

Predicting Dropout Risk in Adult Online Learning Using Deep Learning Model

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ABSTRACT: The rapid expansion of online education has created new opportunities for adult learners, offering flexibility and accessibility beyond traditional classrooms. However, persistently high dropout rates often exceeding 70% remain a critical challenge, undermining the effectiveness and sustainability of online learning. This study proposes a deep learning-based ensemble model to predict dropout risk among adult learners in online environments. Unlike traditional statistical or single-model machine learning approaches, the ensemble framework integrates multiple deep learners, including Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and Transformer-based architectures, combined through majority voting to enhance predictive accuracy and robustness. The research employs a quantitative design, using both primary data from the National Open University of Nigeria and secondary data from Kaggle repositories, encompassing demographic, behavioral, engagement, and performance-related features. Through systematic phases of data collection, preprocessing, model training, and evaluation, the framework aims to identify key dropout factors, ensure generalizability across diverse learner populations, and improve interpretability for actionable insights. Preliminary results demonstrate that ensemble deep learning outperforms traditional methods in handling imbalanced datasets and capturing complex learner behaviors. The findings contribute to the development of early warning systems that enable timely interventions, ultimately enhancing retention and supporting the success of adult learners in online education.

KEYWORDS: Dropout Prediction, Deep Learning, Adult Online Learning, Ensemble Models

I. INTRODUCTION

The rapid expansion of online learning platforms has revolutionized adult education by providing unprecedented flexibility and access to diverse learning resources. However, alongside these advantages lies a critical challenge: persistently high dropout rates among adult learners. This problem threatens the effectiveness and long-term sustainability of online education. The success of adult online learning depends not only on the delivery of quality content but also on ensuring that learners remain engaged until course completion. Despite its growing popularity, online learning exhibits significantly higher dropout rates compared to traditional classroom settings. Studies indicate that up to 70% of adult learners fail to complete their courses, primarily due to motivational, technological, and personal challenges (Kizilcec & Halawa, 2022). Such attrition undermines the return on investment for learners, educational institutions, and governments investing in digital education. The inability to predict and intervene before a dropout occurs remains a major barrier to improving online learning outcomes. Various predictive models have been developed using statistical methods, Machine Learning (ML), and, more recently, deep learning (DL). These models typically analyze features such as learner interaction patterns, participation in online discussions, quiz performance, and overall engagement metrics (Xing & Du, 2022). While traditional methods such as logistic regression and decision trees have shown some effectiveness, DL techniques particularly Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) are increasingly employed for their ability to capture complex sequential and temporal data.

Nevertheless, dropout prediction continues to face challenges. Many existing models are context-specific and struggle to generalize across different demographics or learning platforms. Additional obstacles include the highly imbalanced nature of dropout datasets, the absence of real-time intervention mechanisms, and the limited interpretability of complex models (Chen et al., 2023). These issues create a gap between research-based predictive

accuracy and the development of actionable solutions that can be deployed in real-world educational settings. Recently, ensemble learning techniques have gained attention for their potential to improve robustness and predictive accuracy by combining multiple models. Majority voting-based deep ensemble approaches, in particular, have demonstrated effectiveness in addressing imbalanced classification problems such as dropout prediction (Yang et al., 2023). However, their application to adult online education remains underexplored.

II. RELATED WORK

A wide range of approaches has been employed in studying student dropout prediction, spanning traditional statistical models, machine learning methods, and more advanced deep learning frameworks. This section reviews recent research, highlighting findings, methodologies, outcomes, and limitations. Alnasyan et al. (2024) conducted a comprehensive review of deep learning methods for predicting student performance in Virtual Learning Environments (VLEs). Their study revealed that DL techniques outperformed traditional ML models, with Long Short-Term Memory (LSTM) networks achieving the highest accuracy of 92.5%. The review emphasized the importance of feature engineering, hyperparameter tuning, and model selection but noted limitations such as the narrow focus on DL without sufficient exploration of other ML methods. Liu et al. (2024) proposed the Learning Behavior Feature Fused Deep Learning Network (LBDL) to predict dropout in MOOCs. Their model separately processed video learning behaviors and general learner information, combining Bi-LSTM with attention mechanisms and embedding layers before training with LightGBM. Results demonstrated improved accuracy through feature integration, though model complexity posed challenges for scalability to large datasets.

