Multifaceted approach for anticipating learner performance using parameter weightage and ensemble algorithm fusion

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ABSTRACT

Anticipating student performance has garnered significant attention in education research for offering early insights that enable timely interventions and personalized support, ultimately improving student success and retention rates. This research focuses on enhancing the accuracy and efficiency of student performance prediction models by employing a hybrid ensemble framework that integrates weighted feature selection with meta-learner-based approaches. A weighted feature selection method was employed to prioritize the most influential of the 23 parameters in the dataset, enhancing prediction accuracy while reducing the computational burden. These parameters were then used to build a hybrid ensemble model by combining base learners with meta-learners, systematically tuned using hyperparameter optimization. This approach aimed to further improve prediction accuracy by fusing multiple base learners, leveraging the strengths of different algorithms for more accurate predictions. The proposed hybrid model was validated across different features selected based on feature importance using random forest (RF). An accuracy of 98.38% was achieved when all 23 features were considered and an accuracy of 97.13 % was achieved when the top 10 features were used. The research highlights the significance of early prediction for prompt intervention and demonstrates how feature weighting can boost model efficacy.

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1. INTRODUCTION

There has been a tremendous growth in the adoption of online learning platforms primarily driven by the ease of accessibility to these courses and also due to the COVID-19 pandemic. While this shift has greatly benefited students and faculty alike, it also presents challenges such as maintaining learner engagement and motivation throughout the course. Hence gaining insights in to factors that affect learners' performance and providing early intervention is required by educators to identify the students who are at risk of dropping out of these courses or underperforming [1], [2].

The literature review explores the existing research on predictive models in education, focusing on the efficacy of parameter weighing and ensemble algorithms. It examines various studies that have investigated factors influencing learner performance and the success of early intervention strategies in online learning environments. The application of various classification models was emphasized to forecast student performance, highlighting the importance of feature selection and the influence of various attributes on prediction accuracy [3]. The integration of explainable artificial intelligence (XAI) was explored with predictive models, offering a novel perspective on how these technologies can not only predict outcomes but also provide actionable insights through prescriptive analytics [4]. A comparative analysis of different predictive models was provided in the context of public schools in Brazil, underscoring the effectiveness of ensemble methods in improving prediction accuracy [5]. A systematic review was conducted of predictive modeling techniques, identifying key trends and challenges in the field, particularly the variability in model performance across different educational contexts [6]. Lastly investigation of the use of machine learning (ML) algorithms for forecasting student performance, demonstrating that models incorporating a broader set of features, including behavioral and demographic data, tend to yield more accurate predictions [7]. Collectively, these studies underscore the potential of predictive modeling in education, while also pointing to the need for more sophisticated techniques, such as ensemble learning and XAI, to enhance model performance and usability in real-world educational settings.

The integration of predictive modeling in educational environments has garnered substantial attention in recent years, with a particular focus on enhancing model accuracy through feature selection and parameter weightage. This review synthesizes findings from key studies that have employed these methods to predict academic performance. The use of multisource, multifeatured behavioral data to predict academic performance. The researchers employed an ensemble of ML algorithms to analyze data from various sources, including student demographics, online activities, and physical behaviors. The study found that incorporating diverse features from multiple sources significantly improves the prediction accuracy of academic outcome. This highlights the importance of considering a wide range of features when developing predictive models in education [8]. Improving dropout forecasting during the COVID-19 pandemic using feature selection techniques and a multilayer perceptron neural network has proven effective in enhancing model performance, particularly in a challenging context like a pandemic. By carefully selecting the most relevant features, the accuracy of dropout predictions was significantly improved, underscoring the essential role of feature selection in predictive modeling [9]. A systematic review of ML applications in determining the attributes that influence academic performance was conducted. The review identified key factors such as socioeconomic status, attendance, and engagement as critical predictors. The study also emphasized the need for more research on the application of feature selection methods to refine these predictors further, suggesting that a focus on parameter weightage could yield even more accurate models [10].

