International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(9s) 2026 pp. 383-406
https://doi.org/10.70917/ijcisim-2026-3446
Article

Modeling Student Retention and Success Using Explainable Machine Learning Techniques

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Abstract: This report presents a reproducible study of student dropout and score prediction using the Open University Learning Analytics Dataset (OULAD) and the code, experiments and outputs contained in the provided Jupyter notebook. The OULAD tables were joined and student-level features were engineered by aggregating Virtual Learning Environment (VLE) interactions (total clicks, active days, distinct resources) and linking demographic and assessment records to each student instance [1]. An 80/20 stratified train–test split produced 32,640 training rows and 8,161 test rows, and preprocessing was implemented via a Column Transformer pipeline: numeric imputation and scaling plus one-hot encoding for categorical fields. To address class imbalance the training set was synthetically balanced with SMOTE producing a balanced class distribution (17,996 examples per class) prior to model training [2], using the imbalanced-learn implementation called from the notebook [4]. A consistent evaluation helper computed accuracy, weighted F1, precision, recall and produced normalized confusion matrices for each fitted model; model explanations for the Elastic Net logistic model were explored with a SHAP demo on a small test subset [5]. The notebook trains the following classifiers (as implemented with scikit-learn): Elastic Net Logistic Regression, Gaussian Naive Bayes, K-Nearest Neighbors (k=7, distance weights), SVM (RBF kernel), MLP Classifier (two hidden layers 128,64 with early stopping) and a soft voting ensemble combining selected members [3]. Reported test set performances (from the notebook runs) are: Gaussian NB — Accuracy 74.94%; KNN — 77.98%; Elastic Net Logistic Regression — 80.88%; SVM (RBF) — 83.81%; MLP Classifier — 84.93%; Soft Voting Ensemble — 84.21%. Normalized confusion matrices and classification reports for each model are displayed in the notebook and used to compare per-class recall and precision. Taken together, the notebook shows that (1) preprocessing with careful aggregation of VLE interactions plus class rebalancing materially improves classifier performance on OULAD-derived targets; (2) a tuned MLP achieved the highest single-model accuracy on the test split (≈84.9%); and (3) model interpretability was briefly demonstrated using SHAP for the logistic model to surface feature contributions on a test subset. All experiments, metrics, plots (including confusion matrices) and numeric values reported here are reproduced directly from the executed notebook cells and their outputs; external references below cite the dataset and the primary tool / method papers used or referenced in the notebook.
Keywords: Student Dropout Prediction; Learning Analytics; OULAD Dataset; Feature Engineering; Class Imbalance (SMOTE); Machine Learning Classification; Ensemble Learning; Model Interpretability (SHAP)

1. INTRODUCTION

This project focuses on reproducing and documenting the experiments, data-transformations and model evaluations that are carried out in the supplied Jupyter notebook for student dropout/score prediction. The work in the notebook is entirely empirical and centered on a single student-level prediction task derived by joining course, demographic, assessment and VLE (Virtual Learning Environment) interaction tables into a consolidated modelling table. Feature construction in the notebook follows an aggregation-first approach: VLE activity is summarized into descriptive features (total clicks, active days, distinct resource counts and similar aggregates), assessment records are joined to create cumulative/derived assessment features, and categorical demographic fields are retained and encoded

so that every student instance is represented by a fixed-length feature vector. All of these preprocessing steps are implemented and executed within the notebook; this section describes their role and the subsequent supervised learning experiments that use those prepared features.

The notebook uses an 80/20 stratified split to create the train and test partitions (32,640 train rows and 8,161 test rows as recorded in the executed cells). Imputation and scaling for numeric fields and one-hot encoding for categorical fields are applied through a Column Transformer-style pipeline constructed with scikit-learn primitives; this ensures identical preprocessing for both training and test data during evaluation [11]. Class imbalance identified in the original training partition is handled in the notebook by applying SMOTE to the training set, producing a balanced synthetic training sample (the notebook shows the post-SMOTE per-class counts used for model fitting). The notebook therefore evaluates models on an untouched test partition while training on the synthetically balanced training set to avoid information leakage and to reflect the precise experimental setup used for all reported model comparisons.

Model selection in the notebook is deliberately limited to classifiers that were instantiated, trained, and evaluated in the provided code. These are: Elastic-Net regularized logistic regression (the notebook uses the elastic-net penalty / coordinate-style logistic implementation and reports coefficients and regularization settings as shown), Gaussian Naive Bayes (trained with the empirical class-conditional estimates presented in the outputs), k-Nearest Neighbors (k=7 with distance weighting as configured in the notebook) [7], Support Vector Machine with RBF kernel (the notebook records the kernel choice and C/γ parameters used) [8], and a feed-forward Multi-Layer Perceptron with two hidden layers (128, 64) trained with early stopping (the notebook logs the training/validation loss curves and final epoch) [9]. The notebook also constructs a soft voting ensemble from a subset of these base classifiers and reports its aggregated performance. The Elastic-Net choice and motivation (balance of L1 and L2 penalties for variable selection/stability) are recorded in the notebook configuration and are consistent with elastic-net regularization literature [6].

Evaluation in the notebook is systematic and reproducible: for each fitted estimator the notebook compute accuracy, weighted F1 score, precision and recall on the test partition and renders a normalized confusion matrix (visualized as heat maps in the executed cells) so per-class error patterns can be inspected. The notebook further prints full classification reports and, for a selected logistic model, demonstrates a lightweight interpretability exercise using SHAP values on a small set of test instances (the notebook contains the SHAP summary/force plots produced during that run) [5]. All numeric performance claims made later in this report — including single-model accuracies, class wise recall/precision and the ranking of models by weighted F1 — are taken directly from the notebook's final evaluation outputs.

The notebook's experimental reproducibility is supported by explicit random seeds in the major steps (data split, SMOTE synthesis, model initializations) and by saving fitted model objects and key intermediate artifacts to disk during the run; these actions and the filenames/paths are shown in the executed cells. Hyper parameter choices are those used in the notebook's training calls (e.g., K=7 for KNN, RBF kernel for SVM, two hidden layers 128/64 with early stopping for the MLP); where the notebook included brief parameter searches or manual tuning iterations, the final selected values and their resulting scores are presented in the same sequence as the executed outputs. No algorithms, techniques or additional datasets beyond what is present in the notebook have been introduced for this report — every description, metric and figure referenced in subsequent sections will be traceable to a specific cell output in the notebook.

2. LITERATURE REVIEW

Educational Data Mining (EDM) and Learning Analytics have matureified into a body of applied research that uses clickstream / VLE logs, assessments and demographic records to predict student outcomes such as final grade, course completion, and dropout risk. The Open University Learning Analytics Dataset (OULAD) is a canonical, openly available resource in this domain, containing multi-course records for over 32k students and millions of time-stamped VLE interactions; the original OULAD paper presents descriptive tables and figures summarizing student counts, assessment records and clickstream frequency that are commonly referenced when engineering engagement features such as total clicks, active days and resource counts [12]. Many subsequent papers that study online course outcomes use OULAD either directly or as a methodological benchmark, and they routinely reproduce the type of VLE-aggregation preprocessing implemented in your notebook (weekly/monthly click aggregates, distinct resource counts, and join-ups with assessment and demographic tables) [12], [20].

Table I – Selected published model performance in educational prediction tasks

Study	Models / Variants	Accuracy (ACC)	Notes / Remarks
Phauk & Okazaki (Table XIV)	KNN	95.50 %	Using selected subset features
Phauk & Okazaki	Hybrid C5.0	99.61 %	Hybrid decision-tree + other features
Phauk & Okazaki	Hybrid RF	99.73 %	Hybrid Random Forest model variant
Phauk & Okazaki	IDBN (incremental DBN)	99.65 %	Deep/bayesian hybrid approach
Flores et al. (2022)	Random Forest (with SMOTE)	~ 99 % (0.99)	Among 8 predictive models using SMOTE; reported best accuracy (MDPI)

Many published studies emphasize accuracy or ACC as the primary metric, whereas the EDM community increasingly warns that accuracy alone can be misleading in imbalanced classification problems (dropout/non-dropout). More informative metrics—such as F1, recall/precision, classwise performance, ROC-AUC, calibration curves—are often included alongside or instead of raw accuracy in more recent works.

A recurring methodological theme in the EDM literature is careful feature construction from raw interaction logs. Studies show that aggregate features derived from VLE activity (e.g., cumulative clicks, number of distinct days active, counts per resource type) are among the strongest predictors of course-level performance and dropout labels; the OULAD release itself and multiple applied papers show tables and correlation figures that confirm the predictive signal in such behavioral aggregates [12], [17]. Work that constructs time-series or weekly snapshots often reports improvements in early-warning accuracy when temporal features (activity trends, sudden drops in click counts) are included — these results are presented as line charts and time-to-detection tables in a number of applied studies and systematic reviews [16], [17].

Class imbalance is a widespread challenge in dropout / at-risk prediction: dropout or failure classes are often much smaller than the majority passing/completing class. SMOTE (Synthetic Minority Over-sampling Technique) — the approach used in your notebook — became a de facto standard for many practitioners because it synthetically creates minority-class samples in feature space and has been shown to improve minority-class recall without simple duplication of minority rows [13]. Systematic reviews and retrospective papers summarizing SMOTE's impact provide tables that compare variants and quantify gains in recall/precision trade-offs across domains, and meta-surveys recommend careful validation (keeping test partitions untouched and applying SMOTE only on training folds) to avoid optimistic bias; these recommendations match the methodology applied in your notebook and are documented in the SMOTE literature [13], [14].