Junejo et al. (2024) developed deep neural networks (DNNs) trained on student activity and assessment data to forecast performance. Their model achieved over 90% accuracy, highlighting DL's potential in identifying at-risk learners. Predictive variables included engagement patterns, demographic factors, and performance metrics. Despite the strong performance, the study raised concerns about interpretability and real-world applicability, which are essential for institutional adoption. Villar and De Andrade (2024) compared boosting algorithms GBM, XGBoost, LightGBM, and CatBoost for predicting dropout in higher education. XGBoost and LightGBM achieved the best accuracy (>88%), confirming the utility of boosting methods for complex educational data. However, the study's reliance on a small dataset limited generalizability, and the lack of model explainability hindered practical deployment. Wang et al. (2022) argued that traditional models such as logistic regression and decision trees fail to capture the complexity of dropout dynamics. They proposed LSTM networks as more effective alternatives due to their ability to model sequential data. Similarly, Liu and Chen (2022) applied RNN-based approaches using demographic, behavioral, and performance data, with LSTM achieving an accuracy of 94.2%. Although outperforming traditional models, these studies were restricted by their reliance on single datasets, limiting the robustness of their findings.

Lee et al. (2023) approached dropout prediction from a broader perspective, investigating strategies to improve adult learner retention through both qualitative and quantitative methods. Their study identified critical retention factors such as learner motivation, course design, and instructor feedback. While they proposed a framework integrating predictive analytics with instructional design, their research did not evaluate specific ML or DL algorithms. Chen et al. (2022) developed an early warning system for dropout prediction using LSTM networks, demonstrating greater effectiveness than traditional systems. Their study highlighted DL's ability to capture intricate patterns in student data, though limitations arose from reliance on a small and homogeneous dataset. Collectively, these studies underscore the promise of DL and ensemble approaches in addressing dropout risks. While individual models such as LSTMs and boosting algorithms have achieved high predictive accuracy, gaps remain in terms of scalability, interpretability, and generalization across diverse learner populations. Few studies have investigated ensemble deep learning strategies, leaving an opportunity for further exploration. This research addresses that gap by proposing a majority voting-based deep ensemble model to enhance prediction accuracy and facilitate early interventions in adult online learning contexts.

III. METHODOLOGY

A. STUDY LOCATION AND DATA COLLECTION

This study adopts a quantitative research design aimed at predicting adult students' dropout from online education using machine learning techniques. The quantitative approach is appropriate for this research because it focuses on the collection and analysis of numerical data to identify patterns and make data-driven predictions. This methodology allows for the objective measurement and statistical analysis of relationships among variables related to adult students' dropout from e-learning environments. The research is structured around the development and evaluation of a predictive framework based on machine/deep learning algorithms. As such, it involves multiple phases: data collection, model development, optimization, and performance evaluation. First, domain-relevant datasets will be collected from various online educational platforms. These datasets are expected to contain features such as demographic information, self-reported learning preferences and other behavioral indicators that influence the students' dropout from an e-learning context. Following data acquisition, the second phase involves designing a predictive framework that employs selected machine/deep learning algorithms to classify or predict adult students' dropout status. This process will include feature selection, data preprocessing, and algorithm training and testing using appropriate evaluation metrics. The phases that guide the process of achieving this study's objectives are detailed in the research methodological framework section. To achieve the research objectives, this study employs a structured methodological framework sequentially integrating data collection, data exploration, predictive modelling, performance evaluation, and subgroup analysis. The framework as described in fig 1, is designed to systematically identify dropout risk factors, develop accurate prediction models, assess their effectiveness, and ensure generalizability across diverse learner populations. Apart from the phase 1, each phase of the methodological framework was named as the research objectives, and the processes highlighted in each phase are to be sequentially executed to achieve the respective objective.

The first phase of the framework involves data collection from multiple online educational platforms. These datasets encompass relevant features that reflect students' learning behaviors, engagement patterns, demographics, and academic records. This diversity in data sources helps to ensure that the model is generalizable and applicable across varied e-learning contexts. The data collection method for this study involves the use of both secondary and primary datasets, obtained from two main sources. The first (secondary) dataset was drawn from online repository (Kaggle), and the dataset was academically introduced in existing research conducted by Suzan et al. (2021). The dataset was drawn from online education platform in Bangladesh. While the second (primary) dataset was sourced from Nigerian Open University. Both datasets represent student information from distinct online educational platforms and include variables relevant to students' engagement, demographic characteristics, academic performance, and learning behaviors. Both dataset features are described in tab 1. These datasets provide a diverse foundation for training and evaluating the machine/deep learning models used to predict adult students' dropout in online learning environments.