The challenge of improving time complexity and accuracy in ML algorithms was addressed by selecting top 'k' features with the highest weights from intricate datasets. The study demonstrated that focusing on a smaller subset of highly weighted features can result in notable enhancements in both the efficiency and precision of predictive models. This approach is particularly relevant in educational settings where datasets are often complex and feature-rich [11]. A critical feature selection method employing ensemble meta-based models was proposed to predict multiclass outcomes. Their study showed that combining multiple models and focusing on critical features can lead to more accurate predictions, particularly in scenarios involving multiclass classification. This finding is crucial for educational contexts where outcomes can be varied and complex [12].

Various measures of feature importance were evaluated to explain classification models. Their research highlighted the differences in how different algorithms assess feature importance and the implications this has for model interpretability. Understanding feature importance is essential for educators and policymakers who need to interpret and act on model predictions [13]. A flexible feature selection approach was developed for predicting student performance in online courses. Their study emphasized the need for adaptable methods that can handle the unique challenges of online education. By employing a flexible feature selection strategy, they were able to improve the accuracy of their predictive models, demonstrating the importance of adaptability in feature selection [14].

A comprehensive survey of feature selection techniques spanning over more than two decades of research was provided. They highlighted the evolution of these techniques and their increasing relevance in ML applications, including educational data mining. The survey suggested that ongoing advancements in feature selection methods will continue to play a critical role in enhancing predictive modelling [15]. Another extensive review focused on feature selection across various fields of ML. Their findings underscored the importance of feature selection in improving model accuracy and reducing computational complexity. The study also highlighted the need for domain-specific feature selection techniques, particularly in education, where the relevance of features can vary widely [16].

Table 1 shows comparison of techniques for learners' performance prediction. Overall, these studies demonstrate the significant impact that feature selection and parameter weightage can have on the accuracy features, researchers can develop more accurate and interpretable models, ultimately leading to better educational outcomes. This review underscores the critical role that feature selection and parameter weightage play in enhancing predictive modeling accuracy in educational contexts. It also highlights the need for continued research in this area to refine these techniques further and apply them to a broader range of educational scenarios.

Table 1. Comparison of techniques for learners' performance prediction

Author	Methodology used	Focus of research	Key findings	Limitations
Ray *et al.* [17]	Ensemble methods and deep learning models	Academic performance prediction	Ensemble methods improve accuracy in predicting academic performance.	More diverse datasets are needed for broader applicability.
Afshar *et al.* [18]	Ensemble of meta-learners	Ranking and combining predictive models	Ensemble techniques reduce prediction variance, improving overall performance.	Lack of labeled data affects the robustness of the predictions.
Li *et al.* [19]	Intelligent fuzzy regression classification (IFRC) model with ensemble techniques	Predicting student performance in music education	Robust framework provided by ensemble techniques significantly enhances prediction accuracy.	Focuses specifically on music education, limiting its generalizability.
Niyogisubizo *et al.* [20]	Two-layer ensemble approach using Stacked Generalization	Predicting student dropout in university classes	The two-layer ensemble model with stacked generalization accurately predicts student dropout.	The model's complexity might limit its scalability to larger datasets or different educational contexts.
Alsulami *et al.* [21]	Ensemble techniques including RF, XGBoost, and light gradient-boosting machine (LightGBM) models	Enhancing the prediction accuracy of e-learning student performance	LightGBM shows the best performance in predicting e-learning student outcomes.	The study is limited to a specific e-learning platform, which may affect the generalizability of the results.
Al-Ameri *et al.* [22]	Ensemble model with multimedia-based big data	Academic success prediction using multimedia data from learning management system (LMS)	Ensemble model shows high accuracy in predicting student success.	Requires a large amount of multimedia data, which may not always be available.
Pek *et al.* [23]	ML models including RF, SVM, and decision tree (DT)	Identifying at-risk students and minimizing failure	ML techniques effectively reduce student failure rates by early identification, with RF being the most successful.	The study might miss factors, causing inaccurate predictions.
Zhang *et al.* [24]	Ensemble model combining DT, RF, and GB	Predicting student achievements in learning Portuguese	Ensemble models, especially gradient boosting, excel in predicting achievements.	The study is limited to language learning, which may limit the generalizability of the findings to other subjects.
Bakyalakshmi *et al.* [25]	Multi-view deep learning with ensemble techniques	Predicting student performance and identifying high-risk students	Multi-view deep learning approach increases accuracy in early identification of high-risk students.	Limited to educational settings, may not apply to other domains.
Teoh *et al.* [26]	Ensemble learning techniques including bagging, boosting, and stacking	Predicting student performance in video-based learning environment	Ensemble learning with Boosting increases accuracy in video-based performance prediction.	The study focuses solely on video-based learning, which may not reflect other forms of learning.