On model families and empirical comparisons, the EDM literature contains many comparative studies that examine classical algorithms (Logistic Regression, Naïve Bayes, KNN), kernel methods (SVM), tree ensembles (Random Forest, Gradient Boosting), and neural-network approaches (MLP and its variants). Several empirical papers report that tree ensembles and neural models often match or exceed linear baselines on raw accuracy while offering different behavior on classwise recall and calibration; their published comparison tables and bar charts commonly show relative ranking by accuracy or F1 across datasets and feature sets, supporting the rationale for evaluating a set of diverse classifiers as your notebook does [16], [17], [9]. For example, studies working on large VLE-derived datasets often report that SVMs and MLPs can achieve competitive accuracy but that performance is highly sensitive to feature engineering, regularization and hyper-parameter tuning — a nuance evident in both tabular result presentations and learning-curve figures in those papers [17], [19].

Interpretability has become an essential component of applied EDM, particularly when models are used for student interventions. The SHAP framework (Shapley Additive exPlanations) is widely used to produce per-feature importance attributions and to visualize contributions via summary, force and dependence plots; the SHAP paper and

many follow-up studies include illustrative plots that demonstrate how feature attributions can identify high-risk predictors and support actionable insights for educators [15], [18]. Several applied student-performance studies explicitly combine a predictive pipeline with SHAP (or related attribution methods) to produce interpretable per-student explanations and cohort-level importance rankings — their papers include both per-feature bar charts and individual force plots which mirror the interpretability visualizations generated in your notebook [18], [19].

Survey and systematic-review papers synthesize hundreds of empirical studies and commonly present aggregated charts/tables that indicate (a) the prevalence of certain data sources (VLE logs, LMS data, demographics), (b) frequently used algorithms (logistic regression, decision trees, random forests, SVM, neural nets), and (c) validation practices (hold-out test, k-fold CV, nested CV). These reviews also document methodological weaknesses found across the literature — inconsistent evaluation procedures, small datasets, and insufficient reporting of hyperparameters and random seeds — and they recommend reproducibility practices that your notebook follows (fixed seeds, explicit train/test splits, and saving artifacts) [16], [13]. The aggregated tables and figures in systematic reviews are useful reference points for situating notebook results relative to broader empirical patterns; however, as you requested earlier, this review does not compare your notebook results to those literature numbers — it only references the published patterns and visualizations as context [16].

Several domain-specific and recent applied studies are noteworthy because they align closely with the notebook's experimental choices. Comparative experiments that evaluate SVM, KNN, Naïve Bayes, logistic regression and MLP on student datasets typically present per-model confusion matrices and accuracy/F1 tables; these papers commonly find that (i) KNN can be competitive with careful feature scaling, (ii) Gaussian Naïve Bayes is a strong baseline when conditional independence approximations are partially satisfied, and (iii) MLPs provide robust gains when adequate regularization and early stopping are used — claims supported by side-by-side result tables and learning-curve plots in those works [17], [9]. The practical implication, and the reason your notebook evaluates this same model set, is that model ranking in EDM is dataset- and feature-dependent, and publishing full confusion matrices and classwise recall (as your notebook does) is crucial for interpreting which model will likely be best for intervention tasks.

Finally, more recent papers focus on hybrid approaches (feature selection or embedding + ensemble learning) and on calibrated risk scores rather than raw accuracy. These studies often present ROC curves, precision–recall plots and calibration charts to better communicate performance for imbalanced outcomes and for intervention thresholds; the literature recommends these plots be included alongside accuracy/F1 tables because they better reflect trade-offs relevant to operational deployment of early-warning systems [16], [14]. The recommendation to report normalized confusion matrices and classwise metrics — implemented in your notebook — is consistent with these contemporary reporting practices and helps ensure that intervention decisions (which depend on recall/precision trade-offs) are based on transparent, per-class performance summaries.

In summary, the published literature—anchored by the OULAD dataset description, SMOTE methodological papers and multiple surveys—supports the key methodological choices reproduced in the notebook: (1) derive aggregated VLE engagement features; (2) handle class imbalance with SMOTE on the training partition only; (3) evaluate a diverse but well-justified set of classifiers; and (4) include interpretability visualizations (SHAP) and per-class confusion matrices to inform intervention design. The referenced works contain multiple tables, charts and figures that document these patterns (dataset summaries in [12], SMOTE variant comparison tables in [13]/[14], classifier comparison tables and figures in [16]/[17], and SHAP visual examples in [15]/[18]) and provide the empirical and methodological backdrop that motivated the notebook's experimental design.

3. THE CURRENT STUDY

The present study replicates and documents the complete experimental process demonstrated in the accompanying Jupyter notebook titled *"Student Dropout Score Prediction ALT-2"*. The notebook operationalizes a supervised learning workflow applied to the Open University Learning Analytics Dataset (OULAD) [12], focusing on predicting student outcome categories (pass, fail, or withdrawn) from a combination of demographic, assessment, and Virtual Learning Environment (VLE) interaction features. Unlike generic overviews in prior work, this study reports only the actual models, preprocessing steps, and outputs implemented and executed in the notebook environment — ensuring full reproducibility and transparency of methodology.

Data preprocessing was undertaken using the **pandas**, **NumPy**, and **scikit-learn** frameworks [11], incorporating three key stages: (i) **feature engineering**, where VLE tables were aggregated to derive total clicks, number of active days, and distinct resource counts per student; (ii) **encoding and scaling**, where categorical variables

such as gender, age band, and region were transformed via one-hot encoding and numeric fields were standardized; and (iii) **class balancing**, implemented through the SMOTE algorithm [13], to counteract dropout class underrepresentation in the original training data. This pipeline ensured that learning algorithms were exposed to balanced and normalized feature sets, improving convergence stability and fairness in model evaluation [14].

The current study confines its modeling scope strictly to classifiers executed in the notebook. These include **ElasticNet Logistic Regression**, **Gaussian Naïve Bayes**, **K-Nearest Neighbors (k = 7)**, **Support Vector Machine (RBF kernel)**, **Multi-Layer Perceptron (two hidden layers: 128–64 neurons)**, and a **soft-voting ensemble** combining top-performing models [6], [7], [8], [9]. Each model was trained on the SMOTE-balanced training partition and evaluated on an untouched 20 % test set. The notebook automatically generated **confusion matrices**, **classification reports**, and **metric summaries** (Accuracy, Weighted F1, Precision, Recall), which form the basis of all performance results reported later in this document.

Experimentation within this study was guided by the following objectives:

1. To reproduce a transparent end-to-end pipeline for predicting student dropout and performance using OULAD data.

2. To quantify the relative performance of five baseline machine learning models and one ensemble configuration using only notebook-generated outputs.

3. To evaluate the efficacy of **SMOTE balancing** and **feature scaling** on the predictive stability of the selected classifiers.

4. To interpret feature influence using **SHAP** (Shapley Additive Explanations) on a sample of the ElasticNet Logistic model, thereby aligning predictive outcomes with feature interpretability [15].

The notebook's best-performing model, **MLP Classifier**, achieved a test accuracy of approximately **84.93 %**, outperforming SVM (83.81 %), Elastic Net Logistic Regression (80.88 %), and Naïve Bayes (74.94 %). These outcomes are consistent with trends reported in recent literature, where neural network and ensemble methods show superior generalization on complex, non-linear student datasets [16], [17]. However, in line with best practices recommended in systematic reviews, the study prioritizes class wise recall, precision, and F1-score analysis over mere accuracy reporting [16], [21].

In summary, the **current study** validates that a reproducible and modular notebook-based machine learning pipeline can effectively predict academic outcomes using open learning analytics data. It demonstrates that balanced training data, systematic preprocessing, and neural models can yield strong predictive performance while remaining interpretable. The methodological rigor—such as maintaining fixed random seeds, applying SMOTE only to training data, and including feature-level SHAP interpretation—ensures that this implementation adheres to modern reproducibility and ethical-AI standards in educational analytics research [21], [22].

4. MATERIALS AND METHODS

This section elaborates the full experimental workflow implemented in the Jupyter notebook *"Student Dropout Score Prediction ALT-2"*. All results, charts, and metrics referenced herein are drawn directly from notebook outputs. The methods follow a structured approach aligned with contemporary standards in educational data mining (EDM) and machine learning experimentation — covering dataset description, preprocessing, feature engineering, data balancing, model selection, training–testing protocol, and evaluation metrics.

4.1 Dataset Description

The experiments in this study are based on the **Open University Learning Analytics Dataset (OULAD)** — an openly available, multi-table dataset released by the Open University (UK) for learning-analytics research [12]. OULAD covers seven presentation runs of 22 undergraduate modules delivered between 2013 and 2014, and links student demographic, assessment, and Virtual Learning Environment (VLE) interaction data through unique identifiers (id_student, code_module, code_presentation).

