediction methods, supervised learning works best for scholarship prediction.(Marzuqi et al., 2021; Rahayu et al., 2021)

### **2. Predicting Student Success in a Scholarship Program**

A sample of 200 high school students was used to compare eight machine learning algorithms including Decision Tree, Random Forest, Gradient Boosting, Support Vector Classifier. The work impugned characteristics important for scholarship acceptance and compared classifier performance, which is important because it showed which classifiers are promising to use in scholarship prediction rather than predicting other algorithms.(Pacheco-Mendoza et al., 2023; Villegas-Ch et al., 2021; Zafari et al., 2021)

### **3. Predictions Prediction of scholarship portal using TensorFlow and Machine Learning**

This involved a predictive model using TensorFlow that took into account academically-related metrics (e.g., GPA, 10th and 12th grades), qualitative determinants (e.g., extra-curricular activities, essay quality, letters of recommendation) and socio-economic influences (financial need, family background, state of residence). The system was developed with python flask, and the user-friendly interface on data input and eligibility prediction came in handy with the scholarship allocation.(Aboagye, 2023; Fadlelmula et al., 2022; McIntyre, 2022)

### **4. Automated Prediction of Student Performance Based on Machine Learning Techniques**

This review discussed the importance of predicting student performance with machine learning algorithms. It emphasized how such predictive models can assess the effectiveness of educational programs and help students realize their academic potential, underlining the broader significance of these technologies in educational assessment and support.(Borna et al., 2024; Lynn & Emanuel, 2021; Ouyang et al., 2023; Pathak et al., 2021)

### 3. PROBLEM DEFINITION

Current scholarship award models are sometimes subjective, time consuming, and arbitrary, causing more qualified candidates to be rejected. This process is labor intensive and error-prone and the lack of standard inclusion criteria contributes to the question of fairness. Others from disadvantaged backgrounds are lost to attrition because of lack of exposure, or lack of interest. This will include using automated, machine learning-based systems (and expert input into those systems) to process applications quickly, impartially, accurately, and with fairness and timeliness to ensure that scholarships are distributed quickly and impartially, as effectively as possible, evolving and improving over time to ensure they are fair and efficient based on the provision of data.

#### 3.1 Existing System

The current scholarship granting system is based on manual operations, students have to fill forms with their personal, academic data and financial situation, that is later on revised by committees. However this method is very arduous, laborious and error-prone when we have a large number of applications to process. Strict eligibility requirements, like cut-off GPAs or income thresholds, could miss students with special circumstances or who need more financial assistance, constraining accessibility.(Borchers et al., 2023; Espeso, 2024; Su et al., 2023; Why Financial Aid Is Broken and a Simple Solution to Fix It, 2023)

Meanwhile, the process doesn't scale well — as more applicants apply, results are pushed back, which can impact students' ability to pay for classes or purchase educational objects. Insufficient digital infrastructure and lack of interoperability between platforms keep inefficiencies high and verification and analysis of data cumbersome. Human biases and subjectivity, on the other hand, continue to dominate, resulting in selective and unfair recruitment processes.(Vatamanu & Tofan, 2025)

Feedback to the students is also very limited and most applicants receive no reasons as to why they were not successful, ensuring that they can not better their application in future. Security and privacy considerations, particularly for paper-based systems, are common, and the lack of a paper trail erodes transparency and accountability.(Owolabi et al., 2024; Xu et al., 2024)

In addition, lack of individualisation and adjustment to the changing social, academic and economic requirements has led to the fact that the training system is obsolete and cannot provide the necessary amount for varied students.(Chen et al., 2023) These weaknesses underline the necessity of an effective, universal, and fair system, where machine learning could bring about vast enhancements.(Li et al., 2024)