The literature review reveals several critical gaps that remain unaddressed in current research. These gaps highlight opportunities for further exploration to enhance the accuracy and applicability of predictive models in education. Although there has been some work that has been done on the impact of factors such as student demographics, online activities and learning styles on student performance prediction but there is a lack of in-depth analysis on how these factors impact the prediction outcome on an individual basis. This emphasizes the need for more research on the application of feature selection methods to refine these predictors further, suggesting that a focus on parameter weightage could yield even more accurate models.

While ensemble techniques have proven effective in predicting student performance, there is limited or no research on the impact of combining these techniques with meta-learners. The potential for meta-learners to further enhance the predictive power and robustness of ensemble models remains underexplored, representing a significant gap in the current literature. To address the identified gaps in the literature, our research focused on a two-fold approach. Firstly, we conducted a comprehensive analysis of the impact of using weighted parameters on student performance within ensemble prediction models. By integrating these variables into the predictive models, we aimed to enhance the interpretability of the predictions and provide actionable insights that can guide more effective educational interventions. Secondly, we explored the novel integration of meta-learners with ensemble techniques to investigate their potential in improving prediction accuracy and robustness. This involves the development and testing of hybrid models that combine various ensemble methods with meta-learners, such as stacking and blending. Our research will employ a rigorous experimental design, utilizing cross-validation techniques and performance metrics to assess the effectiveness of these hybrid models compared to traditional ensemble methods. This approach not only fills the existing gaps but also contributes to the advancement of predictive analytics in education by offering more comprehensive and powerful models for predicting student performance.

2. METHOD

2.1. Research design

This research utilizes a quantitative approach to examine the effectiveness of parameter weightage and ensemble algorithm fusion in predicting learner performance. The research method involves utilizing historical learner data to develop and validate predictive models. Each step is meticulously designed to ensure robustness and accuracy in the predictive model. The process workflow is depicted in Figure 1, illustrating the sequential steps from data collection to the final prediction and evaluation. The workflow begins with dataset acquisition and preprocessing, ensuring the data is clean and appropriately structured for analysis. The study focuses on the identification and evaluation of key features influencing learner performance, employing statistical techniques and ML algorithms. To ensure robust model evaluation, stratified 10-fold cross-validation was applied, and hyperparameter tuning was conducted to optimize model performance. The ensemble model, built using a voting technique, integrates predictions from multiple base learners, aiming to improve accuracy and reliability. We provide a detailed explanation of each phase of the methodology, ensuring that every aspect is thoroughly covered to facilitate replication and validation of our approach.

