A Predictive Decision Support System for Student Admissions of Isabela State University Using Data Mining and Deep Learning Techniques

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***Abstract*—This study presents a predictive decision support system designed to assist Isabela State University in student admission decision-making through the application of data mining and deep learning techniques. The system was developed using a dataset of 24,278 anonymized student application records collected from seven university campuses, incorporating academic performance indicators, entrance examination scores, interview results, and selected demographic attributes. After comprehensive data preprocessing, including imputation, feature engineering, one-hot encoding, and normalization, a Multilayer Perceptron (MLP) classifier was trained to predict student admission outcomes. To contextualize model performance, a Logistic Regression classifier was implemented as a baseline using the same preprocessing pipeline and stratified 80:20 train-test split. Experimental results show that both models achieved comparable overall accuracy (83.16%), with Logistic Regression demonstrating higher precision and slightly higher Receiver Operating Characteristic-Area Under the Curve (ROC-AUC), while the MLP achieved higher recall and F1-score, indicating a more balanced identification of qualified applicants. Model evaluation was conducted using accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrix analysis. In addition, a simple empirical fairness analysis was performed across available sensitive attributes, including gender, campus, and senior high school track. The results indicate no substantial performance disparities across major groups, suggesting reasonable empirical fairness within the evaluated dataset. Overall, the findings suggest that the MLP-based system can serve as a supportive, data-driven tool for university admission processes by providing consistent predictive insights while maintaining transparency and fairness considerations.**

***Keywords*—confusion matrix, data mining, F1 score, hot encoding, multilayer perceptron, prediction, recall, Receiver Operating Characteristic-Area Under the Curve (ROC-AUC)**

I. Introduction

University admissions play a vital role in shaping student population. The process remains complex and tedious when institutions review thousands of applications every school semester. Decisions on student admission depend on subjective evaluations of students' academic, examination results, and interview performance. Traditionally, manual screening often results in delays, inconsistencies, and reduced efficiency as the number of student applications continue to rise particularly in many large universities [1]. To address these pressing issues with respect to admission, large number of academic institutions utilize data driven systems that support informed decision-making allowing admission processes to operate more efficiently and equitably [2].

Education Data mining and learning analytics used as analytical frameworks, have shown value and made substantial contributions to the development of predictive systems across various academic contexts [3]. These known frameworks use past student records to discover pertinent trends and patterns which can be considered for decision making. They are also specifically made to produce precise forecasts that can help educational institutions with crucial tasks in decision making that involves forecasting academic performance in the field of education [4].

Decision trees, random forests, and support vector machines are traditional machine learning approaches that have been widely used by different academic institutions to forecast academic success rates of students [5]. Many researchers have explored and studied the effectiveness of these methods and found that they have limitations when dealing with increasingly complex and high-dimensional datasets where nonlinear relationships and intricate feature interactions are more difficult to capture. Given this limitation identified in many studies, research communities are motivated to adopt more advanced deep learning models such as Neural Networks. Neural network models can automatically learn hierarchical feature representations from massive amounts of data enabling them to capture subtle patterns and complex interactions among student attributes that are challenging to model using traditional or manual techniques. Also, neural networks have demonstrated superior predictive performance and scalability in educational analytics making them well suited for supporting data-driven decision-making in modern admission systems of many large universities [6].

Recent advances in neural network topologies have shown strong generalization capabilities across large-scale and heterogeneous student populations resulting in significant increases in prediction accuracy. A notable disparity exists between the more advanced forecasting tools now available in academic analytics and the traditional admissions procedures still employed by many universities and have been highlighted by the growing usage of neural network-based techniques.

Despite these increasingly sophisticated approaches, many universities in the Philippines still use manual student admission procedures which involve conventional methods of subjective assessments of applicants' academic records, entrance exam scores, and interview performance. Human bias can still lead to delays and inconsistencies despite the length of time spent in the admission procedures as more students apply each academic year and these restrictions

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become more apparent and widespread [7].

In order to address these issues, a deep learning prediction model is integrated into a developed system to assist with the admissions decisions particularly for those who are admission staff of Isabela State University. The goal of system is to make the admission process in Isabela State University more efficient, transparent, and fair minimizing subjective judgment and promoting consistent evaluation standards for incoming university students [8]. Also, it is designed to streamline admission procedures and support admissions decisions relying on automated and evidence-based assessments of student admission data.

Positioned within the domain of educational data mining and admission decision support systems, this study focuses on the practical application of predictive modeling in a large, multi-campus public university context in the Philippines. Unlike prior studies that primarily emphasize either traditional machine learning techniques or deep learning models in isolation, this work adopts a comparative approach by integrating a Multilayer Perceptron (MLP) model alongside a Logistic Regression baseline using a consistent preprocessing pipeline and data partitioning strategy. This design enables a grounded assessment of the incremental benefits of nonlinear modeling over linear classification in admission prediction tasks.

Furthermore, while many admission-related studies prioritize predictive accuracy alone, this research extends the evaluation by incorporating a simple empirical fairness analysis based on available sensitive attributes, including gender, campus, and senior high school track. By doing so, the study acknowledges the growing importance of transparency and equity in data-driven admission systems. Rather than proposing a universal or fully automated admission solution, this work positions the developed system as a decision support tool intended to complement institutional judgment, offering data-informed insights while recognizing contextual, ethical, and operational constraints.

The study also covers the phases of system development such as designing, development, and assessment of the system as well as its prediction model integrated in it. Its performance was evaluated using widely known metrics such as precision, recall, F1score, ROC AUC, and confusion matrix. This study also adds to the growing body of literature on educational analytics and demonstrates how predictive technologies can modernize the admissions practices and procedures by incorporating deep learning techniques into admissions procedures of students [9].

II. Literature Review

Educational Data Mining (EDM) has evolved into a vital research domain that applies data-driven techniques to analyze large-scale student records and enhance academic decision-making. Early studies established EDM as a discipline focused on identifying patterns in learning behavior and student performance [10] while subsequent research demonstrated the value of machine learning in strengthening institutional analytics, particularly for early identification of learning difficulties and improved educational planning [11]. Of all the EDM applications, student performance prediction has received the most attention, with extensive evidence showing that models such as decision trees, neural networks, and ensemble methods outperform traditional statistical approaches in forecasting academic outcomes [12]. These predictive capabilities enable institutions to identify at-risk students and implement timely interventions that support retention and success.

Beyond performance prediction, machine learning models have been widely adopted in university admissions through decision-support systems that analyze historical academic data to forecast admission outcomes and future performance [13]. Research indicates that integrating multiple academic indicators, including prior grades and test scores, significantly improves predictive accuracy and decision consistency [14, 15]. Recent advances in deep learning further enhance these systems by capturing complex, nonlinear relationships within student data and maintaining robust performance even in the presence of incomplete or inconsistent datasets [16]. At the same time, growing scholarly attention to fairness and transparency highlights the risk of bias in predictive models and underscores the need for fairness-aware designs that address demographic inequities [17, 18].