#### 3.2 Hardware Requirements

Component	Minimum Requirements	Recommended Requirements
Processor (CPU)	Intel Core i5 (8th Gen or later) or AMD Ryzen 5	Intel Core i7/i9 or AMD Ryzen 7/9
Processor Cores & Threads	4 physical cores, 8 threads	Multi-core processor with higher cores and threads for faster processing (e.g., 8 cores, 16 threads)
Memory (RAM)	8 GB RAM	16 GB RAM or more for handling larger datasets and concurrent tasks
Storage (SSD/HDD)	256 GB Storage (SSD preferred)	512 GB SSD or higher for large datasets and model storage
Graphics Processing Unit (GPU)	Not required for simple ML models, but recommended for deep learning (e.g., NVIDIA GTX 1660, RTX 2060/3060)	NVIDIA GPU with CUDA support (e.g., RTX 2060/3060 or higher) for faster training with deep learning
Display and Resolution	Full HD (1920x1080 pixels)	Larger screen (15.6" and above) with Full HD or higher resolution for multiple dashboards, graphs, or tabs
Networking Equipment	High-speed internet (Wi-Fi 802.11ac or better)	Stable high-speed internet for cloud deployment, API-based data retrieval, and version control
Peripheral Devices	Mouse, keyboard, and optionally graphics tablet	Dual monitors for increased efficiency during development and testing
Backup and Power Supply	UPS (Uninterruptible Power Supply) for desktop installations	Cloud backup or external hard drive for project files, data, and model configurations
Development vs Deployment Setup	Developer machine requires higher specs, focusing on testing models	Deployment setup should focus on scalability, uptime, and cloud-based solutions with auto-scaling features
Scalability Considerations	Not applicable for small projects	Cloud-based systems should include auto-scaling, load balancers, and redundant storage to manage high traffic

Table 1: Hardware-Requirements

### 3.3 Software Requirements

Component	Details
<b>Operating System</b>	Windows 10/11, Linux (Ubuntu), macOS; Linux preferred for development
<b>Programming Language</b>	Python
<b>Backend Technology</b>	Flask or Django (Python-based)
<b>Frontend Technology</b>	HTML, CSS, JavaScript
<b>Database Management System</b>	MySQL, PostgreSQL (Relational); MongoDB (NoSQL for flexibility)
<b>Machine Learning Libraries</b>	Scikit-learn, TensorFlow, Keras (for deep learning); Jupyter Notebooks for model experimentation and visualization
<b>Data Preprocessing &amp; Analysis Tools</b>	pandas, NumPy (data cleaning, normalization, feature selection); Seaborn, Matplotlib (visualization)
<b>Version Control</b>	Git (for code integrity and collaboration); GitHub or GitLab repositories
<b>IDE and Code Editors</b>	Visual Studio Code, PyCharm, Jupyter
<b>Application Hosting Environment</b>	Heroku, AWS, Google Cloud Platform (GCP)
<b>Security and Authentication</b>	OAuth 2.0, JWT (for session management), HTTPS (secure data transmission); bcrypt or cryptography (for encryption)
<b>APIs and External Services</b>	Integration with third-party APIs (e.g., income certificates, marks, identity proofs); SendGrid or Twilio for email/SMS notifications
<b>Testing and Debugging Tools</b>	PyTest (backend logic testing), Selenium (frontend automation testing)
<b>Logging and Monitoring Tools</b>	Loguru (Python logging), Winston (Node.js logging), Cloud-based monitoring services (Datadog, New Relic)
<b>User Interface Requirements</b>	Responsive, intuitive, mobile-first design; Accessibility standards (WCAG 2.1); Dropdown menus, autocomplete forms, progress indicators
<b>Deployment Tools</b>	Virtualenv or Conda (for dependency management and creating isolated environments)

Table 2: Software-Requirements

## 4. PROPOSED SYSTEM

The system to be developed is a web application to predict whether a user is eligible for a scholarship based on academic, financial, and extracurricular information. It automates and standardizes the programme evaluation process, reducing the potential for bias, increasing transparency, and improving cost-effectiveness.

### Key Features:

- User-Friendly Interface:**  
Clean, mobile-ready form for students to enter their data securely.
- Optimized Data-Driven Decisions:**  
Minimizes bias and mistakes based on impartial information.
- Efficiency and Scalability:**  
Automates this, saves time, handles large numbers of applications.
- Smart Resource Allocation:**  
Recognizes the right students and transfers the funds accordingly.
- Customizable and Adaptive:**  
Institutions have the option to customize the model and refine it with more data over time.