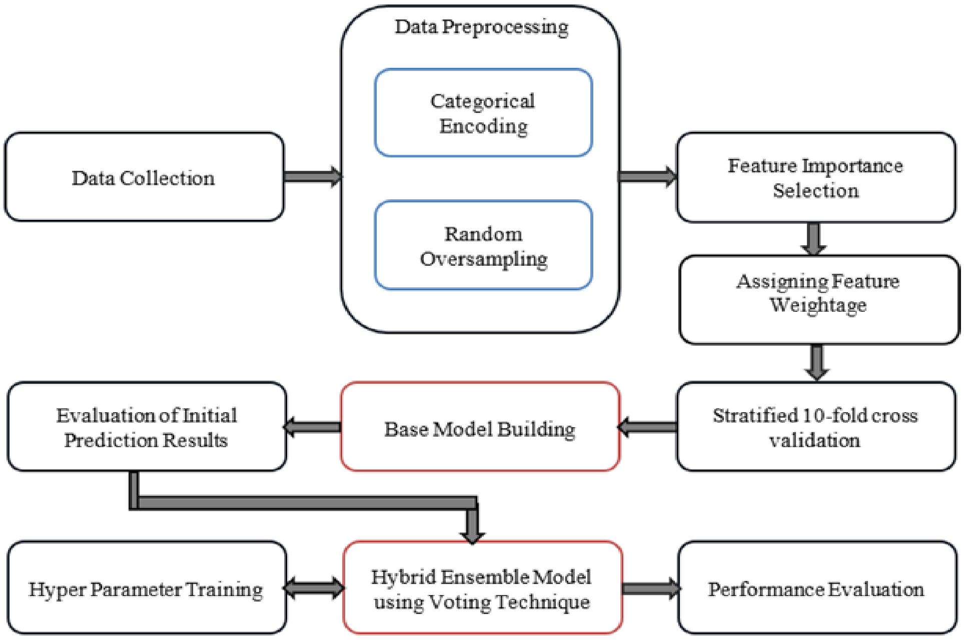


Figure 1. Process flowchart

2.2. Data Collection

The dataset utilized in this study was collected from the Government Polytechnic of Karnataka state and encompasses a comprehensive set of features aimed at capturing various aspects of learners' demographics, behavior, and participation on the online platform. A stratified sampling method was employed to ensure diverse representation across different performance levels, incorporating data collected from both LMS and offline sources, resulting in a comprehensive dataset comprising 1,002 student records with 23 distinct characteristics. This research adopts a cross-sectional approach, utilizing data collected over a single academic year to build and validate predictive models. This rigorous data collection process provides a solid foundation for the subsequent analysis. The features as in Table 2 were considered for analysis.

Table 2. Dataset description

Attribute	Description
SSLC medium of study	Medium of study in the Secondary School.
Weekly login frequency	The number of times a student logs in per week.
Duration of online lecture viewing	The average time spent watching online lectures.
Time Spent on online assignments	Total time spent on completing online assignments.
Basic computer skills	Proficiency in basic computer skills.
Physical activity	Frequency of engagement in physical activities.
Residing region type	Type of region where the student resides.
Family yearly income	Annual income of the student's family.
Diet	Dietary habits of the students.
Sleep duration	Average duration of sleep per day.
Library visits	Frequency of visits to the library.
Smartphone usage for study purposes	Frequency of using a smartphone for study purposes.
Participation in team activities online	Involvement in collaborative team activities online.
Video pause frequency	The number of times a student pauses video while watching a lecture.
Frequency of video repetition	How often students repeat the video lecture.
Activities completed	Proportion of assigned activities completed.
Lectures watched	The percentage of total lectures watched.
Access to internet	Availability of internet connectivity.
Ease of online communication with teachers	Perceived ease of communication with teachers online.
Login to portal	Does students log in to portal daily.
Engagement in online forums	Active participation in online discussion forums.
Perceived Ease of online learning	Student perception of the ease of online learning.
Interaction with peers in online forums	Level of engagement with peers in online forums.

2.3. Data preprocessing

Data preprocessing is a pivotal phase in the ML pipeline, crucial for ensuring the dataset's quality and reliability before model development. In this study, a rigorous preprocessing approach was undertaken to address challenges such as data inconsistency, missing values, and class imbalances. To handle missing data, eight records with significant missing values were eliminated, while four records with partial missing data were corrected using mean imputation.