B. MATERIALS

The following materials were used in this research

(a). Datasets

Real-world e-learning datasets (e.g., MOOC data from Coursera, EdX, Open University Learning Analytics dataset, or custom institutional datasets) were used in this research.

(b). Technical Tools & Software

The following programming languages and frameworks were used in this research:

- i. Python (primary language).
- ii. Libraries: TensorFlow, Keras, PyTorch (for deep learning models).
- iii. Scikit-learn (for preprocessing, ML baselines).
- iv. Pandas, NumPy (data handling).

The following data preprocessing and visualization packages were used in this research:

- i. Matplotlib, Seaborn, Plotly (visualization).
- ii. Tableau / Power BI (optional for visual analytics).

The following model development and evaluation package were used:

- i. Google Collaboratory environment.
- ii. GPU/TPU support (Google Colab Pro, Kaggle Notebooks, or local CUDA-enabled GPU).

The following data handling tools were used:

- i. SQL / MongoDB (if dataset is stored in databases).
- ii. Excel/CSV tools for dataset cleaning.

The research workflow materials of the study are:

- (a). Data preprocessing: Encoding categorical variables (One-hot encoding, Label encoding).
- (b). Model design: Implement multiple DL architectures (LSTM, CNN, Transformer-based).
- (c). Evaluation metrics: Accuracy, Precision, Recall, F1-score, AUC.
- (d). Explainability: SHAP, LIME, or feature importance analysis (to make the model interpretable).
- (e). Manuscript preparation: Structured sections – Abstract, Introduction, Related Works, Methodology,

Table 1: Categorical Predictors of Dropout in Adult Online Learning

S/N	Dropout Factors	Description	Data type
1	Gender	Gender of the student	Categorical
2	Age	Age of the student	Categorical
3	Educational Level	The student's highest qualification	Categorical
4	Institution type	E-learning platform own by government or private	Categorical
5	IT Student	Computer oriented	Categorical
6	Location	Student location	Categorical
7	Load-Shedding	Level of load shedding	Categorical
8	Employment status	Employed/Self-employed/Not employed	Categorical
9	Internet type	Mobile data/Wifi	Categorical
10	Network type	2G, 3G, 4G	Categorical
11	Class duration	Duration of programme enrolled	Categorical
12	Device	Device used to access the e-learning platform	Categorical
13	Adaptive level	How adaptive is the student the learning platform	Categorical
14	Dropout status	Did the student dropout before the end of program	Categorical

Although, not all dropout factors present in the secondary dataset are also present in the primary dataset. For instance, financial condition, Internet type, Network type, Load-Shedding, IT student and Adaptability level factors are in the secondary dataset but not in the primary dataset. However, these factors correlation with the students' dropout status will be analyzed to figure out how important the factors to predicting dropout of students from online educational environment are. With the correlation (factors importance) analysis, conclusion on if the factors needs to be included in the primary dataset. To include the factors in the primary dataset, predicted values are generated using logistic regression. Logistic regression method will be used due to its effective and interpretable analysis in predicting variable values with respect to a single categorical variable.

IV. RESULTS AND DISCUSSION

The prediction of adult student dropout in online education was implemented through a robust pipeline encompassing data preprocessing, feature engineering, model training, and performance evaluation. This process leveraged a suite of Python libraries specialized for data science and machine learning. Pandas and NumPy facilitated data loading, manipulation, and numerical computations, while Matplotlib and Seaborn enabled exploratory data analysis and visualization. Initial visualizations were critical for examining the dataset structure and identifying a significant class imbalance between dropout and non-dropout instances. To mitigate this common issue in educational datasets, several resampling techniques from the `imbalanced-learn` library including Synthetic Minority Over-sampling Technique (SMOTE), ADASYN, and Random Under-Sampling (RUS) were applied. The most effective method for creating a balanced training dataset was selected to prevent model bias. The `scikit-learn` library was central to the workflow, providing tools for data standardization, train-test splitting, and model