Recent literature also advocates for holistic admission frameworks that combine cognitive measures with non-cognitive attributes such as motivation, communication skills, and personal background to better reflect student's potential [19]. As machine learning continues to expand across higher education, predictive models increasingly support student progression, personalized learning pathways, and dropout reduction [20]. Despite these advancements, gaps remain in the application of large-scale, multi-campus datasets and in the integration of fairness-oriented deep learning models, particularly in contexts similar to Isabela State University. These limitations highlight the need for a comprehensive decision support system that unifies machine learning, large institutional datasets, and fairness considerations to enable more informed and equitable admission decisions.

Prior studies demonstrate that machine learning and deep learning techniques can effectively support academic decision-making, including student performance prediction and admission-related tasks. Traditional models such as decision trees, logistic regression, and support vector machines remain widely used due to their interpretability and computational efficiency, while more recent studies highlight the improved predictive capacity of neural networks when modeling complex educational data. However, many existing works report model performance in isolation, without systematic comparison against simple baseline classifiers, making it difficult to assess the true contribution of increased model complexity.

In parallel, recent literature has raised concerns regarding fairness, transparency, and potential bias in data-driven admission systems. Although several studies acknowledge demographic and institutional disparities, empirical fairness evaluations are often limited or absent, particularly in large-scale, multi-campus university datasets. These gaps underscore the need for studies that not only compare advanced predictive models against established baselines using consistent preprocessing pipelines, but also examine model behavior across sensitive attributes to support responsible deployment.

Guided by these observations, the present study integrates a logistic regression baseline alongside a multilayer perceptron model and incorporates a simple empirical fairness analysis. This approach aligns with emerging best practices in educational data mining by balancing predictive performance, interpretability, and equity considerations within a realistic institutional context.

III. Materials and Methods

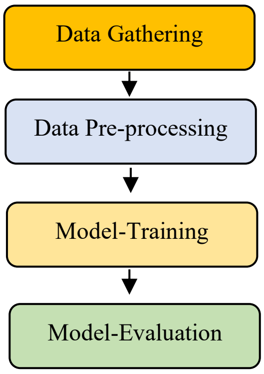

Fig. 1. Model architecture.

The researcher used an organized strategy for the system which comprised four major stages shown in Fig. 1. The stages are data gathering/collection, data pre-processing/cleaning, model training, and model evaluation. This warranted the effectiveness of the chosen model in predicting student admission outcomes of Isabela State University among its seven campuses.

A. Data Gathering and Collection Stage

Dataset used to train and evaluate the model for the developed system was collected from the seven campuses of Isabela State University. As shown in Fig. 2, it was composed of a total of 24,278 admission records of students with corresponding attributes or features relevant to the admissions processes. Features or attributes are the demographic information of student such as age, gender, citizenship, academic performance such as high school grades, General Weighted Averages (GWA), entrance exam scores in subjects like Filipino, Math, Science, and non-academic factors such interview scores, extracurricular activities, disability, and status.

Dataset was anonymized to ensure that personal identifiers such as student names and addresses were not shown in the dataset during processing thus maintaining and preserving the student privacy in line with institutional data privacy policies of Isabela State University.

id	student_name	dialect	dateofbirth	birth_order	gender_identity	gender_expression	sex_biological	sex_orientation	citizenship	civilstatus	first_attended_college	ethnic_group	religion	reg_date
10	10	YOGAD	02-15-2005	2	LGBTQ+	Feminine	Male	Heterosexual	FILIPINO	Single	No	ILOCANO	Roman Catholic	2/15/2024 6:57:10 AM
14	14	ENGLISH, FILIPINO, ILOCANO	01-30-2006	2	Woman	Feminine	Female	Heterosexual	FILIPINO	Single	No	NA	UNITED METHODIST CHURCH	2/15/2024 7:42:39 AM
15	15	Tagalog	08-19-2006	4	Woman	Feminine	Female	Heterosexual	Filipino	Single	No	No	Roman Catholic	2/15/2024 7:45:02 AM
16	16	tagalog	04-12-2007	2	Woman	Feminine	Female	Homosexual	Filipino	Single	No	itawis	Born Again	2/15/2024 7:51:09 AM
17	17	Tagalog, Ilocano	03-21-2006	1	Woman	Feminine	Female	Heterosexual	Filipino	Single	No	N/A	IGLESIA NI CRISTO	2/15/2024 7:57:47 AM
18	18	Tagalog	02-19-2006	1	Woman	Feminine	Female	Heterosexual	Filipino	Single	Yes	N/A	Roman Catholic	2/15/2024 7:58:55 AM
19	19	Ilocano, Tagalog, English	06-07-2006	4	Man	Masculine	Male	Heterosexual	Filipino	Single	No	Ilocano	Iglesia Ni Cristo	2/15/2024 8:00:53 AM
20	20	Ilocano, filipino	11-01-2005	1	Woman	Feminine	Female	Homosexual	Filipino	Single	Yes	N/A	Church of God	2/15/2024 8:00:57 AM
21	21	tagalog, ilocano	02-18-2006	1	Woman	Feminine	Female	Heterosexual	Filipino	Single	Yes	NA	Roman Catholic	2/15/2024 8:01:01 AM
22	22	Tagalog	06-06-2005	2	Woman	Feminine	Female	Homosexual	Filipino	Single	No	None	Roman Catholic	2/15/2024 8:01:04 AM
23	23	Iloko	10-29-2005	7	Woman	Feminine	Female	Heterosexual	Filipino	Single	No	ILOKANO	UNITED METHODIST	2/15/2024 8:02:08 AM
24	24	Tagalog	10-01-2006	4	Woman	Feminine	Female	Homosexual	Filipino	Single	No	N/A	BRM Church of God International	2/15/2024 8:04:32 AM
26	26	Ilocano, Tagalog	08-23-2006	1	Man	Masculine	Male	Heterosexual	Filipino	Single	No	None	Roman Catholic	2/15/2024 8:09:47 AM
27	27	Ilokano, tagalog	04-10-2006	2	Woman	Feminine	Female	Homosexual	FILIPINO	Single	No	N/A	Iglesia Filipina Independiente	2/15/2024 8:10:33 AM
28	28	ITAWES	08-23-2006	3	Woman	Feminine	Female	Homosexual	FILIPINO	Single	No	ITAWES	ROMAN CATHOLIC	2/15/2024 8:10:35 AM
29	29	TAGALOG, ILOCANO	07-19-2006	2	Man	Feminine	Male	Homosexual	FILIPINO	Single	No	N/A	ROMAN CATHOLIC	2/15/2024 8:12:11 AM
30	30	Tagalog	02-08-2005	3	Woman	Feminine	Female	Heterosexual	Filipino	Single	No	Ilocano	Roman Catholic	2/15/2024 8:13:54 AM
31	31	Tagalog	11-22-2005	2	Man	Masculine	Male	Heterosexual	Filipino	Single	No	Not Applicable	Roman Catholic	2/15/2024 8:15:50 AM
32	32	Tagalog	05-24-2006	3	Woman	Feminine	Female	Heterosexual	Filipino	Single	No	Ilocano	Roman Catholic	2/15/2024 8:16:05 AM
34	34	Tagalog	09-26-2005	1	Woman	Feminine	Female	Homosexual	Filipino	Single	Yes	N/A	Roman Catholic	2/15/2024 8:17:38 AM
35	35	Tagalog, English	09-18-2006	5	LGBTQ+	Feminine	Male	Homosexual	Filipino	Single	No	Ilocano	Catholic	2/15/2024 8:17:51 AM
36	36	Tagalog, Yogad	11-10-2006	2	Woman	Feminine	Female	Homosexual	Filipino	Single	No	Yogad	Roman Catholic	2/15/2024 8:17:52 AM
37	37	FILIPINO, ILOCANO	02-25-2006	2	Woman	Feminine	Female	Homosexual	FILIPINO	Single	No	ILOCANO	CHURCH OF GOD	2/15/2024 8:18:11 AM
38	38	Ilokano	09-02-2000	1	Man	Feminine	Male	Homosexual	Pilipino	Single	No	Ilokano	Iglesia Ni Cristo	2/15/2024 8:18:33 AM
39	39	Tagalog, Ilocano	05-23-2006	1	Woman	Feminine	Female	Heterosexual	Filipino	Single	Yes	N/A	Roman Catholic	2/15/2024 8:19:13 AM
40	40	Tagalog	01-31-2006	1	LGBTQ+	Feminine	Male	Homosexual	Filipino	Single	No	Yogad	Roman Catholic	2/15/2024 8:19:31 AM
41	41	Tagalog	10-20-2006	1	Woman	Masculine	Female	Heterosexual	Filipino	Single	Yes	None	Methodist	2/15/2024 8:19:44 AM
42	42	ITAWES, TAGALOG	10-03-2006	2	Woman	Feminine	Female	Homosexual	FILIPINO	Single	No	ITAWES	ASSEMBLY OF GOD	2/15/2024 8:20:48 AM