For categorical variables, both ordinal and label encoding techniques were employed. Ordinal encoding was applied to features with an inherent order, such as 'Family Yearly Income,' 'Access to Internet,' and 'Perceived Ease of Online Learning,' thereby preserving the natural ranking of these categories. Conversely, label encoding was used for nominal variables without intrinsic order, including 'SSLC Medium of Study,' 'Residing Region Type,' 'Basic Computer Skills,' and 'Diet.' Additionally, the target variable 'Grade' was ordinally encoded to facilitate the prediction task by transforming class labels into numerical values.

To address class imbalance, particularly within the 'Grade' classes, random oversampling was implemented. This method involved replicating instances from the minority classes to equalize the class distribution, ensuring each class contained 398 instances. This step was critical in preventing model bias towards the majority class and promoting fairness in the training process. The final pre-processed dataset, incorporating both ordinal and label encoding, provided a robust foundation for building accurate and reliable ML models.

2.4. Analysis

2.4.1. Parameter weightage calculation

In this research, the RF algorithm was employed to assign weights to the 23 features considered for predicting learner performance. RF was chosen for its strong predictive capabilities and its ability to evaluate the relevance of each feature in relation to the target variable, which was the learners' ‘Grade’. This dual functionality of prediction and feature importance made it a valuable tool in the study.

- Training RF classifier: The process began with the construction of a RF model using the pre-processed dataset. The model comprises multiple DT, each trained on a different subset of the data through bootstrapping; while randomly selecting at each split, a subset of features is selected to promote diversity among the trees. This approach reduces the likelihood of overfitting and increases the generalizability of the model. Given a dataset $\mathcal{D} = \{(\boldsymbol{x}_1, y_1), (\boldsymbol{x}_2, y_2), \ldots, (\boldsymbol{x}_n, y_n)\}$ represented instances where $\mathbf{x}_i$ denoted feature vectors and y_i signified corresponding labels., we first construct a RF model F.
- Feature importance calculation: For each feature x_j (for j=1,2 ….23), its importance score I_j determined based on the reduction in impurity it contributes across all trees in the forest as in (1). The feature importance score of the individual parameters is as shown in Figure 2.

$$I_j = \frac{1}{B}\sum_{b=1}^{B} \sum_{t\in T_b} \Delta Impurity(t) \quad (1)$$

Where ΔImpurity(t) is the decrease in impurity at node t when splitting on feature x_j and B is the number of trees in the forest.

- Assigning Weights: The computed weights w_j are subsequently incorporated into the ensemble model, where they influence the prediction process by prioritizing more influential features. The weighted feature vector x_w for an observation is defined as in (2). The final predictive model then operates on these weighted features, enhancing both accuracy and interpretability by accounting for the varying importance of each feature.

$$x_w = \{w_1 \cdot x_1, w_2 \cdot x_2, \ldots, w_p \cdot x_p\} \quad (2)$$

Where p is the number of parameters.