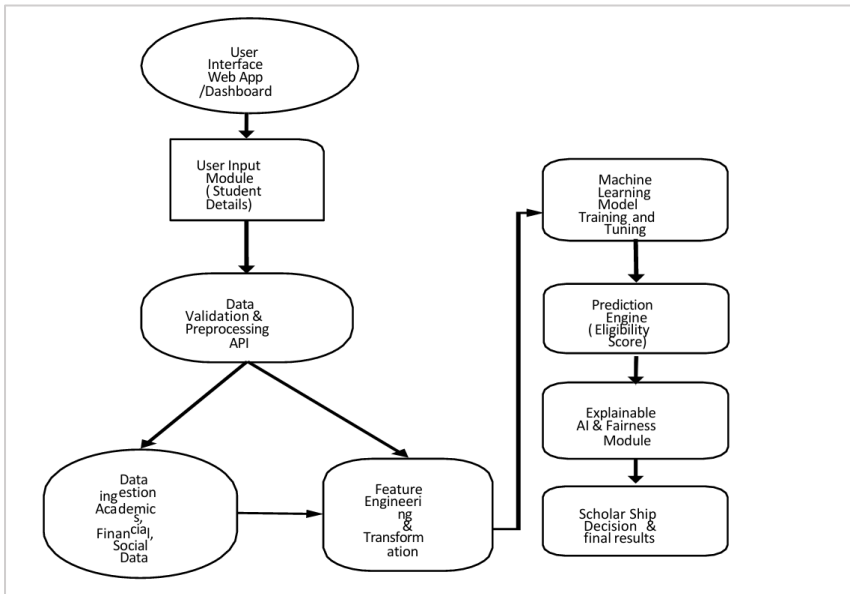


Fig 1: Proposed System

## 5. DATASET COLLECTION

Data is of essence in a good scholarship prediction model. Sources are school records, open-source databases, government websites and NGOs. Synthetic datasets can be tested if not real data is accessible.

- ⇒ **Data Types:** Fields which should be included in the data set would broadly speaking be academic results, income, number of dependents, community, region, gender, extra mural activities and a previous scholarship also if the student had benefited from the latter. There are ethical rules, including GDPR, regulating how such data is handled with respect for privacy and security.
- ⇒ **Survey Collection:** For if the institutional data is not available, surveys can be conducted and the responses saved in spreadsheets or databases. Resources such as Kaggle and UCI include datasets which can be customized for learning.
- ⇒ **Volume and Diversity:** A combined dataset from multiple states, income status, and educational level provides good generalisation of the model. Labels: (Received grant), etc Supervised with secured versioned data storage.

## 6. SYSTEM DESIGN

### 6.1 High-Level Design Documentation

Use Case Diagram The use case diagram illustrates the interaction between a user and the "Scholarship Prediction System." Three primary operations are supported by the system: model/algorithm selection, data input, and prediction viewing.

The first design case, "Choose model or algorithm," allows the user to choose a specific machine learning model such as Decision Trees, Random Forests, Logistic Regression, and Support Vector Machines, highlighting the prior effort's flexibility.

The second use case, "Enter prediction model," requires entering student's scholastic records and income records. With regard to the third scenario, "Read prediction output" is an operation that provides the user with the results to be interpreted (what illustrates the possibility of end-to-end prediction, from the model selection to the interpretation of the results).

