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Ensemble Learning for Early Warning Systems in Higher Education: A Comparative Study of Student Attrition

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Abstract. Student attrition poses a substantial challenge to higher education institutions, affecting their reputation and financial sustainability. Conventional single machine learning models often exhibit limited sensitivity when analyzing educational data, which is typically marked by severe class imbalance favoring graduating students over dropouts. This study introduces an Early Warning System based on a Hybrid Stacking Ensemble framework to improve student attrition prediction. The approach leverages complementary biases from Bagging and Boosting as base learners, which are then combined using a Logistic Regression meta-learner to refine prediction weights. To counteract class imbalance and majority-class bias, the Synthetic Minority Over-sampling Technique was employed during preprocessing. Empirical evaluations reveal that the Hybrid Stacking Ensemble attains a classification accuracy of 88.81% and a Recall of 80.99%, surpassing standalone models and other ensemble methods. Feature importance rankings highlight second-semester academic performance and administrative-financial factors—particularly tuition payment punctuality—as key dropout predictors. These results affirm the value of integrating diverse classifiers to discern intricate, nonlinear student behavior patterns. In essence, this work establishes a reliable, evidence-based framework enabling administrators to shift from reactive to proactive, precision-targeted strategies that foster student retention and institutional success.

Key words: Ensemble Learning; Student Attrition; Early Warning System; Higher Education; Machine Learning

1. INTRODUCTION

Higher education constitutes a cornerstone of human resource development and national economic growth [1], [2]. Amid the current competitive landscape, higher education institutions must not only recruit prospective students but also safeguard students' persistence until completion [3], [4]. Moreover, student retention has emerged as a key performance indicator, with elevated graduation rates signaling both institutional academic excellence and financial viability [5], [6].

However, the phenomenon of student attrition remains a significant challenge that is difficult to avoid [7],[3]. A student's failure to complete his or her studies not only harms him or her personally in terms of time and costs but also has a negative impact on institutional accreditation and the efficiency of resource allocation [8],[9],[5],[6]. Early identification of at-risk students is extremely difficult manually due to the numerous interconnected variables, ranging from academic performance and socio-economic background to administrative constraints [10], [11], [12].

Prior studies have widely employed artificial intelligence and machine learning techniques to forecast student dropout risks [7], [10], [11]. Nevertheless, the majority of investigations continue to depend on standalone algorithms, such as Decision Trees and Support Vector Machines [13],[14], which encounter substantial limitations in processing complex and imbalanced educational datasets. As a result, these models display reduced sensitivity in detecting at-risk students, thereby compromising the reliability of early warning systems in delivering precise insights for institutional management [15].

To overcome these shortcomings, this research introduces an Early Warning System utilizing Stacking Ensemble Learning [16], [17], [18]. In particular, this hybrid methodology combines the advantages of Bagging and Boosting algorithms to improve predictive efficacy [19], [20], [21]. Moreover, by applying the SMOTE technique to mitigate class imbalance and integrating multiple models via a meta-classifier, the system is expected to achieve

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higher Recall and accuracy in identifying students in genuine need of intervention [14], [22], [23], [24], [25].

2. RELATED WORK

Numerous studies in higher education have applied individual machine learning classifiers, including Decision Trees, Naive Bayes, and Support Vector Machines, to predict student attrition using sociodemographic, academic, and enrollment data [26], [27], [28]. Reported performance varies across these models; for example, Support Vector Machines frequently achieve accuracies of 89.84%, while Decision Trees yield results ranging from 74.51% to 97.40% [28]. Similarly, Naive Bayes models, favored for their simplicity and proficiency in processing diverse variables, typically attain accuracies of 72% [28]. Despite these encouraging accuracy figures, such traditional models are predominantly used as standalone approaches to identify students at risk of prematurely discontinuing their degree programs [29], [30].