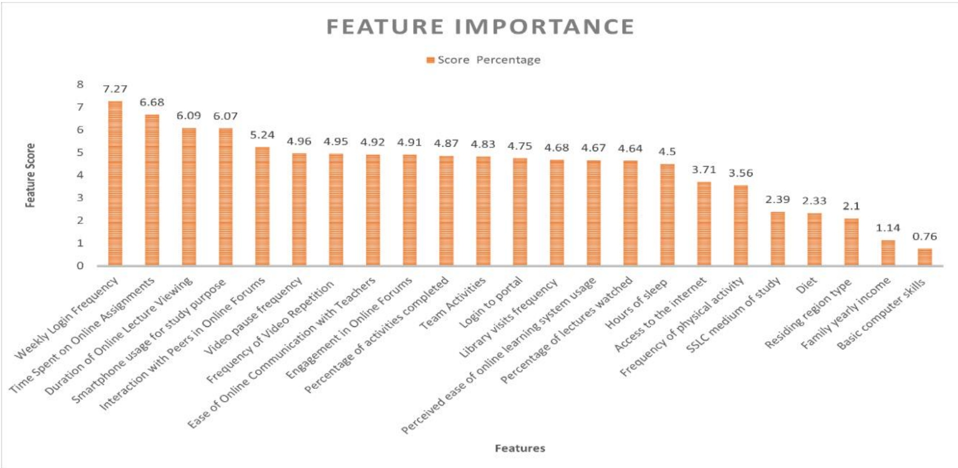


Figure 2. Feature Importance Score

2.4.2. Hybrid ensemble model

In this study, we implemented a multi-level ensemble learning approach as depicted in Figure 3, where base learners were first trained independently, and their predictions were subsequently combined using a meta-learner. This hierarchical model structure is designed to leverage the strengths of different algorithms, reducing the variance and bias inherent in individual models, and thereby improving the overall predictive performance. The ensemble prediction process began by selecting a diverse set of base learners, each of which captures different aspects of the data distribution. The base learners used in this study included K-nearest neighbors (KNN), RF, SVM, gradient boosting (GB), DT, and eXtreme gradient boost (XGB).

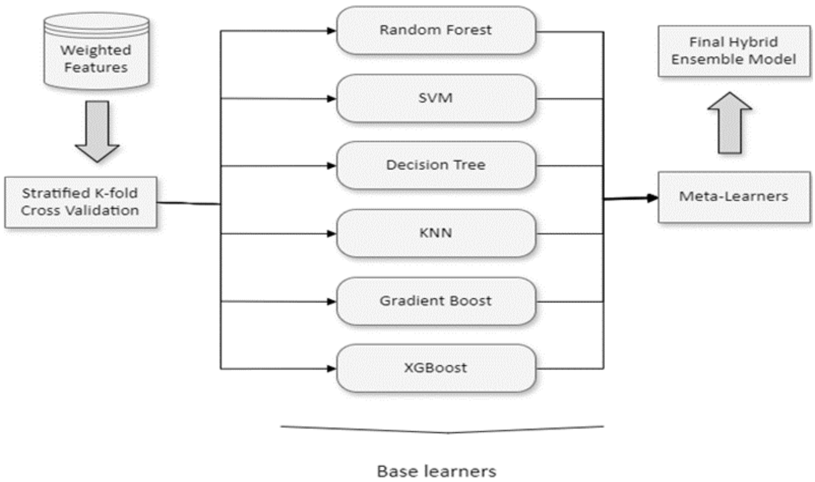


Figure 3. Ensemble model with voting approach

As outlined in Algorithm 1, we selected six diverse base learners to capture different aspects of the data distribution. Each base learner was trained on the training dataset D_{train} and optimized through hyperparameter tuning using cross-validation to maximize individual performance. The predictions from each base learner on a hold-out validation set D_{val} were stored, forming the basis of a new dataset D_{meta}, where each prediction vector from the base learners becomes a feature.

Algorithm 1. Base learner training
For each base learner L_i where i ranges from 1 to 6 (corresponding to RF, SVM, KNN, GB, XGB, and DT):
- Train L_i on the training dataset D_{train}.
- Optimize L_i by tuning its hyperparameters θ_i using cross-validation to maximize its individual performance.
- Store the trained model M_i along with its predictions on a hold-out validation set D_{val}.

Collect predictions from all base learners on D_{val} to create a new dataset D_{meta}, where each prediction vector from the base learners becomes a feature in D_{meta}.

The second level of the ensemble structure, described in Algorithm 2, involves a meta-learner, which is trained on D_{meta} to learn the optimal combination of the base learners' predictions. In this study, we explored multiple algorithms as meta-learners, including RF, SVM, KNN, GB, XGB, and DT, to determine which combination would yield the best predictive performance.