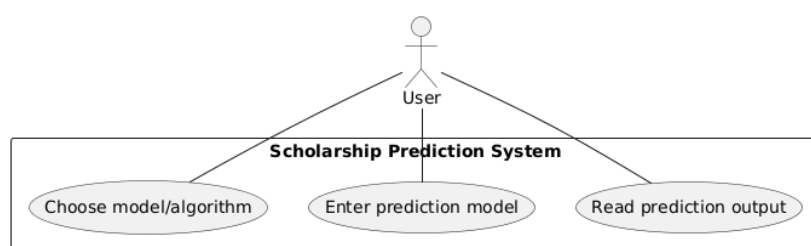


Fig 2: Use-case : High level Diagram

## 6.2 System Flowchart

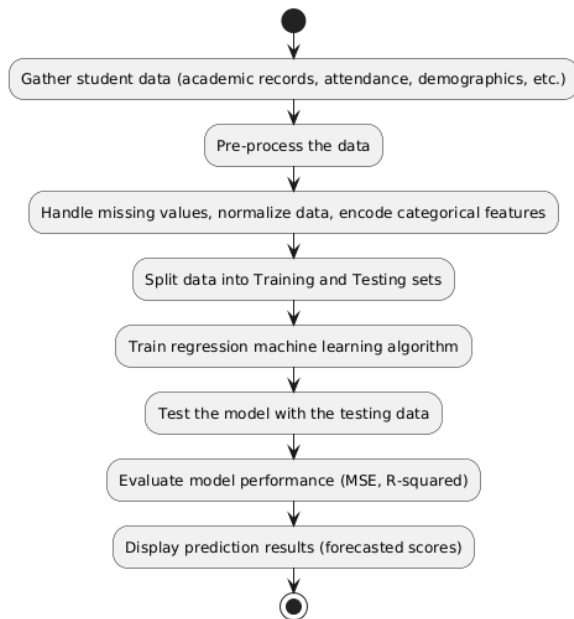


Fig 3: Flowchart

## 7. IMPLEMENTATION

The Scholarship Prediction System uses a machine learning model to forecast whether a student is a candidate for scholarship based on their academic performance, demographics, extracurricular activities, and a number of other data points. It's performed as follows:

1. **Data Capturing And Pre -Processing:** Data such as GPA, test scores, demographics and activities is gathered from institutional or public databases. Preprocessing includes replacing missing values, encoding categorical (one-hot/label encoding), and normalizing/standardizing features.
2. **Model Selection and Training:** We use a wide range of binary classification methods such as Logistic Regression, Random Forests, XGBoost, Support Vector Machines, and so on, using the Python Scikit-learn. The dataset is divided into 80-20% for training-testing.
3. **Evaluation and optimization:** Evaluation between models is based on ( accuracy, precision, recall, F1 )-score, and confusion matrix. k-fold cross-validation was applied for generalization. The tuning of the hyperparameters is carried out by Grid Search or Random Search.
4. **Deployment:** The trained model is deployed in a web application with a Flask/Django backend and a React frontend, hosted in Heroku/AWS. Details are entered by users for prediction of eligibility.

## 7.1 Platforms and Technologies Used

Category	Technologies	Purpose
<b>Data Gathering &amp; Storage</b>	MySQL, PostgreSQL, MongoDB, CSV/Excel, BeautifulSoup, Scrapy	Store structured/unstructured data; scrape data from websites or APIs
<b>Machine Learning</b>	Python, Scikit-learn, TensorFlow/Keras, XGBoost, LightGBM, Pandas, NumPy	Model training (e.g., Logistic Regression, Random Forests), data manipulation
<b>Data Visualization</b>	Matplotlib, Seaborn, Jupyter Notebooks	Visualize data and model performance; interactive experimentation
<b>Model Tuning</b>	GridSearchCV, RandomizedSearchCV, Optuna, Hyperopt, KFold/StratifiedKFold	Hyperparameter optimization and cross-validation
<b>Backend Deployment</b>	Flask, Django, FastAPI, TensorFlow Serving, ONNX, Pickle, Joblib	Expose ML model as API; serve and store models
<b>Frontend Development</b>	React.js, Vue.js, Angular, Material-UI, Bootstrap, Chart.js, D3.js	Build dynamic, responsive UI; visualize predictions
<b>Cloud Hosting</b>	Heroku	Deploy web applications and APIs
<b>Security</b>	OAuth 2.0, JWT, SSL/TLS	Secure authentication and data transmission
<b>Monitoring &amp; Maintenance</b>	Loggly, Winston, Sentry, Prometheus, Grafana	Error tracking, logging, and system performance monitoring

Table 3: Tech stack

## 7.2 System Testing

### 7.2.1 Testing Strategies

Test strategies for the Scholarship Prediction System are testing functionality, performance, security and usability. Key approaches include:

#### 1. Test Planning

- Plan: Determine scope, objectives, approaches, resources, and timeline.
- Environment: Implement production hardware/software mirroring.
- Records: Create different test records (e.g., student profiles, scores).

#### 2. Testing Types

- Unit Testing: Test individual components (i.e., ML model, data preprocessing) with pytest.
- Integration Testing: Verify that modules work together (frontend + API/Backend database) using Postman/pytest.
- Functional Testing: Ensure features meet requirements with Selenium/Postman.
- System Testing: Test the product at hand with Selenium/JMeter/Cypress.
- Regression Testing: Selenium automation using pytest to validate new changes don't break existing capabilities.