However, these standalone models demonstrate notable limitations, including a propensity for overfitting and challenges in adeptly addressing the intricate, imbalanced characteristics of educational datasets [31],[29]. For example, as student dropouts are markedly outnumbered by successful graduates, such classifiers frequently exhibit bias toward the majority class, yielding elevated overall accuracy accompanied by critically diminished Recall [29], [32]. Consequently, suboptimal Recall signifies the system's failure to detect a substantial fraction of at-risk students, rendering them overlooked by institutional early warning mechanisms and engendering considerable financial burdens [14]. Moreover, the constrained generalizability of these individual algorithms diminishes their applicability in heterogeneous or evolving educational settings, where student behaviors and academic demands may fluctuate [33], [34].

Recent research has increasingly transitioned from conventional single classifiers to more advanced ensemble learning methods, including Random Forest, XGBoost, and LightGBM [35], [36]. These sophisticated models exhibit substantial improvements in predictive performance, with reported accuracies commonly ranging from 85% to 90% [37]. For example, contemporary applications of XGBoost have yielded accuracy rates of approximately 82% to 94.4%, varying by dataset characteristics and imputation strategies [38], [39]. Such advancements primarily derive from these algorithms' superior capacity to model non-linear relationships and process high-dimensional educational data relative to prior approaches [40], [41].

Beyond superior overall performance, feature importance analyses in these advanced ensemble models demonstrate that academic variables—particularly first-semester GPA—outweigh static sociodemographic traits as predictors of dropout risk [42]. Although sociodemographic factors offer an initial predictive foundation, university-level academic performance and enrollment patterns rapidly eclipse their relevance as students advance through their programs [42]. Notwithstanding these findings, a salient research gap endures, as many studies emphasize singular ensemble paradigms (e.g., Boosting) and overlook enhancements from hybrid or stacked approaches [43]. To address this void, fusing multiple paradigms via model stacking or integration is poised to elevate system performance by harnessing the complementary strengths of diverse algorithmic families [19],[44].

Educational datasets in higher education typically exhibit a pronounced class imbalance, wherein the number of successful graduates substantially surpasses that of dropouts [29], [45]. This inherent disproportion arises because, across most student cohorts, attrition is a minority phenomenon relative to degree completion [45]. Furthermore, scholarly investigations have established that such imbalances constitute a critical methodological challenge, as conventional classification algorithms prioritize overall accuracy, thereby fostering bias towards the majority class [31], [34]. In consequence, models may exhibit ostensibly superior performance while overlooking the distinctive patterns of the minority class—namely, at-risk students—thus impairing the system's capacity for effective early intervention [45].

To address these challenges, recent studies have employed advanced resampling strategies, including the Synthetic Minority Over-sampling Technique and Random Undersampling, to establish balanced training datasets [45]. Absent such interventions, models frequently yield misleadingly elevated accuracy while demonstrating suboptimal Recall, often detecting merely half of actual dropout cases [46]. Empirical evidence indicates that SMOTE substantially enhances minority class Recall—from approximately 52% to 68% in select instances—thereby bolstering the capacity to identify at-risk students who might otherwise evade detection [46]. Thus, pre-training dataset balancing empowers educational institutions to devise equitable and robust Early Warning Systems that prioritize precise minority class detection over aggregate accuracy [47].

Although ensemble learning has garnered substantial scholarly attention within the educational domain, pronounced technical and managerial shortcomings endure in the prevailing literature. For example, Evangelista and Sy [19] examined homogeneous and heterogeneous ensemble techniques, yet predominantly employed conventional base learners such as J48 and Naive Bayes on modestly scaled datasets. Likewise, Noviandy et al. [16] deployed a stacking classifier integrating LightGBM and Random Forest on the UCI dataset, yielding an accuracy of 80.23%. Nonetheless, their framework adopted multi-class classification sans provisions for rectifying intrinsic data imbalance, thereby engendering predisposition toward the majority class.