Algorithm 2. Meta-learner training
Construct the meta dataset D_{meta} as described in algorithm 1, with each observation representing the output from all base learners for a given input.
For each meta learner M_{meta} (corresponding to RF, SVM, KNN, GB, XGB, DT):
- Train M_{meta} on D_{meta} using the selected algorithm.
- The meta learner learns a function $f_{meta}(x) = \sum_{i=1}^{6} \alpha_i f \ L_i(x)$, where α_i are the coefficients (weights) assigned to each base learner's prediction $fL_i(x)$.
- Optimize α_i to minimize prediction error, effectively fusing the base learners' predictions in a way that maximizes overall accuracy.

Hyperparameter tuning was systematically applied to both the base learners and the meta learners to ensure optimal performance across the ensemble. During the hyperparameter tuning for the base learner a grid search combined with k-fold cross-validation was employed for each base learner to explore a range of hyperparameter values, aiming to minimize cross-validation error and ensure that each model was neither overfitting nor underfitting the data. Where as in the case of meta learners, hyperparameters were tuned to optimize their ability to combine the base learners' outputs effectively. This included tuning parameters such as the depth of trees in RF and DT, the margin parameter 'C' in SVM, and the learning rate in GB and XGB. The specific hyperparameters used for each classifier are detailed in Table 3, reflecting the careful tuning process undertaken to achieve optimal model performance.

Table 3. Hyperparameter configuration

Classifiers	Hyperparameters
RF	(n_estimators=100, max_depth=20, min_samples_leaf=1, min_samples_split=2, random_state = 42, max_features='sqrt', criterion='gini')
VM	(C=500, kernel='rbf', gamma=100, class_weight='balanced', probability=True)
DT	(max_depth=20, min_samples_split=2, min_samples_leaf=1, criterion='gini', random_state=42)
KNN	(leaf_size=10, n_neighbors=3, weights='distance')
GB	(max_depth=4, n_estimators=200, subsample=0.8)
XGB	(max_depth=10, colsample_bytree=0.6, gamma=0.1, learning_rate=0.1, n_estimators=200, subsample=1.0)
Meta-Learner	(estimators=base_learners, voting='hard') {base_learners= (RF, SVM, DT, KNN, GB, XGB), meta_learner=(base_model)}

2.5. Performance evaluation

The effectiveness of the fused ensemble model was assessed by comparing its performance against individual base learners and simpler ensemble methods. Evaluation metrics, including accuracy, precision, recall, and F1-score as defined in (3), (4), (5), and (6), were used to provide a thorough assessment of the model's performance. Each classifier was trained, tested on the test set, and evaluated using these key performance metrics.

$$Accuracy = \frac{True\ Positive + True\ Negative}{Total\ Instances} \quad (3)$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (4)$$

$$Recall = \frac{True\ Positive}{TruePositive + False\ Negative} \quad (5)$$

$$F1\text{-}Score = \frac{2 \times Precision + Recall}{Precision\ x\ Recall} \quad (6)$$

2.6. Implementation details

The experiments for this research were conducted using Google Colab, an interactive environment that provides access to powerful computational resources. The implementation was carried out in Python 3.10.12 (64-bit), leveraging a range of well-established ML libraries, including scikit-learn, TensorFlow, and XGBoost. These libraries were utilized for tasks such as data preprocessing, model training, hyperparameter tuning, and evaluation. The cloud-based environment of Colab facilitated seamless execution of computationally intensive processes, allowing for efficient handling of large datasets and complex models. Furthermore, the integration of Colab with Google Drive ensured the secure storage and easy access of experimental data, enabling reproducibility and collaborative research efforts.

3. RESULTS AND DISCUSSION

The results of this study are presented to assess the effectiveness of the weighted parameter approach and the meta-learner-enhanced ensemble framework in predicting learner performance. The following section discusses the performance improvements, compares them with existing models. It also highlights the importance of these findings in the broader field of educational data mining.

