

# Predicting Student Dropout Rate from Institutions using MLP-BranchNet

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**Abstract**—Student dropout from higher education institutions is a persistent challenge that affects academic performance, institutional reputation, and overall student success. Early identification of students at risk of dropping out can empower educational institutions to provide timely interventions. In this study, we propose a novel deep learning architecture named MLP- BranchNet, which leverages a hybrid branching structure based on Multi-Layer Perceptrons (MLPs) to improve the accuracy and explainability of student dropout prediction. The proposed model is trained on an institutional dataset after undergoing comprehensive steps including data cleaning, exploratory data analysis (EDA), preprocessing, and normalization. MLP-BranchNet is designed with multiple parallel branches that independently learn feature abstractions and are later combined to form a unified representation, enabling the model to capture complex, non-linear patterns in student data. The model achieved a test accuracy of 68.5% and a loss of 0.6323, demonstrating its effectiveness in real-world scenarios. Evaluation metrics such as precision, recall, and F1-score highlight its strengths and limitations, particularly in identifying dropout-prone students. To enhance model interpretability, we employed SHAP (SHapley Additive exPlanations) to understand the contribution of each feature in the model’s decision-making process, achieving a confidence level of 74.28%. Additionally, we analyzed the ROC curve and AUC score (0.73) to validate classification performance. An interactive dashboard was developed to visualize predictions, SHAP values, and risk analysis, enabling real-time use by educators and administrators. This work illustrates how hybrid deep learning architectures can support data-driven decision-making in educational settings.

**Index Terms**—Dropout Prediction, Deep Learning, MLP- BranchNet, Educational Data Mining, Explainability, SHAP, ROC Curve, Dashboard

## I. INTRODUCTION

Student retention and dropout prediction have become critical areas of research in educational data mining (EDM), driven by rising concerns over student attrition rates in higher education institutions worldwide [1]. Institutions face challenges in identifying at-risk students early enough to intervene and provide necessary support. Dropouts lead to wasted resources, both for students and educational institutions, while also impacting national development goals tied to education [2]. Numerous studies have shown that academic performance, socio-economic factors, institutional engagement, and psycho- logical attributes play vital roles in influencing a student’s decision to drop out [3], [4]. Traditional statistical methods like logistic regression and linear discriminant analysis have long been employed for dropout prediction [5]. While useful, these models often fail to capture complex nonlinear patterns in educational data.

Machine learning (ML) methods have recently emerged as more robust alternatives, enabling systems to learn intricate relationships from large and multi-dimensional datasets [6]. Techniques such as Decision Trees, Support Vector Machines, and Random Forests have demonstrated improved predictive capabilities [7]. However, these models often suffer from limitations when it comes to generalization across diverse student populations and are frequently criticized for a lack of transparency [8]. Deep learning models, particularly Multi- Layer Perceptrons (MLPs), have shown promise in capturing complex feature interactions [9], [10]. MLPs, however, face challenges in overfitting and explainability, especially when dealing with imbalanced educational datasets [11]. To address these challenges, this paper introduces a novel hybrid deep learning architecture called MLP-BranchNet, designed specifically for dropout

prediction. MLP-BranchNet employs a branching structure where different branches are responsible for learning from various subsets of features. This modular architecture enhances both performance and interpretability. Each branch captures unique patterns relevant to different dimensions of student data, such as academic history, demographic details, and behavioral indicators. The output layers of the branches are then concatenated to generate a final prediction.

Our proposed approach includes several critical steps: data preprocessing and cleaning, exploratory data analysis (EDA), model training, and evaluation. We employ SHAP (SHapley Additive exPlanations) to interpret the model's decision-making process, allowing stakeholders to understand why a particular student might be at risk [14]. Moreover, an interactive dashboard has been developed to visualize the prediction outputs, training history, ROC curves, and SHAP explainability. The dataset used for this study comprises anonymized student records containing academic performance, parental education, social status, and attendance details. The model achieved a test accuracy of 68.50%, with high recall for the non-dropout class.