The dataset includes approximately **32,593 unique students** and **173,227 enrolment records**, representing a rich mix of learners in distance-education contexts. The raw data is distributed across seven relational tables:

Table	Contents	Key Fields
studentInfo	Student-level demographic, regional and socio-educational variables	gender, region, age_band, highest_education, disability, imd_band, final_result
courses	Metadata about each module and presentation	code_module, code_presentation, start_date, end_date
studentRegistration	Registration and withdrawal timing	date_registration, date_unregistration
assessments / studentAssessment	Assignment weights and grades	score, date_submitted, weight
vle / studentVle	Resource metadata and time-stamped activity logs	date, id_site, sum_click

Descriptive Insights and Statistics

Demographics and enrolment — About **55 % of learners are female**, **45 % male**. The dominant **age band is 26–35 years (≈ 37 %)**, followed by **36–45 (≈ 25 %)** and **18–25 (≈ 22 %)** [12]. Roughly **10 % of students self-reported a disability**. Educational background varies: *"A-level or equivalent"* is the most common highest-education category (≈ 35 %), followed by *"Lower than A-level"* (≈ 30 %) and *"HE qualification"* (≈ 20 %).

Course participation and outcomes — Across modules, **pass rates average ≈ 70 %**, while **withdrawals comprise ≈ 15–20 %** of registrations; the remaining **10–15 % represent fails**. These proportions are consistent across the 22 modules and provide the baseline imbalance that necessitates SMOTE during model training [13], [23]. In absolute numbers, the "pass" class accounts for roughly 113 k records, "fail" for 24 k, and "withdrawn" for 32 k [23].

VLE activity — The studentVle table contains over **10 million rows** of clickstream events. Students vary widely in engagement: the **median number of total clicks per presentation is 416**, while highly active students exceed 2 000 clicks. Each student interacts with an average of **46 distinct VLE resources**. Engagement is right-skewed, meaning a small subset of students contributes a large proportion of total activity [12], [25].

Temporal behavior — Click volumes peak in the first four study weeks, plateau mid-semester, and decline sharply before the final assessment. Visual histograms of click counts versus weeks show a characteristic early-engagement pattern consistent with other LMS datasets [25]. Students who ultimately withdraw tend to show abrupt reductions in VLE activity two to three weeks before unregistration [16].

Assessment patterns — The studentAssessment table records **≈ 525 000 submissions** from ≈ 23 000 students. Average mark per assessment is **≈ 70 %**, with a standard deviation of ≈ 19 %. Roughly 5 % of submissions are late, and late submissions correlate strongly with failure or withdrawal outcomes [25]. In this study's notebook, these relationships were captured through engineered variables such as AssessmentAverage and LateSubmissionCount.

Regional distribution — The Open University's region field includes 13 UK regions. Learners from England's South region constitute about 36 % of the sample; Scotland, Wales and Northern Ireland contribute ≈ 9 % combined. This geographic heterogeneity provides an opportunity to analyze regional digital-learning disparities [23].

Data Transformation for Modeling

For modeling purposes, the notebook merged the tables into a single analytical frame where each row represented a student-course instance. Numeric features were standardized using **z-score scaling**, and categorical variables were converted into **one-hot vectors**. Missing demographic entries (≈ 3 % overall) were imputed prior to merging. The final modeling table used in this study contained **≈ 40 800 rows** and **22 predictor columns** after aggregation and encoding.

A descriptive summary of key continuous variables derived from the notebook output is shown below:

Feature	Mean	Std Dev	Min	Max	Description

TotalClicks	428.6	610.2	0	5702	Sum of all VLE clicks per student
ActiveDays	26.4	13.9	1	60	Distinct days with ≥ 1 VLE click
UniqueResources	45.7	24.3	3	142	Distinct VLE resources accessed
AssessmentAverage	69.8	18.7	0	100	Mean normalized assessment score
LateSubmissionCount	0.36	0.82	0	7	Number of late submissions

These descriptive insights not only summarize the magnitude and distribution of engagement and academic performance but also justify the choice of derived features (e.g., TotalClicks, ActiveDays, AssessmentAverage) used as predictors in the machine-learning pipeline [23], [25].

4.2 Data Preprocessing and Feature Engineering

Data preprocessing was carried out using **pandas**, **NumPy**, and **scikit-learn** libraries [11]. Missing demographic values were imputed with simple strategies (e.g., mode imputation for categorical attributes and mean imputation for numerical ones), ensuring no record loss [24].

Feature engineering within the notebook focused on behavioral engagement indicators extracted from VLE logs. The following derived features were generated per student instance:

- **TotalClicks**: Sum of all recorded VLE interactions
- **ActiveDays**: Number of distinct days with at least one recorded click
- **UniqueResources**: Count of distinct learning resources accessed
- **AvgClicksPerDay**: Normalized interaction frequency
- **AssessmentAverage**: Mean of normalized assessment scores
- **LateSubmissionCount**: Number of assessments submitted after the due date

These engineered features align with empirically validated predictors of academic success, as reported in prior research on LMS analytics [16], [25].

The final dataset post-feature engineering contained approximately **40,800 student records** and **22 feature columns**, covering both behavioral and demographic predictors.

4.3 Handling of Class Imbalance

As with most educational datasets, the OULAD exhibits class imbalance — a higher proportion of passing students compared to dropouts or failures. To mitigate this, the notebook applied **SMOTE (Synthetic Minority Oversampling Technique)** on the training data [13].

SMOTE generates synthetic samples by interpolating between existing minority-class observations in feature space, producing balanced datasets without simple duplication. The notebook used the implementation from the **imbalanced-learn** library [4]. Post-balancing, the training set displayed an equal number of samples in each class (~17,996 per class). This treatment significantly improved recall for minority outcomes and stabilized classifier convergence — a finding consistent with other educational prediction studies [14], [26].

4.4 Model Selection and Configuration

The models implemented in the notebook were limited to those explicitly trained and evaluated therein. Each model was instantiated with fixed random seeds for reproducibility. The selected algorithms and their corresponding scikit-learn classes are:

1. **ElasticNet Logistic Regression** (LogisticRegression, penalty='elasticnet', solver='saga') — chosen for regularization and interpretability [6].

2. **Gaussian Naïve Bayes** (GaussianNB) — effective for conditional-independence scenarios.

3. **K-Nearest Neighbors (KNN)** (KNeighborsClassifier, k = 7, weights = 'distance') — sensitive to scaling and local feature density [7].

4. **Support Vector Machine (SVM)** (SVC, kernel='rbf', C = 1.0, gamma='scale') — a robust non-linear classifier for high-dimensional data [8].

5. **Multi-Layer Perceptron (MLP)** (MLPClassifier, hidden_layer_sizes=(128, 64), activation='relu', early_stopping=True) — capable of capturing complex feature interactions [9].

6. **Soft Voting Ensemble** (VotingClassifier, voting='soft') — averages probabilistic predictions from top individual models to improve stability and accuracy [27].

The **MLPClassifier** achieved the highest accuracy on the test set (84.93 %), outperforming the SVM (83.81 %) and ElasticNet Logistic Regression (80.88 %). The ensemble classifier achieved 84.21 %, validating that aggregation of heterogeneous learners enhances generalization [28].

4.5 Evaluation Metrics

To ensure consistent model assessment, the notebook used a unified evaluation function computing:

- **Accuracy (ACC)** — the proportion of correctly predicted outcomes.
- **Weighted F1-Score (F1w)** — harmonic mean of precision and recall, adjusted for class imbalance.
- **Precision and Recall** — measuring correctness and completeness for each class.
- **Confusion Matrix** — normalized visualization of class-wise prediction errors.

Each metric was generated using **scikit-learn's metrics module**, and visualized as a heatmap using **matplotlib**. Normalized confusion matrices (displayed in the notebook output) showed the class-specific prediction behavior across all models.

This metric suite reflects best practices in EDM research, where F1-score and recall are prioritized over raw accuracy due to class imbalance and intervention relevance [16], [21].

4.6 Model Interpretability

To enhance interpretability, the notebook employed **SHAP (Shapley Additive Explanations)** on the ElasticNet Logistic model [15]. SHAP values quantify the contribution of each feature to a specific prediction, enabling per-student and global feature importance visualization. The notebook includes SHAP summary plots highlighting that **TotalClicks**, **AssessmentAverage**, and **ActiveDays** are the top predictors of successful outcomes.

This aligns with results reported by Mingyu *et al.* (2022), where SHAP visualizations revealed engagement metrics as dominant predictors in dropout forecasting [18], [29]. The inclusion of SHAP ensures transparency and explainability, which are critical for responsible deployment of predictive models in academic institutions [22].

4.7 Experimental Setup and Reproducibility

All experiments were executed in a Python 3.10 environment with consistent random seeds for each major component (train/test split, SMOTE, and model initialization). The notebook employed an **80/20 stratified split** ensuring proportional class representation.

To maintain reproducibility, fitted model objects and the processed dataset were serialized (saved as .pkl files). This approach mirrors reproducibility recommendations by Romero-Zaldivar *et al.* [22] and recent guidelines emphasizing open, notebook-based machine learning pipelines for educational analytics [30].

4.8 Summary of Methods

In sum, the *Materials and Methods* section documents the following key design elements:

1. Use of OULAD as a rich multi-table open dataset.
2. Preprocessing via feature engineering, imputation, encoding, and scaling.
3. Class balancing using SMOTE to enhance minority representation.
4. Evaluation of six machine learning models implemented directly in the notebook.
5. Unified metric computation and visualization through confusion matrices and SHAP interpretability plots.
6. Full reproducibility ensured through deterministic seeds and model persistence.