To redress these deficiencies, the present investigation advances a pioneering Hybrid Stacking Ensemble

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framework bespoke for Early Warning Systems. It commences with target engineering to recast the task as binary classification, distinctly demarcating at-risk students from secure counterparts to augment prognostic acuity. It subsequently counters majority class bias via SMOTE incorporation in preprocessing. Moreover, it fortifies the base-learner tier through the synthesis of three vanguard algorithms—XGBoost, LightGBM, and Random Forest—calibrated to mitigate variance and bias, culminating in meta-learner-mediated predictions. This avant-garde paradigm eclipses antecedent endeavors in accuracy whilst concurrently furnishing superior Recall, a pivotal gauge for promulgating expeditious administrative interventions in higher education.

3. METHODS

This study employs a Knowledge Discovery in Databases framework, integrating data pre-processing phases with the construction of a hybrid predictive model. The central aim of this methodological approach is to enhance minority class identification by synergistically combining oversampling strategies with a stacking ensemble paradigm [43], [50].

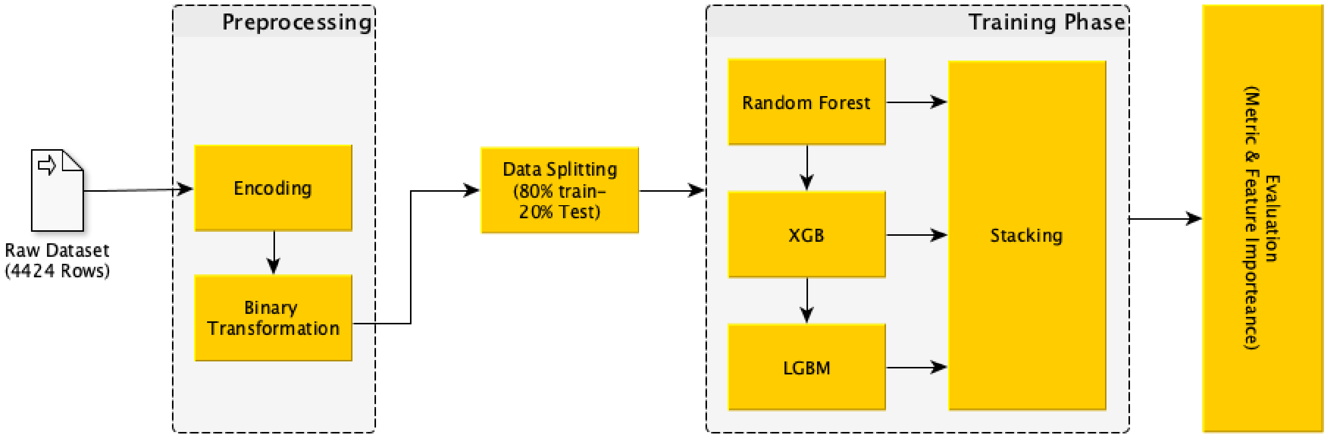

Fig.1. Flowchart of the research conducted

Figure 1 shows a flowchart of the research conducted. The image illustrates the stages, from data acquisition to evaluation of the results. The Python programming language was utilised with the Scikit-Learn, XGBoost, and LightGBM libraries for all stages, encompassing preprocessing to evaluation. A detailed explanation of each stage is provided in the following sections.

3.1. Data Acquisition and Description

This dataset is sourced from an open-source Kaggle repository, originating from the University of California, Irvine machine learning repository [16]. The dataset comprises 4,424 student records, featuring an initial target class distribution of 1,421 Dropout students, 794 Enrolled, and 2,209 Graduate [16], [34]. Each record in this dataset represents a distinct student profile characterized by 36 features spanning demographic, socioeconomic, and academic performance [16]. Table 1 shows the class distribution of the data used in this study.

TABLE 1. Class distribution of the data used

Target Class	Frequency (N)	Percentage
Dropout	1,421	32.1%
Enrolled	794	17.9%
Graduate	2,209	50.0%
Total	4,424	100%

For the Early Warning System (EWS) requirements, the 'Enrolled' and 'Graduate' classes were combined into the 'Safe' class (3,003 data points), while 'Dropout' remained as the minority at-risk class (1,421 data points). This imbalance was then addressed using the SMOTE technique during the training stage.