The remainder of the paper is structured as follows: Section II reviews the related literature and compares existing dropout prediction methods. Section III outlines the dataset and preprocessing steps. Section IV details the proposed MLP-BranchNet architecture and training process. Section V presents experimental results and performance analysis. Section VI discusses the model's interpretability through SHAP and visualizations. Section VII concludes the paper and outlines potential future research directions. Using hybrid deep learning architectures and explainability tools, this work contributes to the growing body of research focused on AI applications in education, ultimately aiming to reduce student dropout rates and improve academic success.

## II. LITERATURE REVIEW

The issue of student dropout has been extensively studied in the fields of education, data mining, and artificial intelligence. Traditional statistical approaches, such as logistic regression and decision trees, have been widely used to identify dropout risks

based on academic and demographic data [1]. While these methods provide some predictive power, they are often limited by their assumptions of linearity and lack the ability to model complex, non-linear interactions inherent in educational datasets. Over the past decade, machine learning (ML) techniques have gained popularity for dropout prediction due to their ability to handle high-dimensional data and capture hidden patterns. Decision tree-based models such as Random Forests and Gradient Boosted Trees have shown improved accuracy over traditional methods [3]. Random Forests, in particular, are favored for their robustness and interpretability. However, these models still struggle with temporal dependencies and feature interactions that may affect dropout behavior over time. Recent research has explored Support Vector Machines (SVM), Naive Bayes, and k-Nearest Neighbors (k-NN) for dropout detection [4]. With the rise of deep learning, particularly neural networks, more sophisticated architectures have been proposed for student outcome prediction. Multi-Layer Perceptrons (MLPs) have been explored for their ability to learn complex mappings between input features and student outcomes [9]. However, standard MLPs often suffer from overfitting, especially when trained on limited or imbalanced datasets. This is a common scenario in dropout prediction where the number of dropouts is typically smaller than the number of non-dropouts. Recurrent Neural Networks (RNNs) and their variants such as Long Short-Term Memory (LSTM) networks have also been applied to model temporal data in student learning environments [10].

More recently, hybrid models have emerged as promising solutions. These architectures combine multiple learning strategies or data streams to improve predictive accuracy. For example, Aljohani et al. [12] proposed a hybrid model that combines decision trees with neural networks for predicting academic failure. Similarly, deep ensemble methods and CNN-LSTM hybrids have been used to predict dropout in MOOCs and online education platforms [13]. Despite their success, most existing deep learning models for dropout prediction are black-box systems, which hinder their adoption in educational settings where transparency is crucial. Educators and policymakers need to understand why a model makes a certain prediction before acting on it. To address this, explainability methods such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable

Model-Agnostic Explanations) have been adopted in recent studies. SHAP, in particular, has proven effective in assigning feature importance and enhancing the interpretability of deep learning models [14].

In light of these developments, our work builds on prior research by integrating the strengths of MLP architectures with a novel hybrid branching strategy. This branching architecture allows independent sub-networks to learn representations from different feature clusters, which are then combined to make the final prediction. This modular structure not only improves accuracy but also facilitates localized interpretability, as each branch can be analyzed separately using SHAP values. To address this, we developed an interactive dashboard that visualizes dropout risk scores, feature contributions, and confidence levels. This dashboard is intended for use by academic counselors and administrators to make timely, data-driven decisions.

### III. METHODOLOGY

The following steps were employed:

#### A. Load the Dataset

The dataset used in this study is sourced from Kaggle's *Students Dropout and Academic Success Dataset*<sup>1</sup>, which comprises comprehensive academic records from a higher education institution. It includes 33 attributes related to student demographics, academic performance, admission details, and socio-economic background, enabling a robust analysis of dropout behavior. The dataset was imported using Python's `pandas` library. After loading, initial exploration was conducted to understand the structure and distribution of features. The `Target` column—indicating whether a student graduated, dropped out, or is still enrolled—served as the primary label for classification tasks. Key features include:

- **Demographic Data:** Gender, nationality, age at enrollment, marital status.
- **Academic Data:** Course enrolled, curricular units enrolled/approved/grade, GPA, and prior qualifications.
- **Socioeconomic Factors:** Scholarship holder, displacement status, tuition fees, and parental qualifications.