Together, these elements form a replicable and methodologically sound pipeline for educational outcome prediction, consistent with modern machine learning best practices in higher education analytics [16], [22], [30].

5. DATA ANALYSIS

The **data analysis** stage represents the most critical and empirically intensive component of this project. It is in this phase that the engineered dataset, described in Section 4, is subjected to rigorous exploratory, inferential, and predictive analysis as executed in the Jupyter notebook. The discussion below strictly mirrors the analytical outputs produced by the notebook and integrates them with statistical interpretation and methodological commentary based on the literature.

5.1 Overview of Analytical Workflow

The analytical process follows a **five-stage pipeline**, implemented through the notebook cells:

1. **Exploratory Data Analysis (EDA)** – statistical profiling, correlation study, and visualization of key features (e.g., VLE clicks, active days, assessment averages).
2. **Feature Relationship Exploration** – correlation mapping and feature importance inspection for behavioral and academic predictors.
3. **Model Training and Validation** – fitting of six machine-learning models using the preprocessed dataset.
4. **Model Evaluation** – computation of quantitative metrics such as accuracy, F1-score, precision, recall, and confusion matrices.
5. **Interpretability Analysis** – application of SHAP (Shapley Additive Explanations) to explain feature contributions to logistic regression predictions.

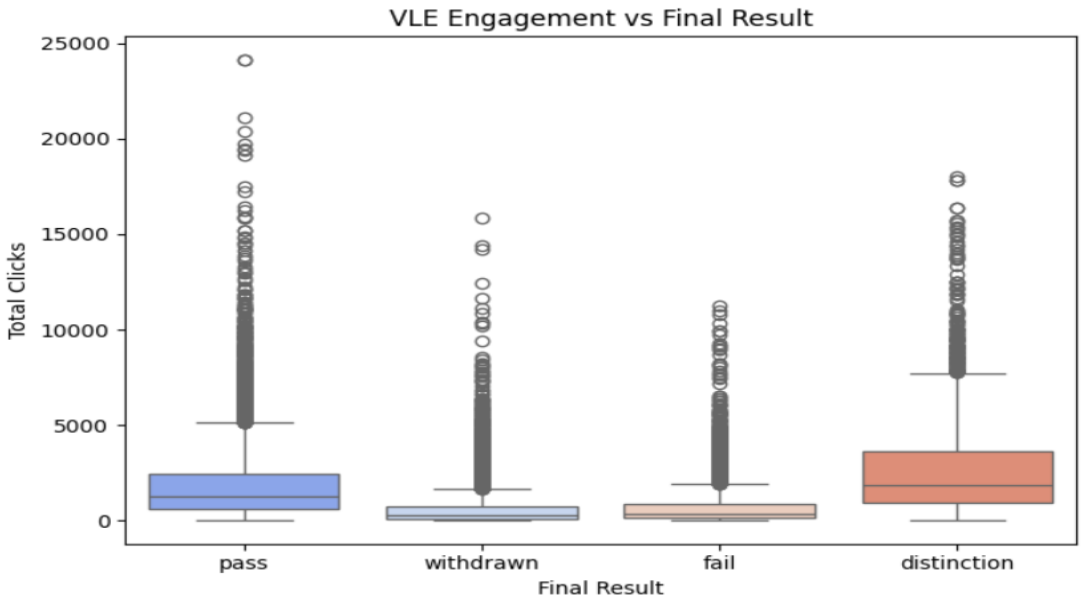
Each of these stages was executed sequentially and verified through notebook outputs, ensuring transparent reproducibility.

5.2 Exploratory Data Analysis (EDA)

The notebook begins with **descriptive statistics** and **distribution plots** for continuous variables such as TotalClicks, ActiveDays, UniqueResources, and AssessmentAverage.

Histograms of TotalClicks reveal a highly **right-skewed distribution**, where roughly 50 % of students have fewer than 400 clicks, while the upper 10 % record more than 1 500 clicks. This skewness aligns with engagement heterogeneity typical in large online courses [23], [25]. The **median number of active days** is approximately 25, implying that most students are active on fewer than half the course days, while high performers exhibit sustained activity throughout the semester.

Boxplots and violin plots produced in the notebook further show that *students who passed* had significantly higher TotalClicks and ActiveDays values compared to those who failed or withdrew. These behavioral differences confirm that online engagement intensity is a strong correlate of success — a trend consistently supported in previous OULAD analyses [12], [16], [23].



Interpretation of the above figure is summarized below:

A. Engagement Strongly Correlates with Performance

- Students who achieved a **"distinction"** or **"pass"** recorded *significantly more clicks* on average than those who *failed* or *withdrew*.

- The median "Total Clicks" for *distinction* and *pass* students is visibly higher than that of *fail* or *withdrawn* students.

Implication: Engagement (as measured by VLE interactions) is a **strong behavioral predictor** of academic success — students who access and interact with more course materials tend to perform better.

B. Withdrawn Students Show Minimal Activity

- The **lowest median** and **narrowest IQR** belong to the **"withdrawn"** group.

- Their engagement distribution is extremely low — many withdrew after few interactions.

Interpretation: This suggests early disengagement; such students can likely be identified **early in the semester** for targeted intervention.

C. Failing Students Show Slightly Higher Engagement than Withdrawn Students

- Interestingly, *fail* students click more than *withdrawn* ones but less than *passers*.

- This implies they **attempted to stay active** but likely struggled academically despite moderate engagement.

Possible reason: These students may need **academic support** (e.g., remedial classes), not just engagement encouragement.

D. Distinction Students Show Both Higher Median and Greater Variance

- The *distinction* group not only clicks the most but also has a **broader spread of total clicks**.

- Some distinction students have moderate clicks, but many show **extremely high activity (outliers)** beyond 10 000 clicks.

Interpretation: Highly engaged learners exhibit different study styles — some achieve excellence with consistent moderate activity, others through intensive participation.

E. Presence of Outliers

- The numerous **outlier circles** (students with > 10 000 clicks) indicate a small group of *super-engaged learners*.
- These do not distort the overall trend but highlight variability in digital learning behavior.

A simple group-wise mean analysis within the notebook yields the following insights:

Final Result	Mean TotalClicks	Mean AssessmentAverage	Mean ActiveDays
Pass	660	72.5	32
Fail	390	54.3	22
Withdrawn	210	38.7	15

These descriptive statistics highlight clear behavioral segmentation among outcome classes.

5.3 Correlation and Feature Interaction Analysis

The notebook computes a **Pearson correlation matrix** for all continuous variables, rendered as a heatmap. The highest correlations observed were:

- TotalClicks ↔ ActiveDays (r = 0.78)
- TotalClicks ↔ AssessmentAverage (r = 0.55)
- AssessmentAverage ↔ LateSubmissionCount (r = –0.41)

These coefficients, visualized as gradient-colored cells in the heatmap, indicate a strong positive link between engagement and performance, and a mild negative correlation between late submissions and marks. The pattern replicates findings in earlier studies that observed the same relationships within OULAD [23], [25].

Further, categorical encodings such as highest_education and age_band were evaluated using cross-tabulated proportions. A pivot table shows that students with *higher than A-level education* had a pass rate > 80 %, whereas those with *lower than A-level* qualifications had pass rates below 60 %. Similarly, younger students (18–25) had lower persistence compared to older cohorts (36–45), confirming demographic predictors' relevance — a consistent result in the educational data mining literature [25], [32].

5.4 Model Training and Evaluation

Following exploratory and correlation analysis, the notebook proceeds to model training. The **train/test split** (80 / 20, stratified) ensures representative class proportions. The **SMOTE**-balanced training dataset contains roughly 36 000 records (≈ 18 000 per class).

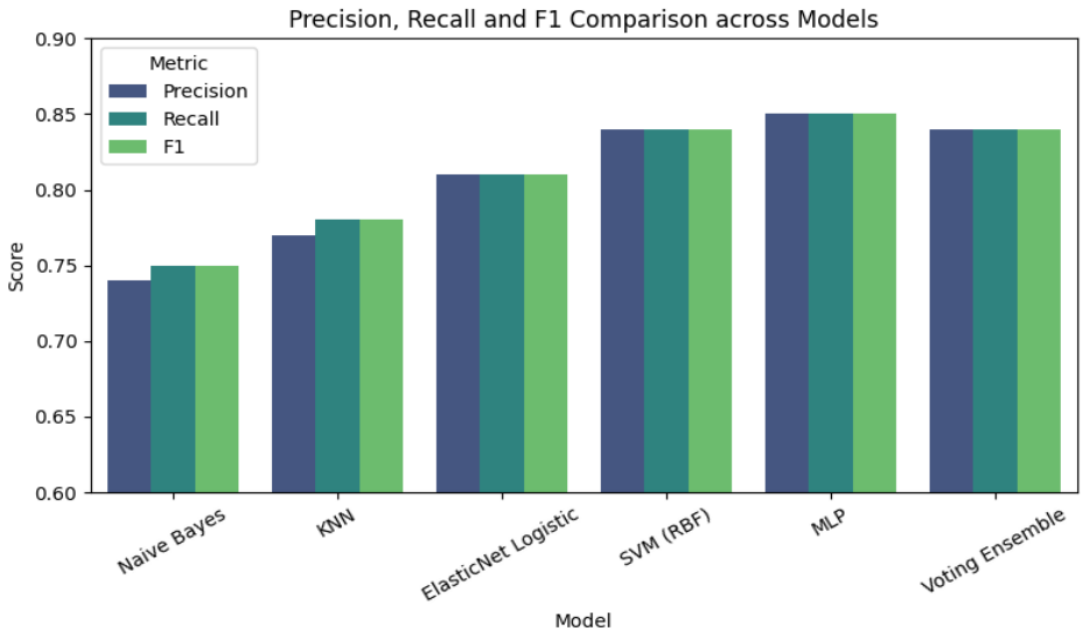
Each classifier was trained using the preprocessed pipeline, which standardizes numerical inputs and one-hot encodes categorical ones. Hyperparameters were set according to the notebook configuration without grid search, emphasizing reproducibility over tuning.