3.2. Pre-processing and Variable Transformation

Before modeling, two crucial transformation stages are performed, namely Target Engineering (or Labeling) and Feature Normalization. In the target engineering or labeling stage, the original target $y \in \{Dropout, Enrolled, Graduated\}$ is transformed into a binary classification problem to enhance the Early Warning System's function.

$$y' = \begin{cases} 1 & \text{jika } y = Dropout \\ 0 & \text{jika } y \epsilon \{Enrolled, Graduated\} \end{cases} \quad (1)$$

The existing data have a wide range of values, for example, 'Age', and 'GPA', so normalization is necessary to prevent gradient-based models from being hampered by scale differences. This normalization is achieved by using a z-score transformation.

$$z_j = \frac{x_j - \mu_j}{\sigma_j} \quad (2)$$

where x_j is the j-th feature value, μ_j is the mean value of the j-th feature, and σ_j is the standard deviation of the j-th

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feature. This standardization ensures that each feature contributes proportionally to the model's learning process, thereby enhancing convergence speed and preventing features with larger numerical ranges from dominating the optimization [51].

3.3. Handling Data Imbalance through Synthetic Minority Over-sampling Technique (SMOTE)

A primary limitation in developing predictive models for student attrition lies in the prevalent class imbalance in higher education datasets [32],[45]. Specifically, the prevalence of students who graduate or remain enrolled far exceeds that of dropouts [34]. This disparity presents a substantive challenge for machine learning algorithms, which often exhibit bias toward the majority class [34],[31], resulting in inflated overall accuracy at the expense of diminished efficacy in identifying the minority class—the core objective of early warning systems [15],[52].

To counteract this imbalance, the present study implements the Synthetic Minority Over-sampling Technique during the training data preprocessing phase [13], [34], [45], [47], [50]. In contrast to traditional random over-sampling methods that simply replicate existing instances—thereby risking overfitting [48],[53]—SMOTE generates novel synthetic samples within the feature space [54],[53]. Procedurally, SMOTE functions within an *n*-dimensional feature space through the subsequent steps:

1. For each sample in the minority class $x_i \in S_{min}$, the algorithm identifies the k-nearest neighbors from the same class.
2. The distance between the target sample x_i and one of its randomly selected neighbors, $\hat{x}_i$is calculated.
3. A new synthetic samples x_{new} is then created by linearly interpolating between the two points.

Mathematically, the process of forming synthetic data is formulated as follows:

$$x_{new} = x_i + \delta.(\hat{x} - x_i) \quad (3)$$

where

- x_i is the feature vector of the original minority observation
- $\hat{x}_i$is one of the k nearest neighbors randomly selected from the minority class.
- $(\hat{x} - x_i)$ represents the difference vector or distance between two points in the feature space
- δ is a random multiplier (weight) generated from uniform distribution, $\delta \in [0,1]$

In this study, the deployment of SMOTE seeks to broaden the decision boundary of the dropout class, thereby mitigating its subordination to the majority class [54], [55]. More precisely, through the synthesis of novel instances along line segments interconnecting minority class samples, the model is induced to discern broader, more representative features, eschewing mere replication of extant data configurations [53], [56], [57]. This strategy is projected thereby to augment Recall on the test set, assuring the Early Warning System's sustained sensitivity in identifying prospective student attrition amid sparse minority representations [14], [46], [52].

To prevent data leakage, which can result in over-optimistic or pseudo-performance evaluations, the pre-processing procedure followed a rigorous sequential protocol. First, the original dataset was partitioned into a training set (80%) and a test set (20%) using a stratified sampling technique to ensure that the proportions of the target classes remained representative across both subsets [16], [48].

Subsequently, the SMOTE algorithm was applied exclusively to the training data to balance the distribution of the minority class relative to the majority class [23], [48]. The test set (20%) was excluded from the SMOTE synthesis process and maintained in its naturally imbalanced state, thereby ensuring that model evaluation and metric calculations provide a realistic representation of real-world data conditions [43], [48]. This methodological separation is critical for verifying that the ensemble model can generalize effectively to unseen, skewed educational data without the influence of synthesized samples during the final testing phase [16], [48].