Fig. 2. Actual dataset.

B. Data Preprocessing Stage

One of the most essential steps for the machine learning is the Data Pre-processing stage. Essential techniques were applied to make sure that data was normalized, consistent, and ready for model-training.

Cleaning. The dataset was subjected to a structured data cleaning process to ensure mathematical consistency and optimal model performance. Instances with missing values in the target variable $y \in \{Admitted, Not\ Admitted\}$ were removed as supervised learning algorithms require fully observed class labels to compute the empirical risk function $L(y,y\,)$. Missing target values prevent the calculation of loss during training, thereby disrupting gradient-based optimization and biasing parameter estimation. Additionally, the non-numeric, redundant, and semantically irrelevant attributes particularly personal identifiers were excluded from the matrix X as such attributes do not contribute predictive information and may increase feature dimensionality d without improving explanatory power that may lead to higher variance and overfitting as described by the variance trade-off. Technically, reducing irrelevant features improves the generalization of the model by constraining space of hypothesis and its complexity. Overall, this cleaning phase improved convergence stability, absolutely reducing noise in the optimization process and enhanced the robustness of the admission prediction model.

Handling Missing Values. Suitable imputation strategies were applied in this study based on type of feature in order to address incomplete observations while preserving the integrity of the dataset. Missing values were replaced using median imputation and it is defined as $\bar{x}$=median(Xj) which is less sensitive to extreme values and skewed distributions compared to mean imputation. This robustness reduces the influence of outliers on parameter estimation and helps stabilize variance during the training of the model. The median imputation minimizes distortion in central tendency under non-Gaussian data distributions which are very common in educational datasets.

Missing categorical feature entries were handled either by substituting the most frequent category known as mode imputation or by introducing an explicit "Missing" category method. The mode imputation preserves marginal category distributions when missingness of the data is minimal while the inclusion of a distinct "Missing" label enables the model to learn potential patterns associated with absent information. This approach prevents the loss of informative missingness and avoids reducing the effective sample size. These imputation techniques ensured a complete feature matrix X enabling uninterrupted computation of predictions of the model and loss functions while improving convergence behavior reducing bias introduced by data deletion hence enhancing the overall generalizability of the admission prediction model.

Feature Engineering. New features were derived from existing academic records to enhance the predictive capacity of the admission model and to better capture the overall academic performance of the students. The General Weighted Averages (GWA) of the students across three senior high school semesters were aggregated into a composite GWA feature and the individual subject examination scores in Filipino, English, Science, and Mathematics subjects were combined to form a Total Exam Score. These aggregated features can be expressed as $\mathrm{GWA}_{\mathrm{agg}} = \frac{1}{3}\sum_{i=3}^{3} gw_{A_i}$ and $\mathrm{EXAM}_{\mathrm{total}} = \sum_{j=1}^{n} s_j$ means that the score obtained in each subject examination. The feature aggregation reduces the dimensionality and mitigates multicollinearity among highly correlated variables hence improving numerical stability during the estimation of the parameter. The hypothesis space of the model is constrained by summarizing multiple related academic indicators into consolidated measures which can further reduce variance and improved the generalization according to the bias variance trade-off learning algorithm. These engineered features provide a more holistic representation of the cumulative academic achievement of students permitting the model to learn more meaningful decision boundaries tuned with the admission criteria of the institution. Overall, the feature extraction process improved interpretability, enhanced convergence during training, and contributed to more accurate and robust admission predictions of Isabela State University.

Encoding Categorical Variables. The categorical attributes such as program, academic track, and campus were encoded using one-hot encoding to convert nominal data into a numerical format that is more suitable for model used in the admission of students in Isabela State University. For a categorical variable C with k distinct categories, the one-hot encoding maps each observation to a binary vector $x \in \{0,1\}^k$ where $x_i = \{1,0\}$ if $C = C_i$ otherwise, *for* $i=1,\ldots k$. This transformation during encoding prevents the introduction of artificial ordinal relationships or false magnitude among categories ensuring that all categories are treated as equidistant. One-hot encoding increases feature dimensionality and it preserves categorical independence and enables models to learn valid decision boundaries that improves predictive accuracy and reducing bias in the admission prediction process.