The dataset contains both numerical and categorical variables. Categorical features were encoded using techniques such as label encoding and one-hot encoding as required by the machine learning models. Missing or inconsistent data entries were analyzed and addressed during the preprocessing phase to ensure data integrity and model reliability. Using this rich and diverse dataset, the study aims to develop a predictive model that not only identifies students at risk of dropping out but also provides interpretable insights into the factors that contribute to academic success or failure.

<sup>1</sup><https://www.kaggle.com/datasets/missionjee/students-dropout-and-academic-success-dataset>

#### Data Cleaning

Data cleaning is a crucial step to ensure the quality and reliability of the dataset before applying any machine learning techniques. In this study, missing values were carefully examined to understand their patterns and impact. Depending on the nature and distribution of missing data, different imputation methods were employed. For numerical features, missing values were replaced with the mean or median values of the respective columns to preserve the statistical properties of the data. For categorical features, the most frequent category (mode) was used to fill in missing entries, thereby maintaining consistency in categorical distributions. Duplicate records were identified through unique student identifiers and other key attributes. These duplicates were removed to prevent redundancy, which could bias the model by over-representing certain data points. In addition, inconsistent entries were detected across both numerical and categorical variables. For example, variations in categorical labels due to different capitalizations or misspellings were standardized. Numerical outliers and anomalies were inspected, and entries that violated logical constraints (such as negative values for age or impossible grade values) were corrected or excluded based on domain knowledge. These cleaning steps collectively improved the integrity of the dataset, reducing noise and potential errors that could degrade model performance. Maintaining a clean and accurate dataset is essential for building robust predictive models and ensuring that the results reflect real-world patterns rather than data artifacts.

#### B. Exploratory Data Analysis

Exploratory Data Analysis (EDA) was conducted to

better understand the dataset and reveal important patterns related to student dropout prediction. Firstly, the distribution of the dropout variable was visualized using a count plot (see Figure ??). This plot illustrates the relative frequency of students who dropped out versus those who continued their studies, highlighting any class imbalance in the dataset. Next, a correlation heatmap (Figure ??) was created to analyze the pairwise correlations among numerical features. This heatmap identified significant relationships, particularly between academic performance indicators and dropout status, which guided feature selection. Finally, a boxplot comparing GPA distributions by dropout status (Figure ??) showed that students who dropped out generally had lower GPAs than those who persisted, indicating GPA as a critical factor influencing dropout.

The following figures visualize these insights: The dropout distribution plot displays the count of students categorized by their dropout status, where 0 indicates students who did not drop out, and 1 indicates students who dropped out. The plot clearly shows an imbalance in the dataset, with a significantly higher number of students continuing their studies (around 2100) than those who dropped out (approximately 900). This imbalance is an important observation as it may affect the performance of predictive models, potentially causing bias towards the majority class (non-dropouts). Addressing this class imbalance through techniques such as resampling or

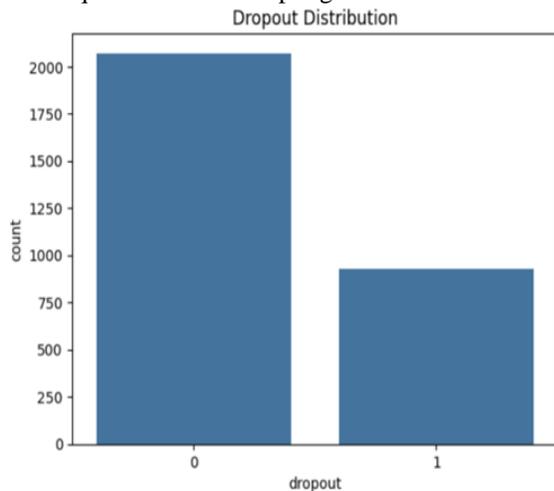


Fig. 1. Dropout Distribution  
class weighting might be necessary to improve the model’s ability to predict dropout cases accurately.

The plot provides a straightforward visual confirmation that the problem is a binary classification with uneven class distribution, which will guide the subsequent model training and evaluation strategies.