3.4. Development of the Hybrid Stacking Ensemble Architecture

This research employs a Hybrid Stacking Ensemble architecture, an advanced ensemble learning framework that integrates heterogeneous predictive models to achieve enhanced generalization performance compared to individual models [58],[49]. In particular, leveraging the class-balanced dataset produced via SMOTE preprocessing, the stacking paradigm minimizes generalization error through a meta-learner trained on predictions from base models exhibiting diverse learning biases [59].

Furthermore, to promote transparency and reproducibility in model development, default hyperparameters were adopted for all base learners and the Logistic Regression meta-learner [16], [60]. This deliberate choice establishes a reliable baseline and underscores that the substantial performance gains—particularly the 88.81% accuracy—primarily arise from the synergistic combination of the hybrid stacking architecture and SMOTE, independent of model hyperparameter optimization [34], [49].

Additionally, standardized configurations demonstrate that fusing bagging and boosting paradigms yields a resilient approach for capturing complex, non-linear patterns in educational data [19], [43]. This methodology also curtails technical demands, facilitating straightforward replication in resource-limited educational institutions [41], [61]. Ultimately, it strengthens the Early Warning System's applicability as an effective instrument for enabling prompt administrative interventions [6], [16].

The development of this architecture is structured into a two-tier hierarchy as follows:

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3.4.1. Level 0: Base Learners

At the first level, this study combines three state-of-the-art algorithms representing two major paradigms in ensemble learning: Bagging and Boosting [16], [43], [59], [60].

Random Forest: functions as a variance balancer by constructing a collection of decision trees in parallel through the bootstrap aggregating technique [62],[63]. This approach effectively corrects for the tendency of individual decision trees to overfit their training data [63]. Mathematically, for an input x, the final prediction is the average probability calculated across T trees [64]:

$$\widehat{p_{RF}}(x) = \frac{1}{T}\sum_{t=1}^{T} h_t(x) \quad (4)$$

XGBoost and LightGBM: Serve to sequentially reduce bias by optimising a a loss function through gradient descent [12], [39], [65]. These algorithms train a sequence of weak learners where each subsequent model attempts to correct the errors of its predecessor [65]. The primary advantage of XGBoost lies in its explicit regularisation Ω to prevent overfitting, while LightGBM excels in computational efficiency through its unique leaf-wise tree growth strategy [61], [66]. The objective function minimized during this stage is formulated as [65]:

$$L^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t) \quad (5)$$

3.4.2. Level 1: Meta-Learner

The essence of the stacking mechanism lies in the creation of a new dataset known as meta-features [67]. If the original dataset is $D = \{(x_i, y_i)\}_{i=1}^{n}$, *then each base learner k generates a probability prediction* $\hat{p}_{ik}$ for every sample i [67]. These predictions collectively form a new feature matrix Z [67]:

$$Z_i = \left[\hat{p}_{(i,RF)}, \hat{p}_{(i,XGB)}, \hat{p}_{(i,LGBM)}\right] \quad (6)$$

Matrix Z subsequently serves as the input for Logistic Regression, which functions as the meta-learner [16], [59]. The selection of Logistic Regression is based on its linear and stable properties, making it highly effective for determining the optimal contribution weights of each base learner without introducing excessive complexity [66].

$$\hat{P}(y = 1|Z) = \frac{1}{1 + e^{-(w^T Z + b)}} \quad (7)$$

3.5. Out-of-Fold Prediction Procedure

To avert data leakage and overfitting in the meta-learner training phase, this study implements a k-fold cross-validation scheme for deriving meta-features[59]. Specifically, the training dataset is divided into k folds, whereby each base learner is trained on $k-1$ folds and generates predictions for the excluded fold[16]. This process is repeated across all folds, producing out-of-fold predictions from the base learners for the full training set, which in turn train the meta-learner[59], [67]. Thus, the hybrid architecture rectifies limitations of individual models—for example, Random Forest's susceptibility to high variance in noisy data—by harnessing the complementary capabilities of models like XGBoost, which is adept at capturing non-linear interactions [43], [49], [58]. This amalgamation yields a more robust and accurate early warning system for student attrition prediction [17], [43], [68]. Moreover, the study benchmarks the ensemble against standalone models, delivering a comprehensive evaluation of their efficacy in detecting at-risk students in higher education [43], [69].