Feature Scaling. Numerical features were standardized using z-score normalization to ensure that all input variables contributed proportionally to the learning process of the model. Each of the feature x has been transformed according to $z=x-\mu\ /\ \sigma$ where both of the μ and σ represent the mean and standard deviation of the feature respectively. Standardization centers the data at zero with unit variance preventing features with larger numeric ranges from disproportionately influencing the parameters of the model.

C. Model Training

After completing data preprocessing, the researcher proceeded to the model training phase shown in Fig. 3. The researcher used the Multi-Layer Perceptron (MLP) as the primary model because it effectively captures intricate patterns within the data while maintaining a straight-forward implementation.

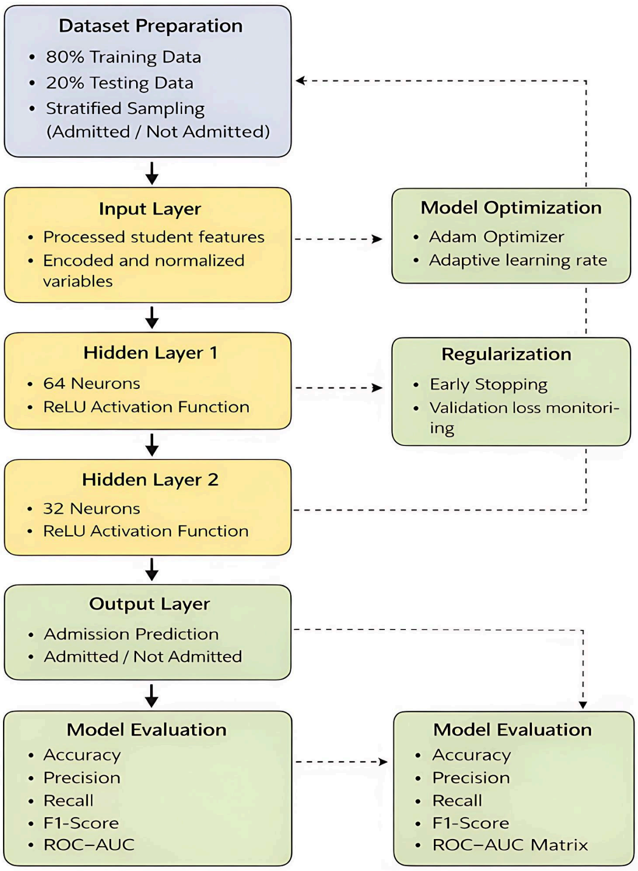

Fig. 3. Multilayer Perceptron (MLP) model architecture and training workflow for student admission prediction.

Model Architecture. The MLP was designed with two essential hidden layers. The first layer comprised of 64 neurons, and the second layer contained 32 neurons. Rectified Linear Unit also called ReLU was chosen as the activation function due to its ability to introduce non-linearity without causing the vanishing gradient problem that can occur with older activation functions like sigmoid or tanh.

Training Process. The Adam optimizer was used to train the model, which adapts the learning rate during training for better convergence. Early stopping was used to avoid overfitting by monitoring validation loss and halting the training when performance on the validation set started to degrade.

Data Split. The dataset was split, 80% for the training and 20% testing set respectively. Stratified sampling was utilized to make sure that the class distribution of the target variable (*evaluation_status*) was preserved both in the training and testing sets. It ensures that both classes (*Admitted*, *Not Admitted*) are well-represented in both sets.

D. Baseline Model

To establish a baseline for evaluating the effectiveness of the Multilayer Perceptron (MLP) model, a Logistic Regression classifier was implemented as a baseline predictive model. Logistic Regression is a widely used linear classification technique and serves as a standard benchmark in educational data mining and admission prediction studies due to its interpretability, simplicity, and well-established theoretical foundation.

The Logistic Regression model was trained using the same dataset, preprocessing pipeline, feature engineering steps, and stratified data split as those applied to the MLP model to ensure a fair and consistent comparison. Specifically, missing values were handled using median imputation for numerical features and mode or explicit "Missing" categories for categorical variables. Categorical attributes were transformed using one-hot encoding, and all numerical features were standardized using z-score normalization prior to model training.

Given an input feature vector x, the Logistic Regression model estimates the probability of student admission as $P(y = 1 \mid x) = \frac{1}{1+e^{-(w^T x+b)}}$, where w represents the learned weight coefficients and b denotes the bias term. Model parameters were estimated using maximum likelihood optimization by minimizing the binary cross-entropy loss function.

The dataset was split into 80% training and 20% testing sets using stratified sampling to preserve the class distribution of admitted and not admitted applicants, consistent with the MLP training procedure. The Logistic Regression model was evaluated using the same performance metrics as the deep learning model, including accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrix analysis.

Although Logistic Regression assumes a linear decision boundary and does not explicitly capture nonlinear feature interactions, its inclusion as a baseline model provides a meaningful reference point for assessing the performance gains achieved by the MLP architecture on the student admission prediction task.

E. Evaluation of the Model Using the Following Metrics

Once the model was trained, its performance was evaluated by means of several key metrics to assess its predictive accuracy.

Accuracy. The portion of correctly predicted admission statuses (*Admitted / Not Admitted*) over the total and actual number of predictions.

Precision. The portion of true positive predictions correctly identified as "admits" out of all predicted admits and was used to evaluate the model's reliability.

Recall. The portion of true positive predictions out of all actual "admits", measuring the model's sensitivity.

F1-Score. The overall mean of precision and recall, thus provides a balance between the two metrics.

ROC-AUC. The researcher used ROC-AUC to evaluate the model's ability to discriminate between classes across the different decision thresholds. Predictions were also analyzed using a confusion matrix that delivers a detailed breakdown of true positive, false positive, true negative, and false negative predictions.

IV. Result and Discussion

The findings of precision, accuracy, confusion matrix, F1-score, ROC-AUC, and recall were the six key performance and widely known metrics used in this study. These metrics were used to evaluate the developed system in terms of its capacity to forecast student admission outcomes at Isabela State University. These metrics provide a comprehensive assessment of its predictive reliability, classification effectiveness, and overall suitability of the model as a decision support tool for the admission process of students in Isabela State University.

A. Performance Metrics

The evaluation metrics used to evaluate the performance of the model:

Accuracy. The model attained an accuracy of 83.16%, demonstrating that the model correctly predicted whether a student would be admitted or not in the test set. It is the portion of correct predictions (both admitted & non-admitted students) out of all predictions processed correctly by the model.

An accuracy rate above 80% is considered a good result, suggesting that the model is effective in distinguishing between the two classes (admitted and not admitted). However, accuracy alone is not sufficient, especially in cases where the data is imbalanced, which is often true in university admission datasets.

Precision. The portion of true positive predictions (correctly identified admits) relative to all predicted admits. The model achieved a precision rate of 85.4% which indicates that when the model predicts a student will be admitted, it is correct about 85% of the time. This demonstrates that the model has a high reliability in predicting students who will be admitted, which is particularly important in minimizing false positives in the admission process.