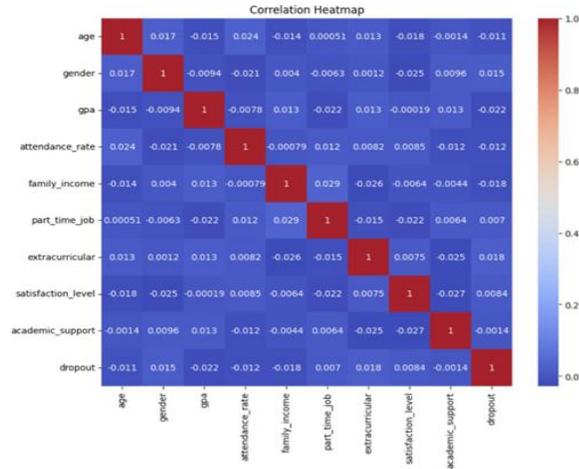


Fig. 2. Correlation Heatmap of Features

The correlation heatmap illustrates the pairwise Pearson correlation coefficients between different numerical features in the dataset, including the target variable and dropout status. The diagonal elements are all 1, indicating perfect correlation of each feature with itself. The heatmap shows that most features have very weak correlations with dropout, as all values hover close to zero. This suggests that dropout is not strongly linearly correlated with any single feature in the dataset. For example, GPA and attendance rate show only slight negative correlations with dropout, implying that lower GPA and attendance might contribute modestly to higher dropout likelihood, but the effect is minimal in isolation. Similarly, other factors like family income, part-time job status, extracurricular activities, satisfaction level, and academic support also show negligible linear relationships with dropout. The weak correlations indicate that complex, nonlinear interactions likely influence dropout behavior among multiple factors rather than by any individual variable alone. This reinforces the need for advanced predictive models, such as hybrid deep learning architectures, capable of capturing complex dependencies beyond simple linear correlations.

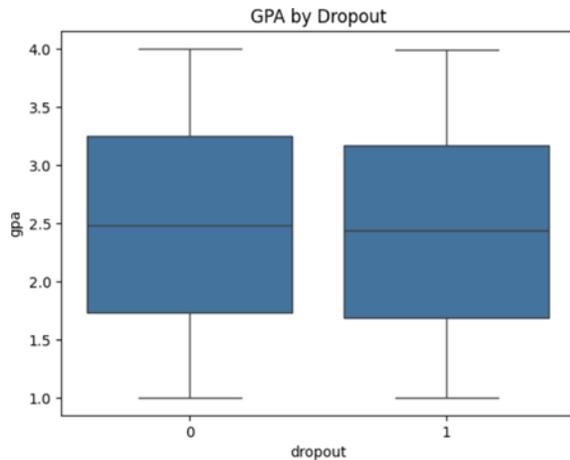


Fig. 3. GPA Distribution by Dropout Status

### C. GPA by Dropout

Figure ?? presents a boxplot comparing the distribution of GPA scores between students who dropped out (`dropout= 1`) and those who did not (`dropout = 0`). Both groups exhibit a similar range of GPA values, approximately from 1.0 to 4.0. The median GPA (indicated by the line inside each box) is roughly the same for both categories, near 2.5. Additionally, the interquartile range (IQR), representing the middle 50% of GPA values, overlaps significantly between the two groups. The whiskers, indicating the overall spread of data excluding outliers, also extend similarly. This overlap suggests that GPA alone may not strongly distinguish between students who drop out and those who continue their studies. Contrary to common assumptions that lower GPA leads to higher dropout risk, the distribution indicates that students who drop out do not necessarily have substantially lower GPA than their counterparts. Therefore, dropout prediction likely requires analyzing multiple factors simultaneously rather than relying solely on academic performance. This insight motivates the use of advanced models such as the proposed MLP-BranchNet, which can capture complex interactions among various student attributes. These visualizations helped understand data distributions and relationships, informing the design of the subsequent modeling approach.