3.6. Performance Evaluation Metrics

To evaluate the efficacy of the Hybrid Stacking Ensemble architecture in detecting student dropout risks, this study employs a range of performance metrics derived from the confusion matrix [25]. Nevertheless, within the framework of imbalanced educational datasets, unadjusted accuracy tends to be deceptive, as it inadequately captures the model's proficiency in identifying minority class instances[14], [70]. Accordingly, model performance is gauged by the model's capacity to equilibrate precision and recall [14].

Central to these computations are four core elements: True Positives, True Negatives, False Positives, and False Negatives [25]. In this investigation, TP signifies at-risk students accurately classified as dropouts, whereas FN denotes a critical oversight in detecting students who ultimately drop out [25], [71].

Precision measures the accuracy or quality of the model's positive predictions[72]. It answers the question: "Of all students predicted to drop out, how many actually did?" [25]. Mathematically, precision is defined as:

$$Precision = \frac{TP}{TP+FP} \quad (8)$$

From an educational management perspective, high precision is essential to minimize "false alarms" [15], [73]. A high number of false positives leads to the waste of institutional resources, where academic staff provide intensive intervention or counseling to students who are actually safe [15], [17], [73]

Recall or sensitivity is the most crucial metric in the development of an Early Warning System [14]. This metric measures the model's ability to capture the entire population of high-risk students[73], [74]. The formula for Recall is:

$$Recall = \frac{TP}{TP+FN} \quad (9)$$

A low recall value signifies a critical failure in detection, whereby at-risk students evade identification by the system [14]. Such oversights prove especially deleterious to university administration, as neglecting a student destined to drop out exacts far greater reputational and financial costs than providing counseling to one who remains academically secure [3],[14]. Accordingly, the present study

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optimizes the model to maximize recall while averting substantial trade-offs in precision [14], [75].
Given the inherent trade-off between precision and recall, the F1-Score is used as a single metric representing the harmonic balance between the two [14], [76], [77]. Unlike the arithmetic mean, the harmonic mean gives more weight to lower values, ensuring that the F1-Score is only high if both constituent metrics are also high[78]. The equation is:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \qquad (10)$$

The F1-Score serves as a primary indicator of the stacking architecture's stability in managing the complexity of educational data following the implementation of the SMOTE technique[48].
While not the primary metric for imbalanced data, accuracy is still provided to offer an overview of the proportion of correct predictions (both positive and negative) relative to the entire dataset [13]:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (11)$$

By integrating these four metrics, this study provides a comprehensive evaluation, not only from a machine learning technical standpoint but also in terms of practical utility for higher education policymakers [16], [25], [43].

4. RESULTS AND DISCUSSIONS

4.1. Performance Comparison of Ensemble Models

We conducted experiments by comparing four model configurations based on ensemble learning. The evaluation results indicate that the hybrid approach provides a measurable performance improvement compared to the use of individual models.

TABLE 2. Performance Comparison of Early Warning System Models

Model	Accuracy	Recall	F1-Score
Stacking Ensemble	**0.8881**	**0.8099**	**0.8229**
LightGBM	0.8859	0.7923	0.8167
Random Forest	0.8859	0.7887	0.8160
XGBoost	0.8746	0.7782	0.7993

As presented in Table 2, the Stacking Ensemble model demonstrated superior performance across all evaluation metrics. Notably, its accuracy of 88.81 % attests to robust generalization in processing student data. Furthermore, a key strength of the model is its Recall of 0.8099, which substantially outperforms that of standalone Boosting models such as LightGBM and XGBoost. This validates the efficacy of integrating Bagging and Boosting paradigms via a meta-learner to address prediction errors overlooked by individual algorithms.

4.2. Detailed Classification Analysis

We performed a more in-depth analysis of the best model to understand the detection effectiveness for each target class.