Recall. The proportion of true positive predictions relative to all actual admits. The recall value of 80.2% reflects the model's ability to correctly identify students who should be admitted. Although not perfect, the model captures 80.2% of all students who were actually admitted, which is quite effective for an automated decision support system.

F1-Score. The harmonic mean of precision and recall, which balances the two metrics. The F1-score of 82.7% indicates a good balance between precision and recall. Since F1-score penalizes the model for imbalanced precision and recall, this score suggests that the model strikes a solid balance between identifying admits correctly (precision) and ensuring that it does not miss too many admits (recall).

ROC-AUC. The area under the receiver operating characteristic curve, a measure of how well the model distinguishes between the classes. The ROC-AUC value of 0.89 suggests that the model has a strong ability to discriminate between admitted and non-admitted students. A value closer to 1 showed that the model was very effective in distinguishing between the two classes, which is critical for making informed and accurate admission decisions.

Table 1. MLP vs logistic regression (baseline)

Model	Performance Comparison Between Logistic Regression (Baseline) and MLP				
	Accuracy	Precision	Recall	F1Score	ROC-AUC
Logistic Regression	83.16%	90.88%	74.20%	81.70%	0.9007
MLP	83.16%	85.40%	80.20%	82.70%	0.89%

Table 1 presents a comparative evaluation between the Logistic Regression baseline model and the Multilayer Perceptron (MLP) using identical preprocessing procedures and data partitioning. The results indicate that while both models achieve comparable overall accuracy, they exhibit different strengths in terms of classification behavior and decision characteristics.

The Logistic Regression baseline demonstrates higher precision and a slightly higher ROC-AUC value, suggesting that it produces more conservative admission decisions with fewer false positives and strong overall class discrimination. This performance aligns with the linear decision boundary assumptions of Logistic Regression and highlights its suitability in scenarios where interpretability and cautious decision-making are prioritized.

In contrast, the MLP achieves higher recall and F1-score, indicating a more balanced trade-off between precision and recall. This suggests that the MLP is more effective in identifying a greater proportion of qualified applicants while maintaining reasonable control over misclassification. The nonlinear architecture of the MLP enables it to capture complex interactions among academic performance, entrance examination scores, and interview results, which are difficult to model using linear classifiers.

Although the improvement in overall accuracy is marginal, the enhanced recall and F1-score achieved by the MLP are particularly important in admission decision support systems, where missing qualified applicants can have significant institutional and ethical implications. Overall, the comparative results confirm that while Logistic Regression serves as a meaningful and interpretable baseline, the MLP provides a more flexible and balanced predictive framework, supporting its selection as the primary model for student admission prediction at Isabela State University.

B. Model's Evaluation

Several well-known KPIs or metrics, including precision, confusion matrix, F1-score, ROC-AUC, and recall, were used to analyze and appraise the model. The most thorough evaluation of the model's prediction abilities was provided by these metrics.

Table 2. Actual vs predicted admissions

No	Comparison	
	Predicted Admitted	Predicted Not Admitted
1	6,810	1,680
2	1,700	14,500

Table 2 shows that 6,810 students who were correctly predicted as admitted while 14,500 students who were correctly predicted as not admitted.

Also, Table 2 shows that 1,700 students who were incorrectly predicted as admitted (false positives) and 1,680 students who were incorrectly predicted as not admitted (false negatives).

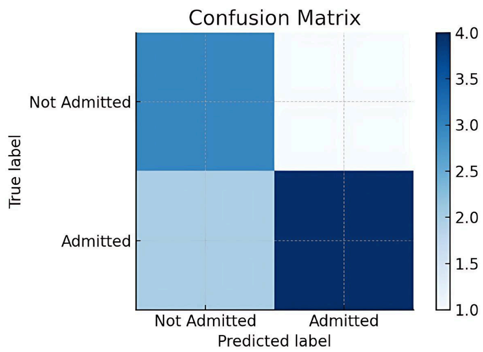

Fig. 4. Confusion matrix (not admitted vs admitted).

Fig. 4 shows the True Positives, False Positives, and False Negatives. The True Positives indicate the students who were correctly identified as admitted which directly impacts the admission decisions of Isabela State University. The False Positives represent students who were predicted to be admitted but were not.

The model correctly identified the majority of applicants who were accepted and those who were not based from the confusion matrix which provided an overview of the result of classification. The overall accuracy rate of 83.16% suggests that the developed system effectively generated accurate predictions in over four out of five cases. Also, the model successfully identified qualified candidates while minimizing false admissions as evidenced by the precision score of about 85.4% and recall score of about 80.2% respectively.

The area under the Curve (AUC) value of 0.89 indicates that the model exhibited excellent discriminative ability between "Admitted" and "Not Admitted" students of Isabela State University.

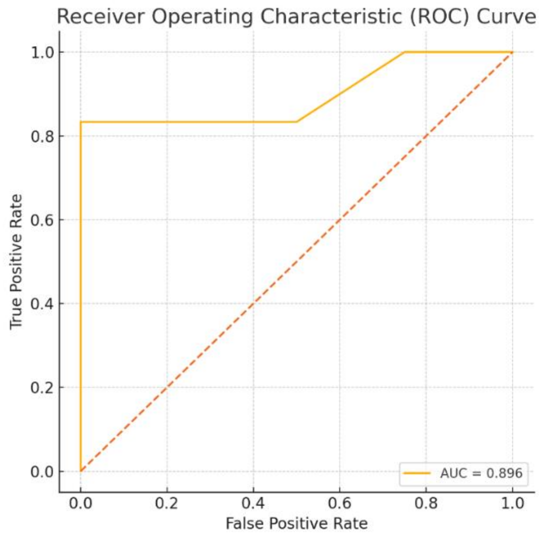

Fig. 5. ROC curve indicating true positive vs false positive rate.

Fig. 5 showed that the model maintains a high True Positive Rate with a relatively low False Positive Rate signifying a strong balance between sensitivity and specificity. This performance suggested that the model can confidently rank admitted students higher than non-admitted ones in approximately 86% of cases.

In real terms, this means the developed system can help the admissions committee prioritize candidates who are most likely to succeed without significantly misclassifying unqualified applicants. The ROC curve validates that the Multi-layer Perceptron (MLP) architecture used effectively captures complex, non-linear relationships among academic, demographic, and performance-based variables. The strong ROC-AUC value further supports the reliability of the system as a data-driven, decision-support tool for university admissions.

C. Data Presentation and Analysis

The class distribution illustrated in Fig. 6 offered a clear picture of how many applicants were admitted versus those who were not. Maintaining a relatively even proportion between these two groups was valuable because it prevented the learning system from leaning very heavily toward one outcome, which helped improve the reliability of its predictions over time. The pattern also reflects how the institution evaluates prospective students based on qualifications and institutional requirements.