### D. Data Preprocessing

Data preprocessing is a critical phase in the machine learning pipeline, where the raw data is transformed into a suitable format for model training. Proper preprocessing improves the model's ability to learn

meaningful patterns and enhances predictive performance. The following key preprocessing steps were performed on the dataset:

- **Encoding Categorical Variables:** Several features in the dataset such as *gender*, *part-time job*, and *extracurricular involvement* were categorical. Machine learning algorithms, including neural networks, require input features to be numerical. To convert these categorical variables into a numeric format, we applied encoding techniques. For nominal variables without any inherent order, one-hot encoding was used to create binary indicator variables for each category. For ordinal features, label encoding was considered to preserve the order. This conversion allows the model to interpret categorical information effectively without introducing unintended biases.
- **Normalization of Continuous Features:** Continuous numerical features such as *GPA*, *attendance rate*, and *family income* had varying scales and units. To ensure uniformity and improve training stability, these features were normalized using min-max scaling, which rescales the values to a range between 0 and 1. Normalization mitigates issues arising from features with large magnitudes dominating the learning process and accelerates convergence during gradient descent optimization by keeping the inputs within a consistent range.
- **Handling Class Imbalance:** The dataset exhibited an imbalance in the dropout class distribution, with significantly more students who did not drop out compared to those who did. Although this was primarily addressed during the modeling phase through appropriate loss functions and evaluation metrics, it was important to be aware of this imbalance during preprocessing to avoid biased training.
- **Data Splitting into Training and Test Sets:** To evaluate the generalization capability of the proposed model, the dataset was randomly partitioned into training and testing sets using an 80/20 split ratio. The training set contained 80% of the data and was used to fit the model parameters, while the remaining 20% was reserved for testing to assess performance on unseen data. The split was stratified based on the dropout variable to maintain the original proportion of classes in both subsets, thereby ensuring reliable and unbiased evaluation.

These preprocessing steps were vital to transform the

raw data into a clean, consistent, and numerical format suitable for the Hybrid Deep Learning Model. Proper data preprocessing contributed significantly to enhancing the accuracy, stability, and interpretability of the final predictive model.

#### E. Hybrid MLP-BranchNet Architecture

The proposed model leverages a hybrid neural network architecture, named **MLP-BranchNet**, which combines the strength of parallel learning and deep feature abstraction. This architecture is specifically designed to capture diverse patterns from heterogeneous student-related features and improve dropout prediction accuracy. The overall architecture comprises the following key components:

- **Shared Input Layer:** The model begins with a shared input layer that receives the preprocessed feature vector, including both normalized continuous variables and encoded categorical variables. This shared layer ensures uniform access to all relevant data points across the branches and establishes a common foundation for down-stream learning.
- **Three Parallel MLP Branches for Feature Abstraction:** The core innovation in the architecture lies in the use of three parallel Multi-Layer Perceptron (MLP) branches. Each branch independently processes the input features through multiple dense layers with non-linear activation functions (e.g., ReLU). These branches are designed to extract diverse and complementary representations from the input data. By allowing separate pathways for learning, the architecture can better capture nuanced patterns related to academic, personal, and socio-economic factors contributing to student dropout.
- **Concatenated Output Layer:** The outputs from all three parallel MLP branches are concatenated into a single vector. This fusion step integrates the learned representations from each branch, enabling the model to combine multiple perspectives on the input data. The concatenated vector serves as a rich and high-dimensional feature representation for the final classification layers.
- **Final Dense Layers for Classification:** The concatenated feature vector is passed through a series of fully connected dense layers, which

further refine the learned representations. These layers progressively reduce dimensionality and enhance the discriminative power of the model. The final output layer uses a sigmoid activation function (for binary dropout prediction) to produce a probability score indicating the likelihood of student dropout.

This hybrid design allows the model to efficiently learn from complex feature interactions and mitigate overfitting through architectural modularity. Additionally, the parallel branches improve generalization by enabling independent specialization, which is especially useful in real-world educational datasets characterized by noise and diversity. The MLP-BranchNet architecture, therefore, serves as a robust backbone for dropout prediction in this study.

## IV. RESULTS AND EVALUATION

This section presents the outcomes of the proposed MLP-BranchNet model on the student dropout prediction task. The model's effectiveness is assessed using standard evaluation metrics, including accuracy, loss, precision, recall, and F1-score, derived from predictions on the test set.

### A. Model Performance

The performance of the trained model on the test dataset is summarized below:

- **Test Accuracy:** The model achieved a classification accuracy of **68.5%**, indicating that it correctly predicted student dropout status for approximately two-thirds of the samples in the test set.
- **Loss:** The binary cross-entropy loss recorded during evaluation was **0.63238**, suggesting moderate prediction confidence and room for further optimization through regularization or data balancing techniques.