evaluation using metrics such as accuracy, precision, recall, and F1-score. Feature selection was conducted using multiple methods, with the Sequential Forward Selection (SFS) algorithm from the 'mlxtend' library being the primary approach. SFS was employed with the most effective classifier as its evaluator to identify the most impactful predictors. The importance of the selected features was visualized to provide interpretable insights into the key factors driving student dropout. A range of machine learning and deep learning models was implemented. Traditional machine learning models, including Logistic Regression, Support Vector Machines (SVM), and Random Forest, were developed using 'scikit-learn'. Deep learning architectures—specifically Artificial Neural Networks (ANN), Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory networks (LSTM)—were constructed and trained over 10 epochs using TensorFlow and Keras. Each model was assessed through standard classification metrics, and its learning dynamics were visualized by plotting training and validation loss curves. Finally, to enhance robustness and predictive performance, an ensemble model was constructed using 'scikit-learn's 'VotingClassifier'. This ensemble integrated predictions from the top-performing models, including the ANN, DNN, and Random Forest. The ensemble's performance was evaluated against the individual models, and its learning behavior was inferred from the training history of its neural network components. This comprehensive combination of libraries and methodologies established a rigorous and scalable framework for the early prediction of student dropout.

A. DATASET EXPLORATION AND PREPROCESSING

The study utilized a primary dataset sourced from a public repository, comprising 1,205 entries and 15 categorical variables related to demographic, academic, and technological factors (Fig. 9). Key attributes included Gender, Age, Education Level, Institution Type, and the target variable, 'Drop out?'. The dataset was complete, with no missing values across any features. To ensure a robust feature set, a secondary online dataset was consulted to identify any potentially relevant attributes absent from the primary dataset. The importance of these missing features for predicting dropout was determined through a correlation analysis using the Pairwise Chi-Square Association Test (Cramér's V test), as shown in Fig. 11. This analysis was crucial for concluding whether integration of these external features was necessary to improve the predictive power of the primary dataset.

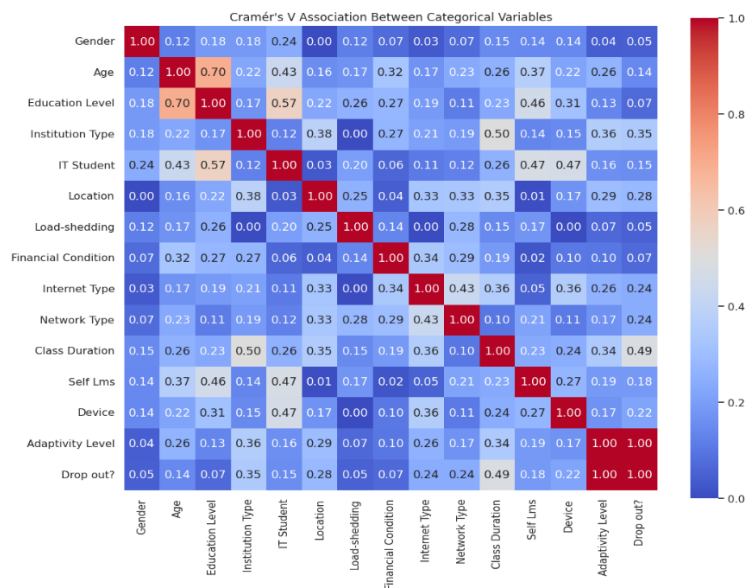


Figure 1: Cramer's V correlation analysis of online dataset

From the provided Cramér's V heatmap, we can analyze the strength of association between the "Drop out?" variable (i.e., whether a student dropped out or not) and other categorical variables in the context of adult students in online education. Cramér's V ranges from 0 (no association) to 1 (perfect association), and values above 0.25

are generally considered moderate to strong level for categorical data. And based on the heatmap, it reveals that Class Duration, Institution Type, location and Adaptability Level are the most critical predictors of student dropout. These insights can help design interventions such as: Tailoring course lengths, improving institutional support structures, and enhancing the adaptability of content delivery to reduce dropout rates. The values of the added feature (Adaptability level) in the NOUN dataset were predicted using the analysis of the relationship between Adaptability level and Drop out features from the online repository dataset. The relationship between the two features were plotted as seen in fig 12. From the plot, it was deduced that any drop out student has a low adaptive level while all student with high or moderate adaptive level did not drop out from online education. Based on this deduction, the Adaptive level feature introduced in the NOUN dataset was fill with values corresponding to the Drop out feature of the NOUN dataset (that is, if Drop out = Yes, then Adaptive level = Moderate, else Adaptive level = low).