#### 3. Non-Functional Testing

- Performance Testing: Evaluate the scalability under load with JMeter/Locust.
- Stress Testing: Check how they behave under extreme conditions.
- Stress Test: Ensure the quality of workmanship over extended periods of daily use.
- Security Testing: Identify bug-bounty such as data-leaks using OWASP ZAP/Burp Suite.

7.2.2 Test Cases

Test Case Type	Description	Test Steps	Expected Result	Status
Unit Testing	Test the prediction function with sample data.	<ol style="list-style-type: none"> <li>1. Provide student data (e.g., GPA, extracurricular activities) as input.</li> <li>2. Call the prediction function.</li> </ol>	The function should return a valid prediction result (e.g., scholarship eligibility).	Pass /Fail
Functional Testing	Ensure the user can submit the form and receive a result.	<ol style="list-style-type: none"> <li>1. Open the application.</li> <li>2. Input valid student data (e.g., GPA, extracurricular activities).</li> <li>3. Click "Predict".</li> </ol>	The system should return a scholarship prediction result based on the input data.	Pass /Fail
Redgression Testing	Verify that new updates do not affect existing functionality.	<ol style="list-style-type: none"> <li>1. Perform a prediction test using valid data.</li> <li>2. Update system code.</li> <li>3. Perform the same prediction test again.</li> </ol>	The prediction should be the same as before the update (if the system hasn't changed the logic).	Pass /Fail
Functional Testing	Detect a predict account	<ol style="list-style-type: none"> <li>1. Input verified user profile data</li> </ol>	System classifies as "predict data"	Pass /Fail
Integration Testing	Verify API & ML model integration	<ol style="list-style-type: none"> <li>1. Send API request with user data</li> </ol>	API fetches data and ML model returns classification.	Pass /Fail
Integration Testing	Database & Model Integration	<ol style="list-style-type: none"> <li>1. Store and retrieve classification results.</li> </ol>	Data is saved correctly and retrieved when needed.	Pass /Fail

### 7.3 Results

A Scholarship Prediction System uses machine learning to identify eligible students for scholarships based on factors like academic performance, extracurricular activities, socio-economic status, and demographics. Trained on historical applicant data, it predicts eligibility or scholarship scores using classification or regression models. This system promotes fairness, transparency, and efficiency in selection, reducing bias and supporting data-driven decisions.