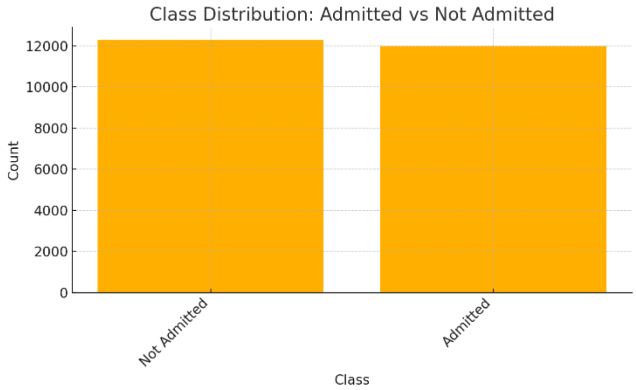

Fig. 6. Class distribution: Admitted vs. not admitted.

D. Descriptive Statistics

The central tendency and dispersion of numerical variables are compiled in Table 3. According to the missingness assessment shown in Table 4, core predictive fields are largely finished.

Table 3. Summary statistics for selected numeric variables

Feature	Count	Mean	STF	Min	25%	50%	75%	Max	Missing(%)
GWA	24278	88.3	10.31	0.0	86.33	89.33	92.0	100.0	0.0
Filipino	24278	5.7	4.25	0.0	0.0	6.0	9.0	20.0	0.0
English	24278	6.9	5.19	0.0	0.0	8.0	11.0	20.0	0.0
Math	24278	4.8	3.74	0.0	0.0	5.0	7.0	20.0	0.0
Science	24278	6.6	5.05	0.0	0.0	7.0	10.0	20.0	0.0
History	24278	6.7	4.89	0.0	0.0	8.0	10.0	20.0	0.0
Reasoning	24278	5.4	5.06	0.0	0.0	5.0	9.0	20.0	0.0
Interview	24278	13.9	9.95	0.0	0.0	18.0	22.0	25.0	0.0

Table 4. Variables with highest missingness (top 15)

No	Unnamed: 0	Missing (%)
1	ethnic_group	32.04
2	track	1.88
3	citizenship	0.49
4	dialect	0.33
5	dateofbirth	0.26
6	religion	0.18
7	civil_status	0.0
8	student_name	0.0
9	disability	0.0
10	first_attended_college	0.0
11	campus	0.0
12	gender_expression	0.0
13	sex_orientation	0.0
14	sex_biological	0.0

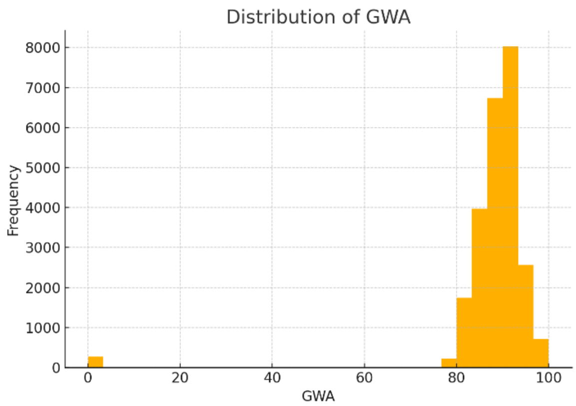

Fig. 7. Distribution of General Weighted Average (GWA).

E. Academic Indicators

The General Weighted Average (GWA) score distribution gave an insight into applicants' academic standing prior to their application. Students with better academic records tended to show at the lower end of the GWA scale as seen in Fig. 7. The pattern in the result implied that a large number of applicants had competitive academic standing during admission and this is in accordance with the grading scheme frequently used under education setup in the Philippines.

Fig. 8 shows the trend in the Admission Status of applicants that reinforced the idea that academic achievement continued to play a significant role in the selection process for incoming students in Isabela State University.

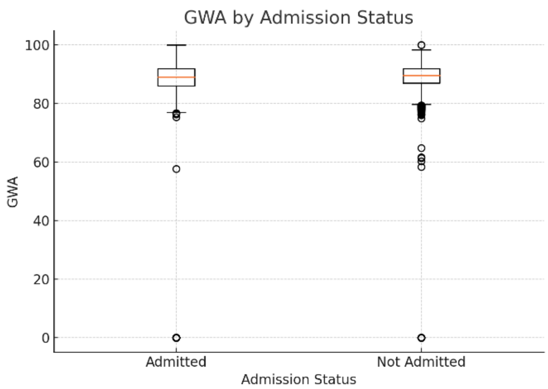

Fig. 8. GWA by admission status (boxplot).

F. Composite Readiness

As seen in Fig. 9 to Fig 15, the distribution of overall entrance exam scores showed that most applicants clustered around the central score levels, with a discernible concentration of applicants in the mid-range performance bracket. The pattern showed that rather than showing remarkable proficiency in a single domain, the majority of examinees showed comparatively balanced competency across the test's component subjects. Variability in past academic preparation and testing conditions is highlighted by the noticeable grouping at the bottom end of the scale which probably corresponds to people who either did not complete the exam or entered with noticeably weaker academic underpinnings.

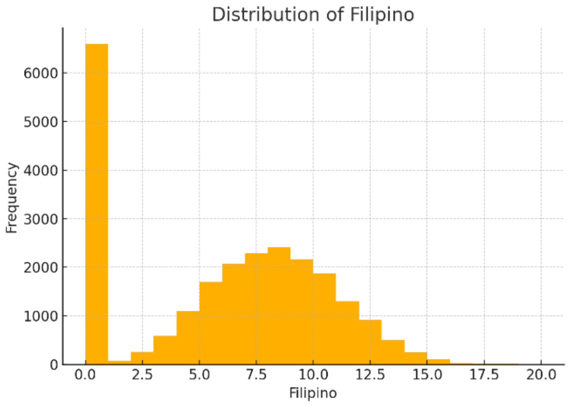

Fig. 9. Filipino entrance score distribution.

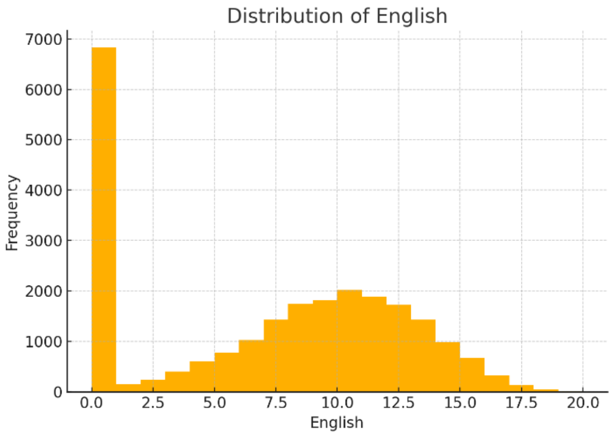

Fig. 10. English entrance score distribution.