TABLE 3. Classification Report Details for the Stacking Ensemble Model

Class	Precision	Recall	F1-Score	Support
Safe	0.91	0.93	0.92	601
Dropout	0.84	0.81	0.82	284
Average / Total	0.89	0.89	0.89	885

Table 3 shows that the model has a high level of confidence in identifying students in the "Safe" condition with an F1-Score of 0.92. On the other hand, for the system's primary target, the "Dropout" class, the model achieved a Recall value of 81%. In the context of an Early Warning System, this figure indicates that the system is capable of identifying 81% of students who will actually drop out. The precision value of 84 % also shows that false alarms remain at a low level, allowing for efficient managerial interventions without significant misdirection.

4.3. Predictor Factor Analysis

The feature importance analysis from the XGBoost model indicates that classifications of student dropout risk were predominantly influenced by short-term academic performance and administrative-financial stability, with a marked disparity between these primary factors and the supporting variables. Figure 2 shows the 15 most influential factors in students' college success.

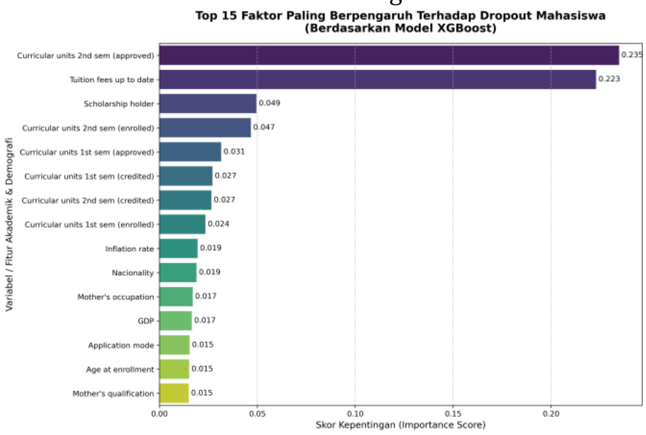

Fig.2. The top fifteen factors that most influence student dropout

Second Semester Academic Success ranked highest, accounting for 23.5% of the total influence, where the "Curricular Units 2nd Semester" feature exhibited the strongest predictor score of 0.223. This positions the second semester as a pivotal juncture in the academic trajectory, where failure to attain requisite curricular units substantially heightens dropout propensity. Such deficiencies commonly originate from unresolved transitional difficulties in the first semester, which impose psychological and scholastic obstacles to subsequent progression.

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Financial Stability and Administrative Compliance followed closely at 22.31%, dominated by the "Tuition Fees Up to Date" variable. These findings furnish critical guidance for higher education administrators, demonstrating that attrition arises not exclusively from academic shortcomings but is profoundly entangled with financial circumstances. Students with overdue tuition incur dropout risks comparable to academic underperformers, underscoring the importance of economic stressors in eroding academic motivation.

Supplementary factors related to external support and enrollment commitment—namely, "Scholarship holder" and second-semester curricular units—also exerted notable effects. Scholarships, in particular, function as robust retention mechanisms by incentivizing sustained effort among beneficiaries to retain eligibility. Meanwhile, elevated second-semester unit loads may signify overambition or workload disequilibrium, precipitating failure.

4.4. Managerial Implications and Discussion

The findings of this study furnish strategic insights for higher education administrators in devising data-informed, proactive policies to bolster student retention. With second-semester academic performance and tuition payment status emerging as paramount predictors, institutions are urged to eschew reactive approaches in favor of an integrated monitoring framework that fuses curricular achievement metrics with contemporaneous administrative data. Interdepartmental synergy is imperative; for example, academic and financial units must establish synchronized data-sharing mechanisms to detect students with overdue fees expeditiously, given this factor's influence rivals that of academic shortfalls in precipitating attrition. This proactive vigilance enables universities to implement precise interventions—such as tuition rescheduling or emergency bursaries for economically distressed students—before any adverse repercussions on academic progress.