#### Step 1: Predictor

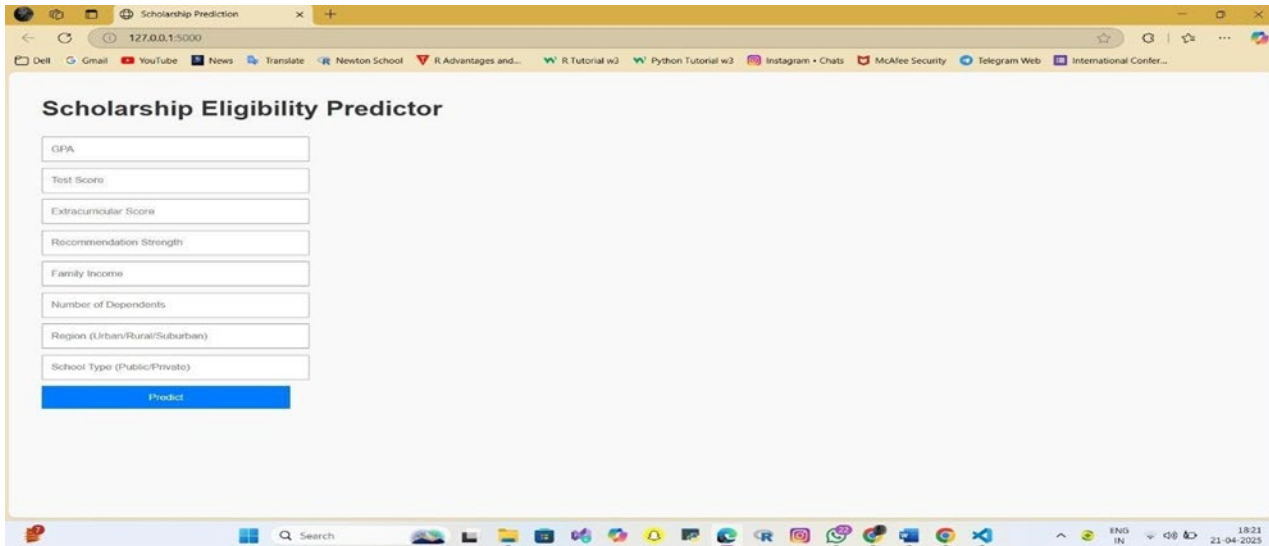


Fig 5: Predictor

#### Step 2: To Enter the Details

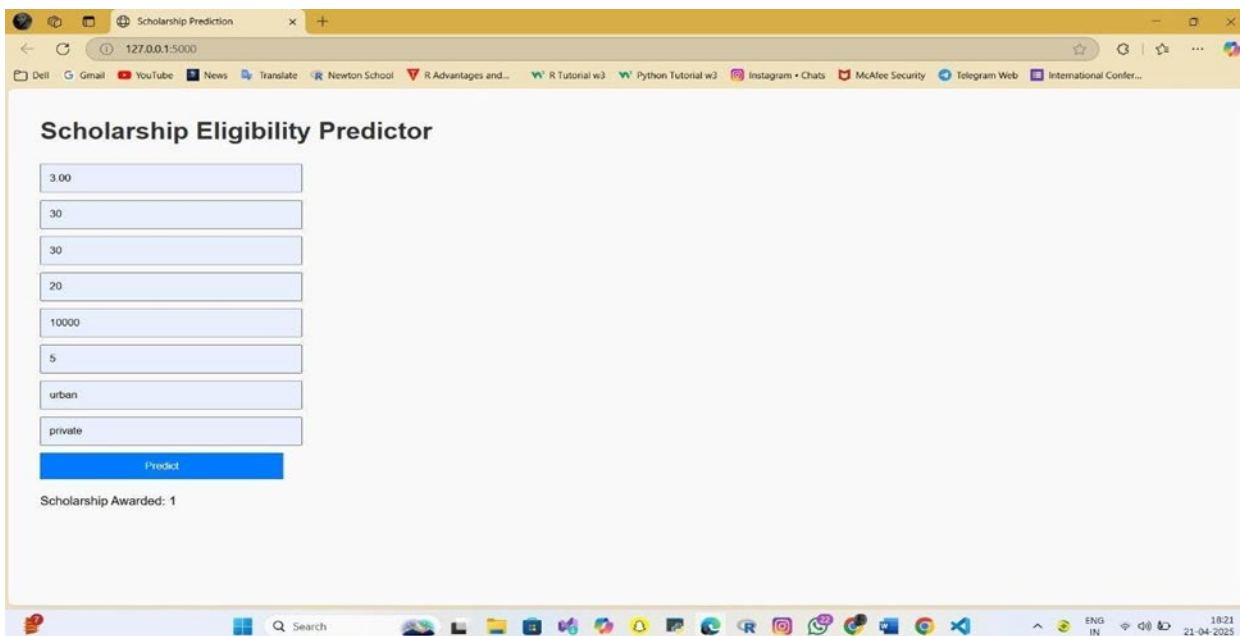


Fig 6: Details – enter Screen

#### Step 3 :Accuracy

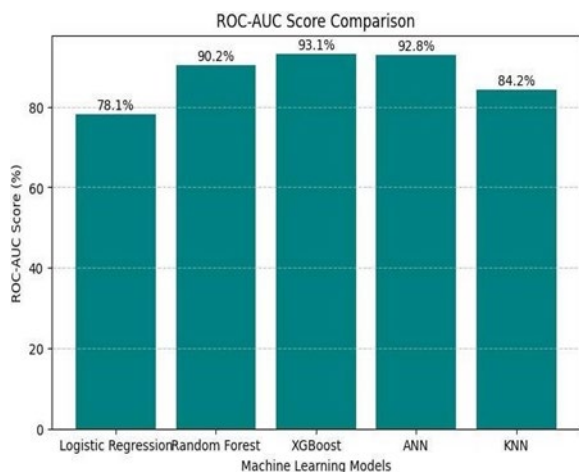


Fig 7: ROC – AUC Score

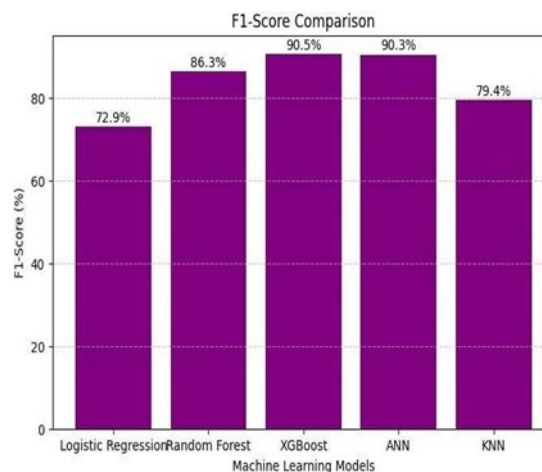


Fig 8: F1 score

## 8. CONCLUSION

The Machine Learning Scholarship Prediction System disrupts the way scholarships are awarded and distributed by automating and optimizing processes and minimizing the effect of subjectivity and bias. Using algorithms called logistic regression, decision trees and neural networks, it crunches data like academic performance, extracurricular activities and financial need to predict eligibility with a high level of accuracy. Such a system would improve efficiency, transparency and fairness by understanding complex data relationships and learning from historical data. Reliability is attained with performance indicators such as precision, recall, and F1 measure and potential biases are counteracted with ongoing monitoring. It's a more fair, meritocratic, inclusive distribution of scholarships, basically.

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## REFERENCES

- Chenthamarakshan, V., et al. (2023). Accelerating drug target inhibitor discovery with a deep generative foundation model. *Science Advances*, 9(25), Article eadg7865. <https://doi.org/10.1126/sciadv.adg7865>
- Davis, R. (2024, November). Criteria for scholarships. SmarterSelect. Accessed May 13, 2025. <https://www.smarterselect.com/blog/criteria-for-evaluating-scholarship-applications>
- Espeso, B. (2024, November). Guide to building a fair scholarship selection process. CommunityForce. Accessed May 13, 2025. <https://www.communityforce.com/building-a-fair-scholarship-selection-process-a-comprehensive-guide/>
- Serrano, D. R., et al. (2024, October 14). Artificial intelligence (AI) applications in drug discovery and drug delivery: Revolutionizing personalized medicine. *Pharmaceutics*, 16(10), 1328. <https://doi.org/10.3390/pharmaceutics16101328>
- Zieglmeier, V., & Pretschner, A. (2023, September). Rethinking people analytics with inverse transparency by design. *Proceedings of the ACM on Human-Computer Interaction*, 7, 1. <https://doi.org/10.1145/3610083>