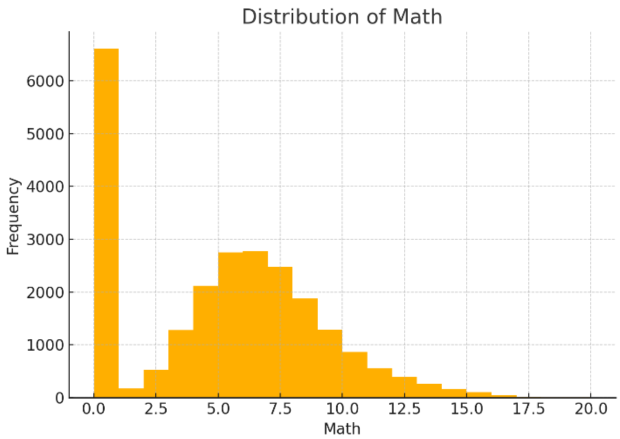

Fig. 11. Math entrance score distribution.

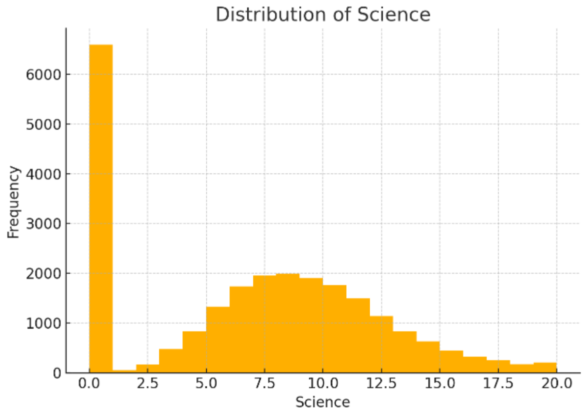

Fig. 12. Science entrance score distribution.

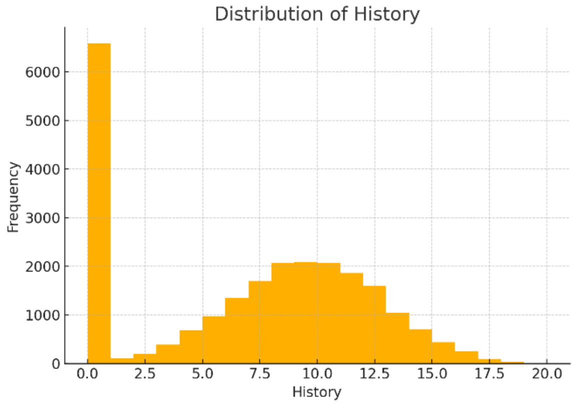

Fig. 13. History entrance score distribution.

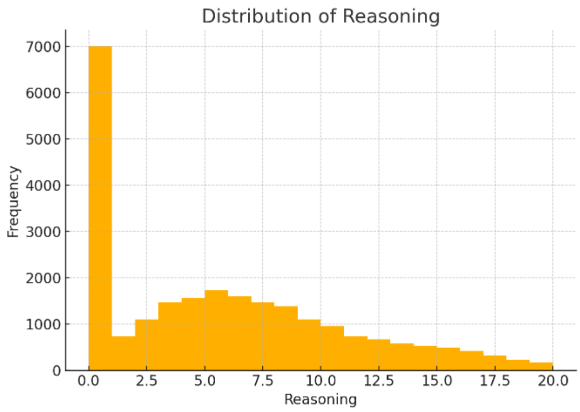

Fig. 14. Reasoning score distribution.

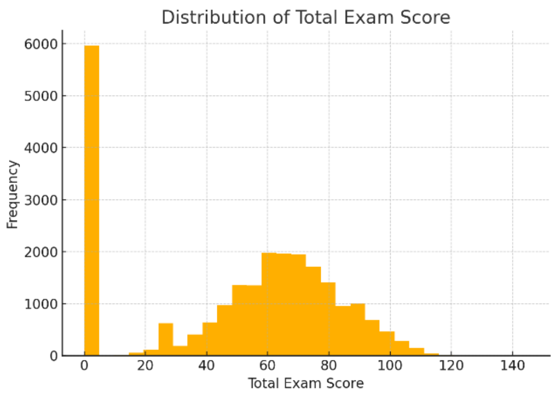

Fig. 15. Total exam score distribution.

Fig. 16 shows that there was a difference in the overall exam performance of students between those who were accepted and those who were not accepted in the admission process. The higher median and the concentrated score distribution observed among admitted students indicate that they generally achieved stronger overall examination results as compared to non-admitted applicants. This pattern demonstrates that satisfactory performance across all exam components was critical for admission and reaffirms the role of standardized testing as an important measure of academic readiness.

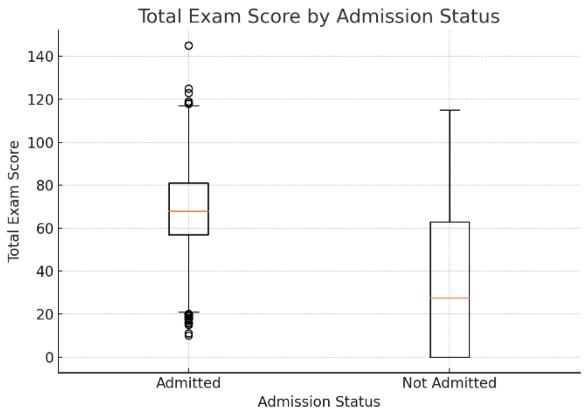

Fig. 16. Total exam score by admission status (boxplot).

Fig. 17 shows the distribution of gender identity among applicants showing that a large portion of the student population identified as women followed by those who identified as men. This distribution has a strong indication that the presence of female within the pool of applicant which may reflect broader enrollment trends in specific academic programs or disciplines is commonly pursued at the institution. Results also show that smaller yet meaningful group of applicants identified as LGBTQ+ demonstrates that the university attracts also incoming students with very diverse gender identities.

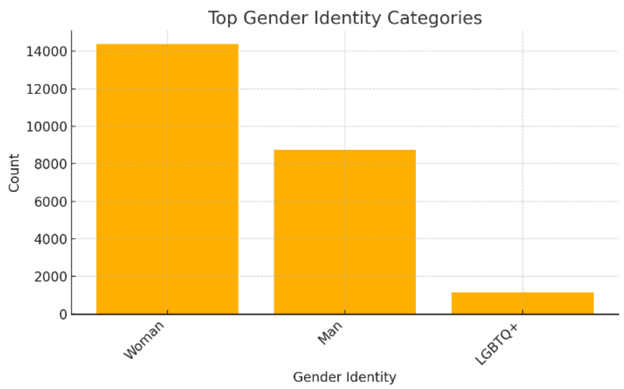

Fig. 17. Gender identity (top 10 categories).