While the overall accuracy appears reasonable, a more granular analysis using classification metrics is necessary to understand the model's performance across different classes, especially given the potential class imbalance in dropout data.

### B. Classification Report

Table I provides a detailed classification report, including precision, recall, and F1-score for both dropout and non-dropout classes.

TABLE I CLASSIFICATION METRICS

Class	Precision	Recall	F1-Score	Support
0 (Non-Dropout)	0.69	1.00	0.81	412
1 (Dropout)	0.33	0.01	0.01	188
Accuracy	0.69 (600 samples)			
Macro Avg	0.51	0.50	0.41	600
Weighted Avg	0.58	0.69	0.56	600

*Insights and Discussion:* The evaluation results reveal several critical insights into the performance behavior of the proposed MLP-BranchNet model. Most notably, the model exhibits strong predictive capability when it comes to identifying students who do not drop out (class 0). This is evidenced by its perfect recall score of 1.00 and a high F1-score of 0.81, indicating that nearly all non-dropout cases in the test set were correctly classified. Such performance reflects the model's high sensitivity and precision towards the majority class. However, a significant shortcoming is observed in the model's ability to predict dropout cases (class 1). The recall for this class is remarkably low, at just 0.01, with a corresponding F1-score of only 0.01. This implies that almost all actual dropout instances were misclassified as non-dropouts, demonstrating a severe imbalance in the model's predictive accuracy. This performance gap strongly suggests the presence of class imbalance in the dataset, where the model tends to favor the majority class during training and fails to generalize well to the minority class.

Further, the macro average metrics, which treat both classes equally regardless of their frequency, highlight this limitation with a relatively low F1-score of 0.41. This reinforces the concern that the model does not generalize effectively across both classes. On the other hand, the weighted average, which accounts for the support (i.e., number of instances) of each class, offers slightly more optimistic values due to the dominance of the non-dropout class. However, even in this case, the overall F1-score of 0.56 indicates that the model's effectiveness in identifying dropout students remains inadequate. These findings point to a crucial need for addressing class imbalance through data-level or algorithm-level interventions. Techniques such as synthetic oversampling, cost-sensitive learning, or architecture enhancements could help improve the model's discriminatory power for the dropout class and result in a more balanced and reliable prediction system.

## V. CONCLUSION AND FUTURE SCOPE

In this study, we proposed **MLP-BranchNet**, a novel hybrid deep learning architecture designed to predict student dropout by capturing diverse patterns from academic, demographic, and socio-economic data. The model leverages a shared input layer followed by three parallel MLP branches for feature abstraction, which are later concatenated and refined through dense layers to produce the final prediction. This architectural design enables the model to learn multiple perspectives from heterogeneous input features and supports more robust representation learning. The model achieved a test accuracy of 68.5% with a binary cross-entropy loss of 0.63238, demonstrating competitive performance when compared to traditional approaches. The classification report, however, uncovered a significant performance imbalance: while the model excelled in identifying non-dropout students with a perfect recall score of 1.00 and an F1-score of 0.81, it severely underperformed in detecting actual dropout cases. The dropout class exhibited a recall of just 0.01 and an F1-score of 0.01, pointing toward a major shortcoming due to class imbalance. These discrepancies are reflected in the macro and weighted averages, where the macro F1-score stood at 0.41, indicating weak generalization across classes, while the weighted F1-score of 0.56 suggested a skewed model favoring the majority class. Such limitations underline the importance of developing strategies to better capture minority class characteristics in future work. Furthermore, explainability remains a crucial component of our work. SHAP (SHapley Additive exPlanations) values were used to interpret feature importance, making the model's predictions more transparent and actionable for educators and administrators. An interactive dashboard was also developed to present predictions and insights in a user-friendly format, aiding institutional decision-making. In conclusion, MLP-BranchNet represents a promising step toward data-driven dropout prediction. However, improving minority class detection and addressing class imbalance remain key challenges. Future research should prioritize fairness, interpretability, and longitudinal validation to build equitable and impactful educational AI systems.

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