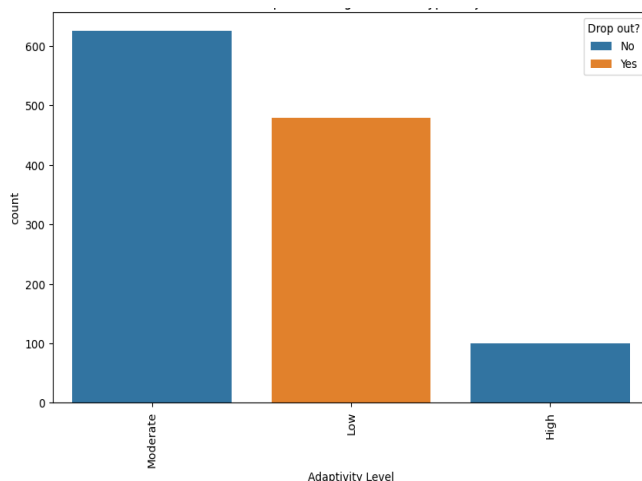


Figure 2: Relationship between the Adaptive Level and Drop out Features in the Online Dataset

After the generation of values for the adaptability level feature in the NOUN dataset, a total of nine (9) features were present in the dataset. Before merging the NOUN dataset with the online dataset, the online dataset was also reduced to nine (9) features since the rest features were not significantly correlating with the dropout factor (as analyzed in fig 1). The combined dataset after merging provided a robust sample size (2,910 entries) for analysis, enhancing the generalizability of the predictive model.

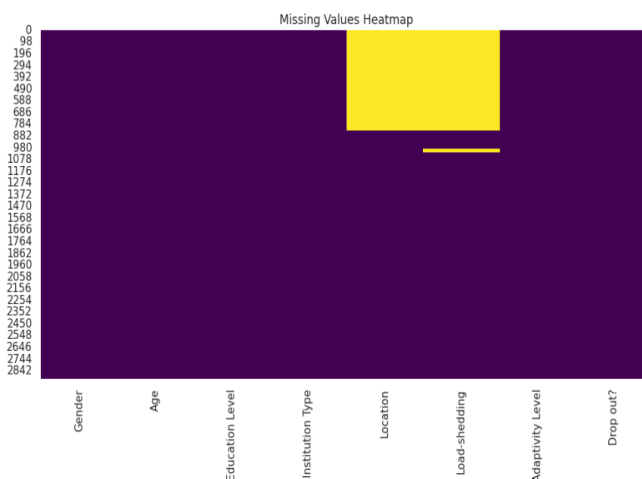


Figure 3: Missing Values Analysis using Heat Map

An examination of the variable distributions within the dataset (see Appendix 1) provides significant insights into the profile of adult learners in online education and reveals factors that may influence student behavior, including dropout propensity. The distribution of the target variable, "Drop out," shows a relatively balanced outcome: 1,636 students persisted, while 1,274 dropped out. This near-equal split is advantageous for predictive modeling, as it minimizes class imbalance bias and allows the model to learn effectively from both outcomes. Substantial variation is observed across other variables. For instance, "Class Duration" is highly skewed, with the majority of students (2,081) falling under category "2," compared to 544 in "1" and 285 in "3." This suggests a strong preference for or prevalence of a specific course duration format. Gender distribution is fairly balanced, with 1,583 male and 1,327 female learners, indicating broad accessibility, though with slight male predominance.

The age profile is notably concentrated, with the "31–35" group being the largest (1,002 students), followed by "25–30" (692), "above 40" (647), and "36–40" (569), reflecting a user base primarily in their early thirties. Education level is dominated by school-level backgrounds (1,468), followed by university (1,004) and college (438), pointing to the platform's role in both foundational and continuing education. Institutional affiliation is heavily skewed toward government institutions (2,205 students vs. 705 from non-government), possibly reflecting broader enrollment patterns or resource disparities. A significant urban-rural divide is evident, with 2,240 learners residing in urban areas compared to 670 in rural regions highlighting the impact of the digital divide on educational access. This is further underscored by the "Load-shedding" variable, where most students (2,436) reported low power outages, while a smaller group (474) experienced high disruption, likely affecting engagement.