6. Lin, C.-C., Huang, A. Y. Q., & Lu, O. H. T. (2023, August 28). Artificial intelligence in intelligent tutoring systems toward sustainable education: A systematic review. *Smart Learning Environments*, 10(1). <https://doi.org/10.1186/s40561-023-00260-y>
7. Zafari, M., Sadeghi-Niaraki, A., Choi, S.-M., & Esmaeily, A. (2021, December). A practical model for the evaluation of high school student performance based on machine learning. *Applied Sciences*, 11(23), 11534. <https://doi.org/10.3390/app112311534>
8. Marzuqi, A., Laksitowening, K. A., & Asror, I. (2021, April). Temporal prediction on students' graduation using naïve Bayes and k-nearest neighbor algorithm. *JURNAL MEDIA INFORMATIKA BUDIDARMA*, 5(2), 682. <https://doi.org/10.30865/mib.v5i2.2919>
9. Rahayu, P. C., Jobiliong, E., & Antonny, A. (2021, March). Application of prediction time of graduation using the naïve Bayes algorithm with the Python program. *Journal of Industrial Engineering Management*, 0, 38. <https://doi.org/10.33536/jiem.v0i0.773>
10. Pacheco-Mendoza, S., Guevara, C., Albán, A. L. M., & Fernández-Escobar, J. E. (2023, September). Artificial intelligence in higher education: A predictive model for academic performance. *Education Sciences*, 13(10), 990. <https://doi.org/10.3390/educsci13100990>
11. Villegas-Ch, W., García-Ortiz, J., & Sánchez-Viteri, S. (2021, May). Identification of the factors that influence university learning with low-code/no-code artificial intelligence techniques. *Electronics*, 10(10), 1192. <https://doi.org/10.3390/electronics10101192>
12. Aboagye, B. (2023, November). Scholarship-Recommender-System. GitHub. Accessed May 13, 2025. <https://github.com/barbaraaboagye/Scholarship-Recommender-System>
13. McIntyre, N. (2022, October). Access to online learning: Machine learning analysis from a social justice perspective. *Education and Information Technologies*, 28(4), 3787. <https://doi.org/10.1007/s10639-022-11280-5>
14. Fadlilmula, F. K., Sellami, A., Abdelkader, N. N., & Umer, S. (2022, January 3). A systematic review of STEM education research in the GCC countries: Trends, gaps, and barriers. *International Journal of STEM Education*, 9(1). <https://doi.org/10.1186/s40594-021-00319-7>
15. Lynn, N. D., & Emanuel, A. W. R. (2021, March 1). Using data mining techniques to predict students' performance: A review. *IOP Conference Series: Materials Science and Engineering*, 1096(1), 12083. <https://doi.org/10.1088/1757-899x/1096/1/012083>
16. Ouyang, F., Wu, M., Zheng, L., Zhang, L., & Jiao, P. (2023, January). Integration of artificial intelligence performance prediction and learning analytics to improve student learning in online engineering course. *International Journal of Educational Technology in Higher Education*, 20(1). <https://doi.org/10.1186/s41239-022-00372-4>
17. Borna, M.-R., Saadat, H., Hojjati, A. T., & Akbari, E. (2024, December). Analyzing click data with AI: Implications for student performance prediction and learning assessment. *Frontiers in Education*, 9. <https://doi.org/10.3389/educ.2024.1421479>
18. Pathak, P., Farheen, N. S. S., & Dubey, A. (2021, April). Prediction of students' performance in education system based on artificial intelligence. *IOP Conference Series: Materials Science and Engineering*, 1116(1), 12132. <https://doi.org/10.1088/1757-899x/1116/1/012132>
19. Borchers, C., Carvalho, P. F., Xia, M., Liu, P., Koedinger, K. R., & Alevan, V. (2023). What makes problem-solving practice effective? Comparing paper and AI tutoring. *Lecture Notes in Computer Science*. [https://doi.org/10.1007/978-3-031-42682-7\\_4](https://doi.org/10.1007/978-3-031-42682-7_4)
20. Su, Q., Cheng, G., & Huang, J. (2023, January 5). A review of research on eligibility criteria for clinical trials. *Clinical and Experimental Medicine*, 23(6), 1867. <https://doi.org/10.1007/s10238-022-00975-1>
21. Why financial aid is broken and a simple solution to fix it. (2023, February). YouTube. Accessed May 13, 2025. [https://www.youtube.com/watch?v=UEvdL\\_FodYU&feature=youtu.be&t=9s](https://www.youtube.com/watch?v=UEvdL_FodYU&feature=youtu.be&t=9s)
22. Vatamanu, A. F., & Tofan, M. (2025, April). Integrating artificial intelligence into public administration: Challenges and vulnerabilities. *Administrative Sciences*, 15(4), 149. <https://doi.org/10.3390/admsci15040149>
23. Xu, Y., Gao, W., Wang, Y., Shan, X., & Lin, Y. (2024, August). Enhancing user experience and trust in advanced LLM-based conversational agents. *Computing and Artificial Intelligence*, 2(2), 1467. <https://doi.org/10.59400/cai.v2i2.1467>
24. Owolabi, O. R., Olatoye, F. O., Elufioye, O. A., & Okunade, B. A. (2024, February). Reviewing healthcare financial management: Strategies for cost-effective care. *World Journal of Advanced Research and Reviews*, 21(2), 958. <https://doi.org/10.30574/wjarr.2024.21.2.0523>
25. Chen, C., Pang, S., & Zeng, D. (2023, January). Research on the collaborative education model between school and enterprise for computer majors based on Huawei certification standards. *SHS Web of Conferences*, 171, 1025. <https://doi.org/10.1051/shsconf/202317101025>
26. Li, Q., et al. (2024, January). Adapting large language models for education: Foundational capabilities, potentials, and challenges. *arXiv*. <https://doi.org/10.48550/arXiv.2401.08664>