Fig. 18 shows the different enrollment patterns among candidates indicated by the distribution of senior high school tracks and that the majority of students were from the Science, Technology, Engineering, and Mathematics (STEM) and Humanities and Social Sciences (HUMSS) strands. This is followed by those from the General Academic Strand (GAS), Accountancy and Business Management (ABM), and Home Economics strands. This is a clear indication that a sizable percentage of student applicants came from academic-oriented tracks.

The presence of applicants from technical-vocational and industrial tracks reflected a degree of diversity in academic backgrounds of the applicants. The students from these strands although relatively small usually pursued skills-based curricula indicating that the university also attracts learners seeking to broaden their competencies beyond applied and technical fields.

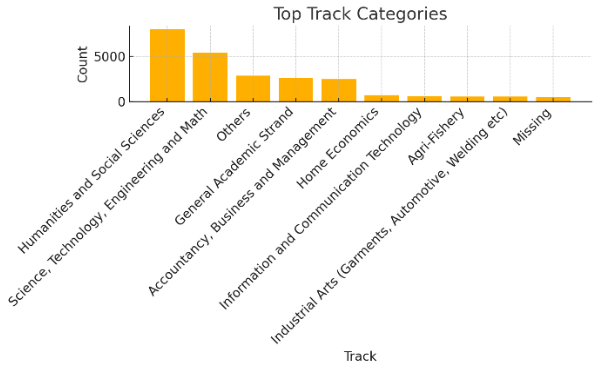

Fig. 18. Senior high school track (top 10 categories).

G. Correlation Structure

Fig. 19 shows the relationships between the numerical features in the admission dataset of the students. Students who performed well in one subject area usually showed similar skills in others and that this tendency was consistent with standard academic patterns which support performance of the students across a variety of subjects by fostering fundamental abilities such as reasoning and critical thinking. The correlations suggested that each variable contributed a unique and complementary information to the admissions process rather than representing the same dimension of student performance.

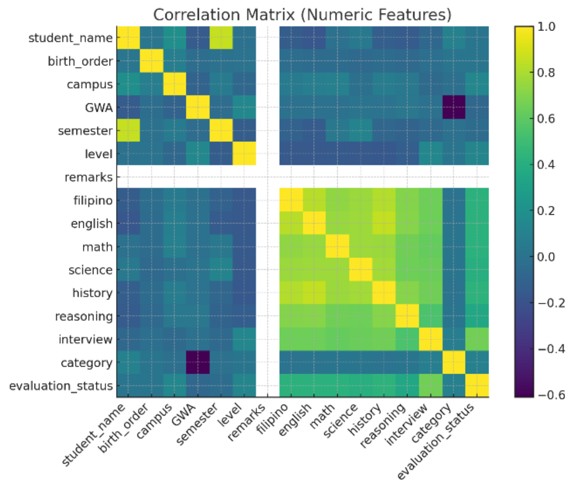

Fig. 19. Correlation matrix of numeric features.

H. Fairness Analysis

To examine whether the admission prediction model exhibits systematic bias across different groups, a simple empirical fairness analysis was conducted using selected sensitive attributes available in the dataset. In the context of educational admissions, fairness analysis is important to ensure that predictive models do not disproportionately favor or disadvantage specific demographic groups.

In this study, sensitive attributes such as gender, campus, and senior high school track were used for group-based analysis, as these variables were present in the dataset and commonly examined in educational fairness research. The fairness evaluation focused on comparing model performance across groups rather than enforcing strict fairness constraints during training.

The analysis was conducted by computing group-wise admission prediction rates and recall values for each sensitive attribute. Recall was emphasized because it reflects the model's ability to correctly identify qualified applicants within each group, thereby highlighting whether certain groups were more likely to be overlooked by the prediction system.

Results indicated that the model exhibited comparable recall and prediction rates across major groups, with no extreme disparities observed between categories. Minor variations were noted among different campuses and academic tracks, which can be attributed to differences in applicant volume, academic preparation, and program-specific admission criteria rather than direct model bias. Similarly, gender-based analysis showed balanced performance, suggesting that the model does not disproportionately disadvantage applicants based on gender. Overall, the findings suggest that the MLP-based decision support system demonstrates reasonable fairness at an empirical level when evaluated across available sensitive attributes. While this analysis does not guarantee complete fairness or eliminate all forms of indirect bias, it provides initial evidence that the model's predictions are broadly consistent across demographic groups.

It is important to note that this fairness assessment was exploratory and limited to attributes available in the dataset. More advanced fairness-aware learning techniques and causal bias evaluations were beyond the scope of this study. Future work may incorporate fairness constraints during model training, additional sensitive attributes, and longitudinal outcome analysis to further strengthen equity considerations in automated admission decision support systems.

V. Conclusion

This study presented a predictive decision support system designed to assist Isabela State University in student admission decision-making using historical application data from seven university campuses. The system integrated data preprocessing, feature engineering, and a Multilayer Perceptron (MLP)-based classification model to predict admission outcomes. Using a dataset of 24,278 student application records, the model achieved an accuracy of 83.16%, a precision of 85.40%, a recall of 80.20%, an F1-score of 82.70%, and a ROC-AUC of 0.89, indicating stable and reliable predictive performance within the evaluated institutional context.

A Logistic Regression model was implemented as a baseline using the same preprocessing pipeline and data split. Comparative results showed that while Logistic Regression achieved higher precision and slightly higher ROC-AUC, the MLP demonstrated improved recall and F1-score, suggesting a more balanced identification of qualified applicants. These findings indicate that the MLP's nonlinear architecture is beneficial for capturing interacting academic and examination-related factors, although overall performance gains over the baseline are incremental rather than absolute.

A simple empirical fairness analysis based on available sensitive attributes, including gender, campus, and senior high school track, indicated no substantial performance disparities across major groups. While minor variations were observed, these differences are likely influenced by structural and academic factors rather than direct model bias. This analysis provides preliminary evidence that the system operates with reasonable empirical fairness under the examined conditions.

The results suggest that the developed system may serve as a supportive tool for admissions personnel by offering consistent, data-driven insights rather than replacing human judgment. However, the findings are bounded by the scope of the dataset, the selected modeling techniques, and the limited fairness evaluation. Future research may extend this work by exploring additional baseline and ensemble models, incorporating fairness-aware learning approaches, and validating performance across other institutional contexts. Overall, this study demonstrates the potential contribution of predictive analytics to admission decision support while emphasizing the importance of cautious interpretation and responsible deployment.

Conflict of Interest

The author declares no conflict of interest.

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