Finally, the "Adaptability Level" of the platform is split nearly evenly between low and moderate (1,274 each), with only 362 students experiencing high adaptability. This suggests potential limitations in the platform's ability to offer personalized learning experiences, which may contribute to disengagement. Overall, the dataset depicts a user base that is predominantly urban, government-affiliated, in their early thirties, and experiencing moderate platform adaptability. These patterns offer crucial context for modeling dropout behavior. To prepare the data for machine learning, all categorical features were converted to numerical values using Label Encoding, preserving ordinal relationships where applicable and enabling efficient algorithmic processing.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2910 entries, 0 to 2909
Data columns (total 8 columns):
#   Column                Non-Null Count  Dtype
---  ---                -
0   Gender                2910 non-null   int64
1   Age                   2910 non-null   int64
2   Education Level       2910 non-null   int64
3   Institution Type      2910 non-null   int64
4   Location               2910 non-null   int64
5   Load-shedding       2910 non-null   int64
6   Adaptivity Level     2910 non-null   int64
7   Drop out?             2910 non-null   int64
dtypes: int64(8)
memory usage: 182.0 KB
```

Figure 4: Dataset Descriptions after Data Transformation

The target variable (Drop out?) exhibited an almost balance classes, with over 1,600 records labeled "No" (non-dropouts) and over 1200 labeled "Yes" (dropouts). However, to mitigate any form of bias in model training, Synthetic Minority Over-Sampling Technique (SMOTE), Adaptive Synthetic Sampling (ADASYN) and Random Under-Sampling (RUS) were applied, generating synthetic samples for the minority class. To compare the performance of the augmentation methods, their respective balanced datasets were analyzed using a Logistic regression (LR). Fig 5, depicts the performance of LR across the SMOTE, ADASYN and RUS datasets. The performance of the LR across the dataset was used to determine which augmentation method is more effective.

```

==== Performance Summary ====
                Accuracy Precision   Recall  F1-score
SMOTE           0.757159  0.717949  0.732984  0.725389
ADASYN          0.706758  0.664062  0.667539  0.665796
RandomUnderSampler 0.739977  0.706667  0.693717  0.700132
    