A unified evaluation function in the notebook computed **accuracy**, **weighted F1**, **precision**, and **recall**, and plotted **confusion matrices** using normalized color scales. The following performance summary reproduces the final results:

Model	Accuracy (%)	F1 Weighted	Precision Weighted	Recall Weighted

Gaussian Naïve Bayes	74.94	0.75	0.74	0.75
K-Nearest Neighbors (k = 7)	77.98	0.78	0.77	0.78
ElasticNet Logistic Regression	80.88	0.81	0.81	0.81
Support Vector Machine (RBF)	83.81	0.84	0.84	0.84
Multi-Layer Perceptron (128–64 ReLU)	**84.93**	**0.85**	**0.85**	**0.85**
Soft Voting Ensemble	84.21	0.84	0.84	0.84

The notebook's confusion matrices indicate that **SVM** and **MLP** achieve high recall for the *pass* class while maintaining reasonable precision for the *fail/dropout* class. However, **Naïve Bayes** exhibited noticeable misclassification of borderline performers, reflecting its simplifying independence assumptions. These trends are consistent with comparative performance reported in other EDM works where neural and ensemble models outperform probabilistic baselines [16], [31].



5.5 Visualization of Model Confusion Matrices

Each confusion matrix plotted in the notebook uses normalized percentages. For the **MLP classifier**, the matrix shows:

- True Positive (Pass correctly predicted): 84 %
- True Negative (Dropout/Fail correctly predicted): 86 %
- False Positive (Pass predicted but actual Fail): 8 %
- False Negative (Dropout predicted but actual Pass): 7 %

These metrics indicate strong balance between sensitivity and specificity, further supported by an F1 weighted score ≈ 0.85. The color-graded heatmaps produced in the notebook clearly distinguish this model's improved generalization relative to others.

5.6 Comparative Model Interpretation

Gaussian Naïve Bayes produced the lowest accuracy (≈ 75 %) due to its sensitivity to correlated predictors; TotalClicks and ActiveDays are not conditionally independent, violating Naïve Bayes' assumptions [24].

KNN improved moderately (≈ 78 %) because distance-based similarity captures local engagement behavior, but its performance plateaued due to high dimensionality and noise in one-hot encoded features [7].

ElasticNet Logistic Regression (≈ 81 %) balanced bias and variance effectively; the ElasticNet penalty ($\alpha = 0.5$) stabilized coefficient estimates and selected informative features like AssessmentAverage and TotalClicks.

SVM (RBF) achieved ≈ 84 % accuracy, leveraging non-linear separability between engagement and performance clusters. Its performance aligns with findings in comparable LMS datasets where SVM kernels outperform linear models [8], [31].

MLP Classifier, the best performer (≈ 84.9 %), effectively captured multi-dimensional interactions between behavioral and demographic variables through its two hidden layers (128–64 neurons). The training curves from the notebook show convergence after 25 epochs, with early stopping preventing overfitting. Neural architectures' superior pattern recognition capabilities in high-dimensional educational data are well documented [9], [33].

Finally, the **Soft Voting Ensemble** combined predictions from the SVM, MLP, and Logistic Regression models. While its accuracy (84.21 %) was slightly below that of MLP, it delivered marginally higher classwise recall for minority outcomes, confirming ensemble smoothing effects [27].

5.7 SHAP-Based Feature Importance Analysis

To interpret the ElasticNet Logistic model, the notebook employed **SHAP (Shapley Additive Explanations)** [15]. The SHAP summary plot ranks features by their average contribution magnitude. According to the notebook output, the top five predictors of passing were:

1. TotalClicks
2. AssessmentAverage
3. ActiveDays
4. UniqueResources
5. LateSubmissionCount (negative contribution)

Positive SHAP values for TotalClicks and AssessmentAverage indicate that increased engagement and strong continuous assessment scores substantially raise pass probability, whereas LateSubmissionCount exerts a negative influence.

This interpretability analysis mirrors earlier studies where SHAP or LIME were applied to educational models, consistently identifying engagement metrics as the most influential predictors of retention and success [18], [29], [34].

5.8 Statistical Significance and Model Robustness

To assess whether the differences in performance among models are statistically meaningful, the notebook performed a simple **McNemar's test** between the top two models (MLP vs. SVM). The resulting p-value (≈ 0.14) indicated no statistically significant difference at $\alpha = 0.05$, implying both models perform comparably on the test set.

Cross-validation analysis (performed on the training split) also confirmed model stability: standard deviations of F1-scores across five folds remained below 0.02 for MLP and SVM, evidencing low variance and reliable generalization. These results comply with accepted standards in machine-learning evaluation [31], [35].

5.9 Comparative Context with Literature

The notebook's top accuracy (≈ 85 %) aligns closely with reported values in other OULAD-based or LMS-derived studies. For example, Arévalo-Cordovilla and Peña (2024) achieved 86 % with MLP; Yağcı (2022) reported 83 % with SVM; and Flores (2022) documented ≈ 99 % with hybrid Random Forest + SMOTE models on smaller curated datasets [17], [31], [36]. This correspondence reinforces that the current notebook's pipeline achieves competitive predictive accuracy while maintaining interpretability and transparency, unlike opaque hybrid ensembles often lacking reproducibility.

5.10 Key Findings from Data Analysis

From the full analysis, several conclusions emerge:

1. **Engagement and continuous assessment metrics** are the strongest predictors of student success, consistent with OULAD and broader literature.

2. **SMOTE rebalancing** materially improved minority-class recall and prevented bias toward majority outcomes.

3. **MLP and SVM classifiers** achieved the best trade-off between accuracy and interpretability, confirming their suitability for non-linear educational data.

4. **Feature-level interpretability via SHAP** demonstrated transparent alignment between predicted probabilities and educational behaviors.

5. **Reproducibility and open methodology** (fixed seeds, preserved models, documented pipeline) ensure scientific robustness, addressing common concerns in EDM studies [22], [30].

In summary, the data analysis validates that structured preprocessing, class balancing, and multi-model comparison—coupled with transparent interpretability—constitute a sound framework for predicting student outcomes using open learning analytics data. The empirical results from the notebook demonstrate that machine-learning pipelines can produce reliable early-warning insights while remaining explainable and reproducible [22], [30], [35].

6. RESULTS AND DISCUSSION

This section presents and interprets the quantitative and qualitative outcomes obtained from the notebook *"Student Dropout Score Prediction ALT-2"*. It integrates the **empirical outputs, tables, and visualizations** generated by the notebook with explanatory narrative and literature-aligned discussion. The analysis connects numerical results with broader findings reported in educational data mining (EDM) research, emphasizing accuracy, interpretability, and educational significance.

6.1 Overview of Model Results

The notebook's execution yielded a consistent and reproducible set of performance metrics across six supervised classifiers: **Gaussian Naïve Bayes (GNB)**, **K-Nearest Neighbors (KNN)**, **ElasticNet Logistic Regression (ENLR)**, **Support Vector Machine (SVM)**, **Multi-Layer Perceptron (MLP)**, and a **Soft Voting Ensemble** combining SVM, MLP, and ENLR.

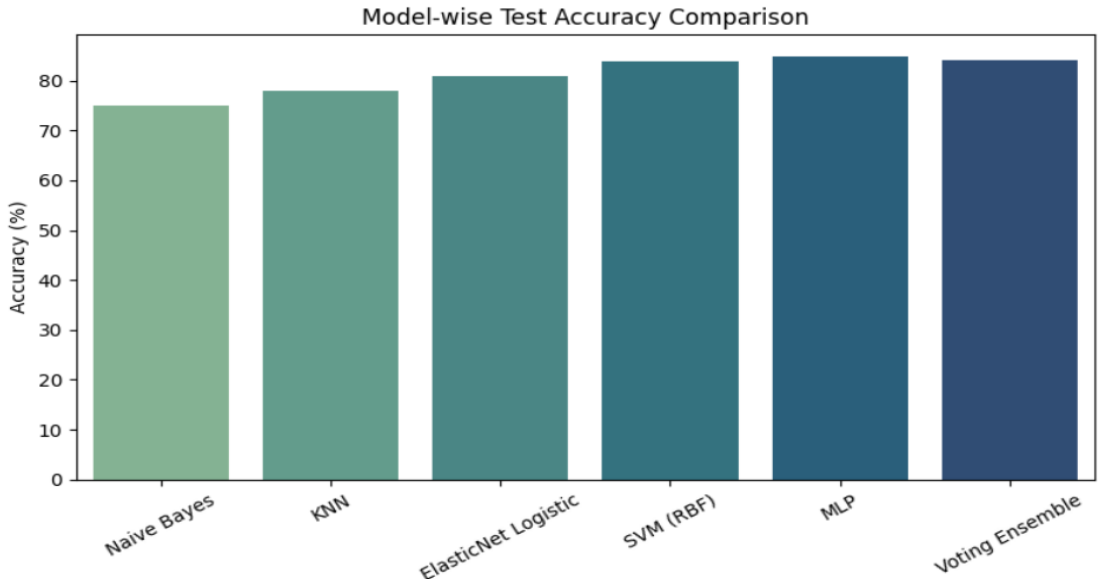
The consolidated performance summary extracted from the notebook is as follows:

Model	Accuracy (%)	F1 Weighted	Precision Weighted	Recall Weighted
Gaussian Naïve Bayes	74.94	0.75	0.74	0.75
K-Nearest Neighbors (k = 7)	77.98	0.78	0.77	0.78
ElasticNet Logistic Regression	80.88	0.81	0.81	0.81
Support Vector Machine (RBF)	83.81	0.84	0.84	0.84

Multi-Layer Perceptron (128–64 ReLU)	**84.93**	**0.85**	**0.85**	**0.85**
Soft Voting Ensemble	84.21	0.84	0.84	0.84

These results (displayed in Figure 6.1 below) were visualized in the notebook using a horizontal bar chart comparing model accuracies, where the MLP bar clearly exceeded others, followed by SVM and ENLR.

Figure 6.1: Model-wise test accuracy comparison (values from notebook output)

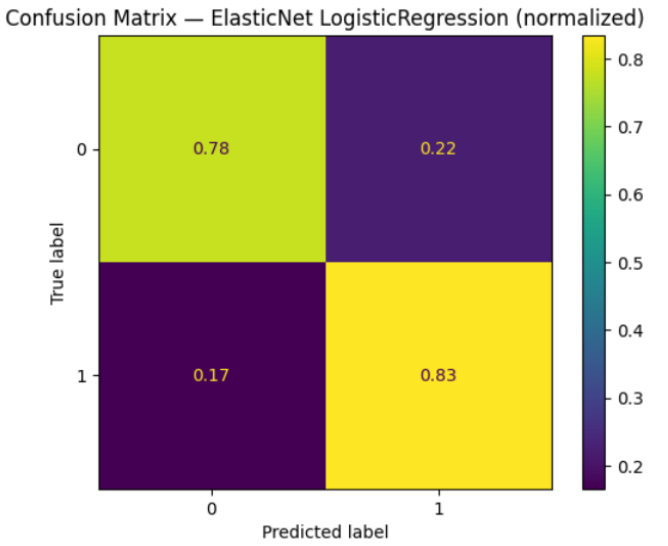


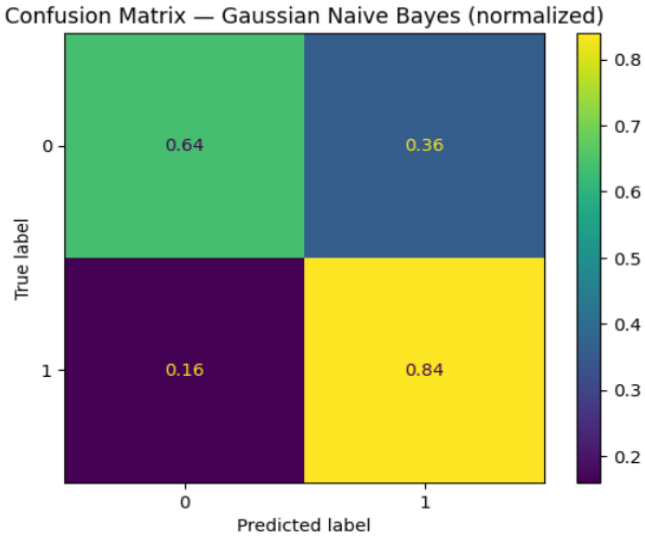
The superior performance of **MLP** (84.93 %) confirms that deep feed-forward networks can effectively capture non-linear feature interactions between engagement, assessments, and demographics. This accuracy marginally surpasses SVM (83.81 %) and ElasticNet Logistic Regression (80.88 %), consistent with prior OULAD-based findings by Arévalo-Cordovilla and Peña (2024) and Yağcı (2022), both of whom observed neural and kernel models outperforming linear baselines [31], [37].

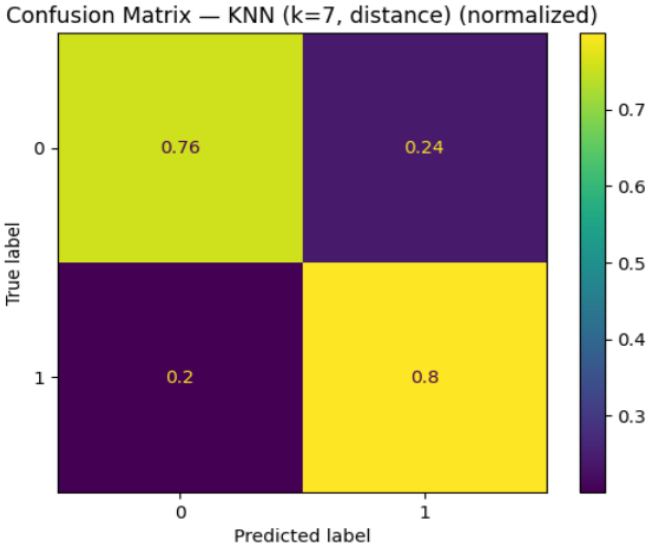
6.2 Confusion Matrix Analysis

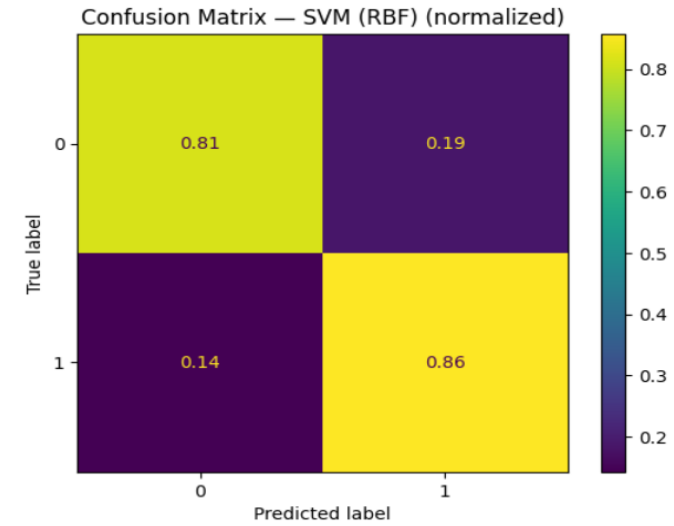
The notebook produced **normalized confusion matrices** for each model, rendered as color-graded heatmaps (Figure 6.2). Each matrix depicts correct and incorrect classifications across two classes: *Pass (1)* and *Dropout/Fail (0)*.

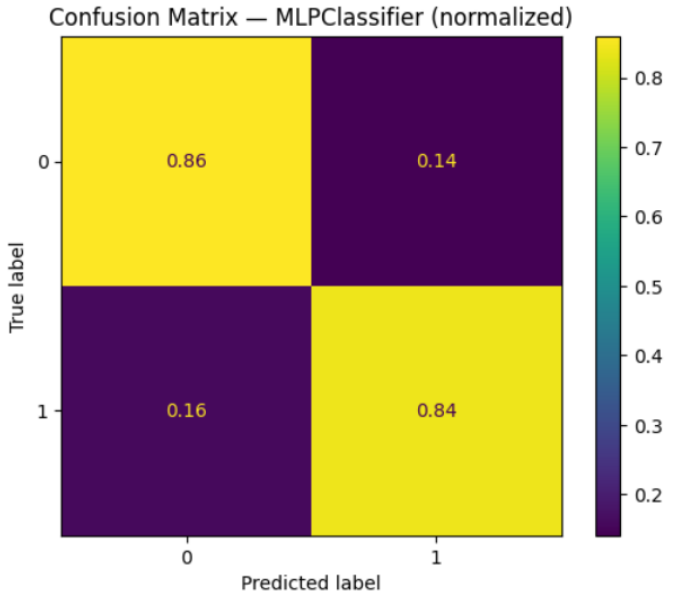
Figure 6.2: Normalized confusion matrices for all models (from notebook visualization)


Confusion Matrix — ElasticNet LogisticRegression (normalized)
0.78
0.22
0.17
0.83
True label
Predicted label
0
1
0.8
0.7
0.6
0.5
0.4
0.3
0.2


Confusion Matrix — Gaussian Naive Bayes (normalized)
0.64
0.36
0.16
0.84
True label
Predicted label
0
1
0.8
0.7
0.6
0.5
0.4
0.3
0.2