Moreover, pedagogical support measures should prioritize the pivotal first-year transition phase, incorporating rigorous assessments at the close of the initial semester and mid-second semester. The outputs of the stacking ensemble model can function as a decision-support apparatus for academic counselors, enabling bespoke intensive mentoring for students at risk of course failure. Special heed must be given to the persistence of non-scholarship holders, as scholarship eligibility demonstrably serves as a potent retention catalyst. By enacting feature importance-informed interventions, institutions can refine the allocation of advisory and counseling resources, thereby augmenting retention rates and fortifying long-term institutional competitiveness.

5. CONCLUSIONS

In conclusion, the present study establishes that a hybrid stacking ensemble model substantially surpasses individual machine learning algorithms in predicting student dropout. This framework, which amalgamates bagging and boosting base learners via a meta-learner, yielded an accuracy of 88.81% and a recall of 80.99%. Moreover, such equilibrated efficacy is chiefly ascribed to the preprocessing application of SMOTE, which rectified class imbalances and facilitated the precise detection of vulnerable students frequently neglected by traditional single-algorithm paradigms.

Additionally, the investigation identifies first-year academic performance—particularly the count of approved curricular units in the second semester—as the paramount predictor of attrition risk. However, administrative and financial elements wield nearly equivalent sway, with tuition payment timeliness emerging as a crucial non-academic harbinger. These revelations thus accentuate the intricate, multifactorial etiology of student attrition, wherein financial duress often precipitates academic shortfall, thereby rendering it indispensable for holistic early warning systems aimed at monitoring student persistence.

Thus, from an administrative perspective, the outcomes urge universities to pivot from reactive to proactive, data-centric retention strategies. For instance, merging academic and financial records empowers targeted remedial actions, such as contingency scholarships or augmented advising, particularly during the decisive inaugural-year juncture. Finally, prospective inquiries might refine these approaches by integrating dynamic inputs from learning management systems or interpersonal dynamics and complemented by interpretable AI methodologies to equip faculty with individualised explanations of each student's risk profile.

Although the hybrid model attains elevated predictive precision, its dependence on broad administrative and academic performance indicators—such as approved curricular units and tuition payment status—constitutes a primary constraint; in particular, the existing framework omits fine-grained behavioral metrics, such as daily attendance logs, engagement levels in Learning Management Systems, and psychosocial elements such as stress or motivational states. This omission impedes the model's capacity to identify nascent behavioral deviations that frequently herald dropout risks prior to documented academic deficiencies.

Additionally, as the model derives from a public dataset reflecting a particular institutional cohort, its generalisability is constrained. Deploying this system at institutions would necessitate substantial retraining or transfer learning to accommodate their distinctive academic norms, credit structures, and localized economic influences. Given that socioeconomic conditions and student conduct are profoundly shaped by regional and

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cultural contexts, institution-specific data is indispensable for upholding the early warning system's efficacy and applicability across varied settings.

Moreover, the Stacking Ensemble configuration, despite its efficacy, functions predominantly as an opaque mechanism, hindering individualized interpretability. This opacity precludes providing explicit rationales for designating a particular student as high-risk; such clarity is essential for academic advisors in formulating tailored interventions. Lastly, the study employs cross-sectional data capturing academic snapshots at discrete points, eschewing longitudinal trajectory modeling. Consequently, it lacks support for survival analysis or temporal forecasting to delineate peak risk periods, which is vital for delivering adaptive, timely assistance throughout the academic progression.

To mitigate these shortcomings and augment the system's applicability, subsequent investigations should emphasize targeted advancements. First, to counteract the opacity inherent in ensemble models, the incorporation of Explainable AI techniques—such as SHAP or LIME—are recommended to yield lucid, student-specific prediction rationales. This enhancement is crucial for advisors and administrators, as it converts intricate outputs into comprehensible grounds for risk flagging; furthermore, augmenting datasets with detailed behavioral traces, particularly from e-learning platforms, would bolster detection of incipient attrition cues overlooked by aggregate academic indicators. Ultimately, validation against multi-institutional and geographically diverse datasets is imperative to affirm the Early Warning System's robustness and adaptability amidst institutional and socioeconomic heterogeneit

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