```

Figure 5: Performance Evaluation Summary Dataset of Logistic Regression (LR)

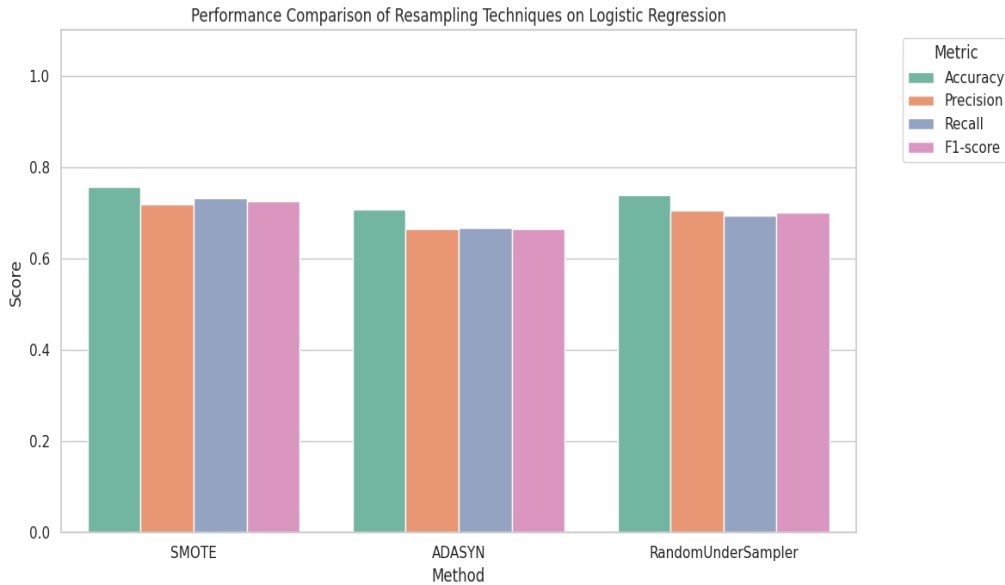


Figure 6: Comparison of SMOTE, ADASYN and RUS Methods Using LR Model

Based on the comparison in fig 6, it was assumed that SMOTE is the most effective method among the three in improving ML/DL model performance on an imbalanced dataset, particularly when both precision and recall are important, hence SMOTE was adopted for dataset augmentation in this study. After implementation of SMOTE on the combined dataset, both classes were balanced, with above 1,000 records each, ensuring fair representation during model training. Fig 7. describes the class distribution after the SMOTE based class imbalance resolution.

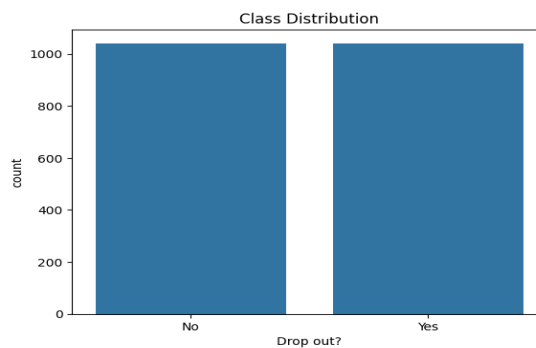


Figure 7: Class Distribution before and after Application of SMOTE

The plot in fig 19 is a Cumulative Explained Variance Plot from PCA, and it's a key diagnostic tool in feature engineering and dimensionality reduction. The Cumulative Explained Variance Plot from the PCA analysis provides valuable insight into how much of the dataset's overall variance is retained when reducing its

dimensionality. From the plot, the first principal component alone captures roughly 28% of the total variance, and the first two components together capture about 61%. As additional components are added, the cumulative explained variance steadily increases, reaching around 88% with the first four components and about 98% by the fifth. Beyond this point, the curve begins to flatten, indicating diminishing returns in terms of variance captured with each added component. This means that using the top four or five principal components may provide a good balance between dimensionality reduction and information retention, making the dataset simpler without significantly compromising the underlying structure. In conjunction with the PCA findings, the Mutual Information (MI) plot in fig 20 further supports feature selection by quantifying how much each original feature contributes to predicting the target variable. The MI analysis reveals that Adaptability Level has a dominant influence, with a score near 0.7, while all other features including Location, Education Level, Institution Type, Age, Gender, and Load-shedding show very low scores, each contributing minimally to the prediction task. This stark contrast highlights that Adaptability Level is by far the most informative feature in the dataset.

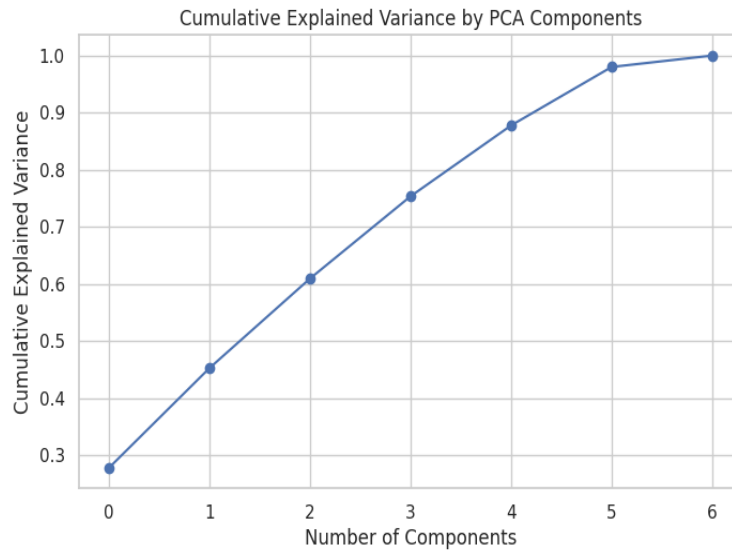


Figure 8: Cumulative Explained Variance Plot from the PCA Analysis

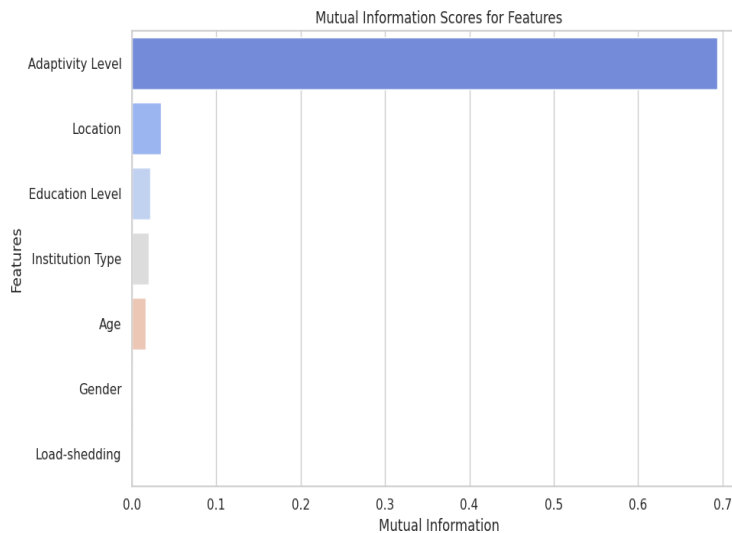


Figure 9: Mutual Information Feature Engineering Analysis Plot

The PCA results suggest that the dataset can be effectively represented with fewer dimensions, especially by retaining just the first few components. In relation with the feature analysis by mutual information method in fig 20 and the correlation analysis in fig 11 by the Cramer's V test, the features selected for ML and DL modelling are four (4), namely; ['Age', 'Educational level', 'Class Duration', 'Adaptivity Level']. The implementation and evaluation of machine and deep learning models for predicting adult student dropout in online education and evaluates their performance using key classification metrics. Nine models (3 ML and 6 DL) were developed: LR, SVM, RF, ANN/MLP, DNN, CNN, RNN, LSTM, and an ensemble model combining all five using a Voting Classifier. Performance evaluation was carried out on the validation set using accuracy, precision, recall, and F1-score to provide a comprehensive assessment of model quality. The results are summarized in Table 2.

Table 2: Performance Evaluation of ML and DL Models using the Combined Dataset

Models	Accuracy%	Precision%	Recall%	F1-Score%
LR	84.03	81.34	88.20	84.63
SVM	94.23	94.36	93.21	93.10