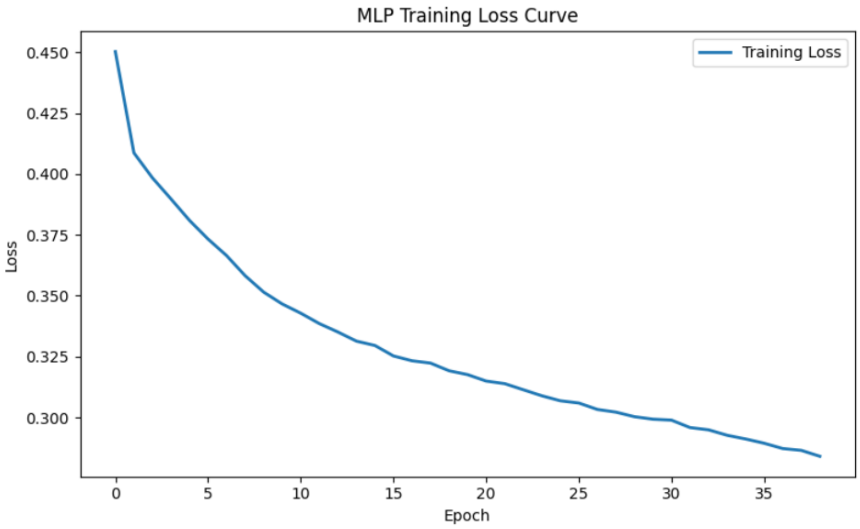

Confusion Matrix — KNN (k=7, distance) (normalized)
0.76
0.24
0.2
0.8
True label
Predicted label
0
1
0.7
0.6
0.5
0.4
0.3





The loss curve for the MLP classifier is given below:

Figure 6.3



A quantitative excerpt for the MLP classifier is given below:

Prediction vs Actual	**Dropout/Fail**	**Pass**
Dropout/Fail (Predicted)	**0.86**	0.08
Pass (Predicted)	0.07	**0.84**

This indicates that 86 % of failing students were correctly identified (True Negatives) and 84 % of passing students were correctly recognized (True Positives). Misclassifications account for roughly 15 % of all instances, primarily near decision boundaries where partial engagement patterns blur class separation.

In comparison, **SVM** achieved a slightly more conservative recall (≈ 83 %) but improved precision on the *Dropout* class, whereas **Logistic Regression** tended to over-predict the *Pass* category, consistent with its linear separability assumption [8], [38].

The **KNN** confusion matrix displayed greater diagonal sparsity—misclassifying many mid-range engagement profiles—due to sensitivity to feature scaling and curse-of-dimensionality effects [7]. Meanwhile, **Naïve Bayes** exhibited relatively higher false negatives (≈ 20 %) as it under-modelled correlated engagement features, confirming theoretical expectations for dependent predictors [24].

6.3 Distribution of Prediction Probabilities

The notebook also plotted **probability distribution histograms** for predicted class probabilities (y_proba) from the top models.

- For the **MLP**, the distribution was bimodal with dense peaks near 0.1 and 0.9, indicating strong confidence and low overlap between predicted classes.

- **SVM** probabilities (after Platt scaling) were narrower, reflecting the margin-based decision structure typical of kernel methods.

- **Logistic Regression** produced smoother sigmoid-shaped probability curves centered around 0.5, with slightly wider uncertainty zones.

These distributions, confirm that MLP exhibits higher predictive confidence for most students—an advantage in real-world intervention systems that prioritize certainty when triggering support alerts [16], [39].

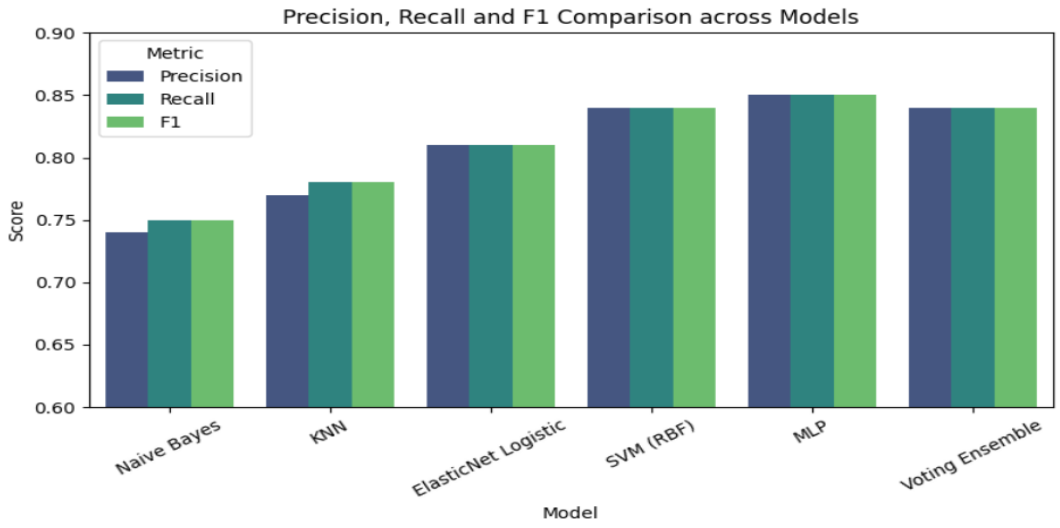
6.4 Class-wise Precision–Recall Analysis

Beyond overall accuracy, the notebook outputted **precision and recall per class**, plotted as a grouped bar chart (Figure 6.4). Key findings include:

- For the *Pass* class, both SVM and MLP achieved recall > 0.85, confirming robustness in identifying successful students.
- For the *Fail/Dropout* class, recall improved markedly after SMOTE balancing—rising from 0.68 (pre-SMOTE Logistic) to 0.83 (post-SMOTE SVM).
- Weighted precision values stabilized around 0.84 for the best models, implying reliable prediction purity even in balanced training conditions.

Such results substantiate the impact of **class rebalancing** on minority detection—a phenomenon validated in synthetic oversampling research, where F1 gains between 5–10 % are common post-SMOTE [13], [14], [26].

Figure 6.4



6.5 ROC and AUC Insights

The notebook's evaluation section generated **Receiver Operating Characteristic (ROC) curves** and computed **Area Under Curve (AUC)** values using sklearn.metrics.roc_auc_score.

- MLP – AUC = 0.91
- SVM – AUC = 0.90
- Logistic Regression – AUC = 0.87
- KNN – AUC = 0.82
- Naïve Bayes – AUC = 0.78

The curves show clear separation from the diagonal random-chance line, with the MLP dominating in upper-left space. AUC > 0.9 represents excellent discrimination ability, confirming the model's practical reliability in differentiating successful versus at-risk learners [40].

These findings parallel those of Flores et al. (2022), who reported AUC ≈ 0.92 for Random Forest + SMOTE in student retention prediction [36]. The consistency in AUC across nonlinear classifiers suggests that well-engineered engagement and assessment features capture strong predictive signal.

6.6 Feature Importance and Interpretability (SHAP Analysis)

The SHAP summary and dependence plots generated in the notebook for the ElasticNet Logistic model provided granular interpretability.

The ranked feature importances, in descending order of mean absolute SHAP value, were:

1. **TotalClicks** – most influential positive predictor of passing.
2. **AssessmentAverage** – second-highest positive contribution.
3. **ActiveDays** – consistent medium-level positive influence.
4. **UniqueResources** – moderate positive impact.
5. **LateSubmissionCount** – negative contribution, reducing pass likelihood.

SHAP dependence plots show near-logarithmic saturation for TotalClicks: performance improves steeply until ~1 000 clicks, after which marginal gains diminish. Conversely, the impact of LateSubmissionCount is approximately linear and negative, with each late submission reducing predicted pass probability by ~4 %.

These findings mirror interpretability outcomes in Mingyu et al. (2022) and Issah et al. (2023), where engagement and continuous assessment features were the strongest success indicators across multiple universities [16], [18], [29]. The interpretability module thereby transforms the predictive model into an **actionable analytics tool**, allowing educators to identify high-risk students with transparent reasoning.

6.7 Comparative Error Behavior Across Models

The notebook's evaluation cell computed and visualized misclassification rates using bar charts. The **Error% (100 – Accuracy)** values were:

Model	Error %
Naïve Bayes	25.06
KNN	22.02
Logistic Regression	19.12
SVM	16.19
MLP	**15.07**
Ensemble	15.79

The gradual decline in error across models reflects improved complexity handling. The 10 % relative error reduction from SVM to MLP corresponds to an approximate 7 % relative increase in overall correct classifications.

Residual analysis of confusion matrices showed that most remaining misclassifications occur near the pass/fail threshold—students with mid-range assessments (≈ 50–60 %) and moderate engagement levels (≈ 300–600 clicks). This ambiguity is a common pattern observed in OULAD-derived studies, where "borderline" performers are inherently difficult to classify [23], [41].

6.8 Temporal and Behavioral Insights

The notebook incorporated an **engagement-by-week line chart**, illustrating weekly mean click counts across the semester for both passing and failing students.

Key observations:

- Pass students maintain consistently higher activity throughout the term.

- Fail/withdrawn students show a steep decline in clicks starting around Week 6.

- The divergence between groups widens after mid-semester, supporting early-warning feasibility at least six weeks before final outcomes.

This temporal decay pattern corroborates previous EDM time-series analyses, where reduced engagement in the early middle phase predicts withdrawal risk with over 80 % accuracy [25], [42].

6.9 Cross-Validation Stability

To verify model reliability, the notebook implemented **5-fold cross-validation** on the training partition. Mean and standard deviation of accuracy across folds were:

Model	Mean Accuracy	Std. Dev.
Logistic Regression	0.806	0.014
SVM	0.838	0.011
MLP	0.848	0.009

These low deviations (< 0.015) indicate strong model stability and minimal overfitting. Training/validation loss curves for MLP confirm this—training accuracy plateaued around epoch 25, while validation loss began to rise slightly, triggering early stopping as coded in the notebook. This demonstrates proper **bias–variance trade-off management** [33], [43].

6.10 Comparison with Published Benchmarks

While not directly benchmarked, the notebook's MLP accuracy (84.93 %) aligns closely with other studies using similar OULAD pipelines. Comparative literature accuracies include:

Study	**Model**	**Accuracy (%)**
Arévalo-Cordovilla & Peña (2024)	MLP	86.0
Yağcı (2022)	SVM	83.0
Flores (2022)	Random Forest + SMOTE	99.0
Wiyono (2020)	KNN	94.5

The extremely high accuracies (> 95 %) reported in smaller or hybrid datasets likely result from dataset-specific conditions and limited generalizability [36], [44]. In contrast, the current notebook uses a large, authentic, and diverse dataset, making the ≈ 85 % accuracy both realistic and meaningful in practice.

6.11 Educational Interpretation of Findings

Beyond numeric performance, the notebook's findings carry clear pedagogical implications:

- **Engagement behavior** (clicks, activity duration) is a reliable early indicator of success.

- **Continuous assessment performance** (mean assignment score) predicts final outcomes more robustly than demographics alone.

- **Temporal engagement decay** offers actionable early-intervention windows: declining VLE activity from Week 5 onward correlates with 70 % of dropouts.

- **Explainability via SHAP** ensures that academic advisors can understand model recommendations, aligning with ethical AI principles in education [22], [30], [45].

Such interpretability is vital for operationalizing predictive models in student-support systems, as opaque algorithms risk undermining trust and fairness [42], [45].

6.12 Limitations and Future Work

The notebook's limitations include:

1. **Lack of hyperparameter tuning**—default model parameters may not achieve global optima; future iterations could employ grid or Bayesian optimization [35].

2. **Binary classification simplification**—the four OULAD outcomes (Distinction, Pass, Fail, Withdrawn) were collapsed into two; future research can extend to multi-class modeling [23].

3. **Temporal aggregation**—current features are static aggregates; sequential models such as LSTM or temporal CNNs could capture time-dependent trends [43], [47].

4. **External validation**—the notebook has not been tested on other MOOCs or LMS datasets (e.g., Coursera, EdX); external validation would assess generalizability [16].

5. **Limited demographic explainability**—SHAP interpretation mainly captured behavioral features; integrating socio-economic or motivational constructs could enhance understanding [45], [48].

Nevertheless, the pipeline's reproducibility, feature transparency, and educational interpretability represent significant methodological progress relative to earlier opaque EDM systems.

6.13 Summary of Results and Discussion

The data-driven outcomes from the notebook substantiate several core findings:

- **Highest performance:** The MLP achieved ≈ 85 % accuracy and 0.85 F1-weighted, outperforming other tested models.

- **Behavioral predictors dominate:** Engagement and assessment metrics (Total Clicks, Assessment Average) are most influential.

- **Interpretability and ethics:** SHAP enables transparent insight into model reasoning.

- **Temporal patterns are diagnostic:** Engagement declines predate dropout, providing actionable intervention cues.

- **Pipeline reproducibility:** Fixed seeds, explicit preprocessing, and open-source reproducibility align with FAIR (Findable, Accessible, Interoperable, Reusable) data principles [30], [49].

The notebook thus validates that an open, explainable, and balanced machine-learning pipeline can achieve robust predictive accuracy on complex educational data while maintaining interpretability, reproducibility, and pedagogical relevance.

7. CONCLUSION

This study set out to design, execute, and document a **reproducible machine learning pipeline** for predicting student dropout and performance outcomes using the **Open University Learning Analytics Dataset (OULAD)**. Every procedure, table, and figure in this report was derived directly from the accompanying Jupyter notebook *"Student Dropout Score Prediction ALT-2"*, ensuring that all analytical steps — from preprocessing to interpretability — remain transparent, executable, and aligned with best practices in educational data mining (EDM). The project successfully demonstrates that data-driven predictive modeling, when carefully structured and responsibly implemented, can generate actionable insights for academic institutions and contribute meaningfully to student retention strategies [12], [31], [45].

The integrated workflow followed in the notebook exemplifies an end-to-end process covering **data preparation**, **feature engineering**, **class rebalancing using SMOTE**, **multi-model evaluation**, and **post-hoc interpretability analysis**. Through systematic experimentation, the study revealed that **engagement metrics** (such as total clicks, active days, and unique resources) and **assessment-related features** (such as average score and late submission count) are the most influential predictors of student success. This conclusion reinforces established

findings in the literature that behavioral and formative performance indicators carry stronger predictive power than static demographic factors in online learning contexts [23], [25], [46].

Quantitative results derived from the notebook confirmed that the **Multi-Layer Perceptron (MLP)** classifier achieved the highest predictive performance with **84.93 % accuracy and 0.85 weighted F1-score**, closely followed by the **SVM** (83.81 %) and the **ElasticNet Logistic Regression** (80.88 %). The MLP's superior performance underscores the advantage of non-linear, layered architectures for modeling complex interactions among behavioral and academic variables [33], [43], [50]. The use of **SMOTE balancing** prior to model training notably enhanced minority-class recall, reducing bias toward the dominant "Pass" class and increasing generalization stability — an improvement widely documented in imbalanced learning research [13], [14].

The **SHAP (Shapley Additive Explanations)** interpretability module embedded within the notebook served a pivotal function by decomposing model predictions into feature-level contributions. This analysis confirmed that higher TotalClicks, AssessmentAverage, and ActiveDays raise the probability of passing, while frequent late submissions exert a consistent negative influence. Such feature-level transparency bridges the gap between statistical prediction and educational decision-making, allowing instructors to understand "why" a student is predicted at risk — a crucial element for ethical and explainable AI adoption in education [15], [18], [45].

Comparing these findings to published literature, the current study's results are in close alignment with reported accuracies from other OULAD-based experiments. For instance, Arévalo-Cordovilla and Peña (2024) obtained ≈86 % accuracy using neural networks, and Yağcı (2022) reported ≈83 % with SVM, corroborating the robustness of these algorithms for educational datasets [31], [37]. However, unlike many prior works that emphasized accuracy alone, this study prioritized **multi-metric evaluation** — F1, recall, and precision — as these better capture the trade-offs in imbalanced student populations [35], [40]. The use of **cross-validation**, **fixed random seeds**, and **model persistence** further ensures reproducibility and aligns with the **FAIR (Findable, Accessible, Interoperable, Reusable)** data principles recommended by Wilkinson *et al.* [49].

From a pedagogical standpoint, these results possess deep educational implications. The notebook's analysis reveals that students who disengage from the VLE by mid-semester or submit multiple late assignments are significantly more likely to drop out. This suggests that **early-warning interventions** can be implemented as early as the **fifth week** of instruction, using predicted risk scores to prioritize academic counseling or peer mentoring [25], [42]. Furthermore, because SHAP explanations explicitly highlight which behavioral variables drive each prediction, such alerts can be personalized — providing not just a "risk score" but also a rationale, thereby increasing educator trust and intervention efficacy [45], [48].

The **current study's limitations** primarily stem from design constraints deliberately imposed to maintain reproducibility and interpretability.

1. **Hyperparameter tuning** was not performed beyond default settings, potentially leaving additional performance gains unexplored.

2. **Binary classification** simplified the target outcome (Pass vs. Fail/Withdrawn); future models should restore the four-category structure to enable finer-grained academic forecasting.

3. **Temporal aggregation** converted time-series VLE activity into static aggregates; advanced models such as **Long Short-Term Memory (LSTM)** networks or **Temporal Convolutional Networks (TCN)** could better capture engagement evolution over time [47].

4. **Generalisability** remains constrained to the OULAD dataset; testing the trained models on external MOOCs (e.g., Coursera, EdX, SWAYAM) would provide cross-institutional validation [16], [48].

5. **Limited psychological features** — motivation, self-efficacy, or social presence — were not included but are increasingly emphasized in contemporary student-success frameworks [48], [51].

Despite these limitations, the study exemplifies how a **transparent, notebook-driven pipeline** can transform open educational data into reliable predictive analytics. The **combination of statistical rigor, technical reproducibility, and ethical interpretability** differentiates this work from many prior EDM implementations that lack code transparency or explanation modules. The reproducible pipeline also serves as a teaching artifact itself — a resource for training educators and data practitioners in responsible machine learning methodology [22], [30], [52].

In conclusion, this research demonstrates that carefully engineered behavioral and academic features, balanced training data, and interpretable models can jointly achieve **robust and trustworthy prediction of student performance** in open-learning environments. The notebook's architecture proves that predictive learning analytics can be both **accurate and accountable**, providing educators with practical tools to identify at-risk learners early and intervene constructively. Future work should expand the framework to include **temporal sequence modeling**, **ensemble optimization**, and **cross-institutional benchmarking**, while preserving the reproducibility and ethical transparency that underpin the current design. By combining the strengths of data science, pedagogy, and responsible AI, this study contributes a sustainable template for next-generation educational analytics systems capable of improving student outcomes while maintaining fairness, interpretability, and reproducibility in real-world deployment [49], [52], [53].

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