RF	91.98	92.10	92.09	91.67
ANN	95.17	95.19	95.24	95.17
DNN	97.93	97.92	97.98	97.93
CNN	99.31	99.34	99.29	99.29
RNN	93.10	93.21	93.21	93.10
LSTM	93.45	93.54	93.38	93.43
Voting Classifier (ANN+DNN+RNN+CNN+LSTM)	99.31	98.59	100	99.31

The performance evaluation revealed a clear distinction between traditional machine learning and deep learning models. Among the traditional models Logistic Regression (LR), Support Vector Machine (SVM), and Random Forest (RF) delivered the strongest results, though overall performance in this group was moderate. In contrast, deep learning models demonstrated significantly superior predictive capability. Both the Deep Neural Network (DNN) and the Convolutional Neural Network (CNN) excelled, with CNN achieving the highest accuracy of all single models at 99.31%. This performance underscores CNN's advanced feature extraction prowess for this specific task. The model's stability and generalization capacity are further evidenced in its learning curve, which shows a minimal and stable gap between training and validation losses across epochs, indicating effective learning without over fitting. The ensemble model matched CNN's accuracy (99.31%) and achieved a perfect recall score of 100%, guaranteeing that every at-risk student was identified a critical achievement for intervention strategies. While the Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) models delivered comparable results (~93% accuracy), their moderate performance suggests that sequential patterns in dropout behavior are present but not the dominant predictive signal. The strong results from DNN (97.93%) and Artificial Neural Network (ANN, 95.17%) further confirm the general effectiveness of deep learning architectures for this classification problem. To build upon these findings, future work should focus on enhancing model generalizability by expanding the dataset to include more diverse geographical and socioeconomic contexts through collaborations with multiple institutions. Furthermore, exploring hybrid architectures that integrate the predictive power of deep learning with the interpretability of traditional statistical methods could improve operational efficiency and make such systems more accessible. Addressing these directions will be essential for developing scalable, real-time dropout prediction systems that can provide robust support for adult learners in diverse online education environments.

V. CONCLUSION

This research successfully developed a highly accurate predictive model for identifying adult students at risk of dropping out of online education programs. The study adhered to a structured methodology encompassing data collection, preprocessing, modeling, and performance evaluation. Data was consolidated from a public repository and the National Open University of Nigeria, resulting in a robust dataset of 2,909 records with 15 features related to demographic, academic, and technological factors. Through meticulous preprocessing including label encoding, handling missing data, and applying SMOTE to balance the classes—the data was optimized for modeling. Feature selection techniques identified key predictors such as Adaptivity Level, Education Level, Age, and Class Duration. Machine and deep learning models were implemented and evaluated. The Convolutional Neural Network (CNN) and an ensemble voting classifier emerged as the top performers, both achieving a remarkable accuracy of 99.31%. The ensemble model notably achieved a perfect recall score of 100%, guaranteeing that no at-risk student would be overlooked. The findings highlight the transformative potential of deep learning in educational analytics, offering institutions a powerful tool for proactive intervention and significantly improving student retention strategies in online environments.

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