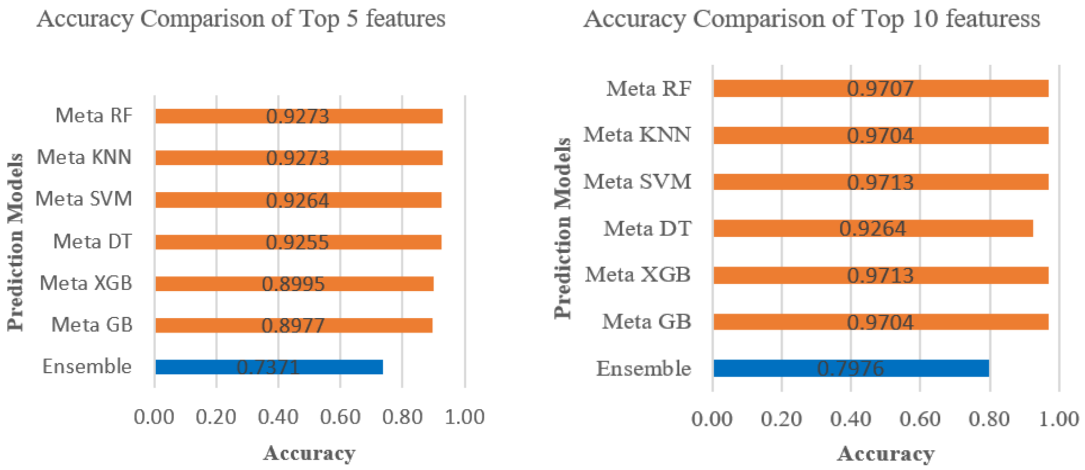
3.1. Results

The introduction of parameter weights significantly improved the performance of the ensemble model. As can be seen in Table 4, the ensemble without parameter weights, the model achieved an accuracy of 86.68%, with a precision of 86.55% and a recall of 86.45%. While these metrics were acceptable, certain features contributed little to the overall prediction accuracy, leading to an inconsistent performance across different student groups. After introducing parameter weights, derived using RF feature importance scores, the ensemble model's accuracy improved to 92.91% a relative increase of 7.2%. Precision and recall also increased to 92.59% and 92.50%, respectively, showcasing the model's enhanced ability to correctly identify at-risk students without sacrificing recall. The weighted ensemble's F1-score further demonstrated a significant improvement, increasing from 86.30% to 92.16%, indicating that the model better balanced precision and recall.

The results of the feature selection and meta-learner comparison provide valuable insights into the impact of reducing the number of features and integrating meta-learners within an ensemble framework. For this we divided the total set of features into groups of 5, 10, 15, 20, and all 23, to observe how computational efficiency and model performance are affected. Furthermore, we evaluated each base algorithm RF, SVM, KNN, GB, XGB, and DT as potential meta-learners, revealing which combination of base learner and meta-learner delivered the most accurate predictions while maintaining computational efficiency. The following results demonstrate the superiority of hybrid ensemble with meta learners over the basic ensemble approach.
Figure 4 illustrates a comparison between meta and basic ensemble model for top '5' and '10' features. As shown in Figure 4(a) the basic ensemble when compared with the hybrid meta-learner ensemble for the top 5 parameters reveals a significant accuracy improvement. The RF and KNN hybrids show the highest gains, achieving 92.73% accuracy versus 73.71% for the basic ensemble. Similarly, we can see in Figure 4(b), for the top 10 parameters, the hybrid approach continues to outperform, with XGB and SVM hybrids delivering the most notable improvements with accuracies of 97.13% as compared to 79.76% of the basic ensemble approach.

Table 4. Performance comparison between weighted and non-weighted ensemble models

Metric	Non-weighted ensemble	Weighted ensemble	Improvement (%)
Accuracy	86.68%	92.91%	7.2%
Precision	86.55%	92.59%	6.9%
Recall	86.45%	92.50%	7.0%
F1-Score	86.30%	92.16%	6.8%

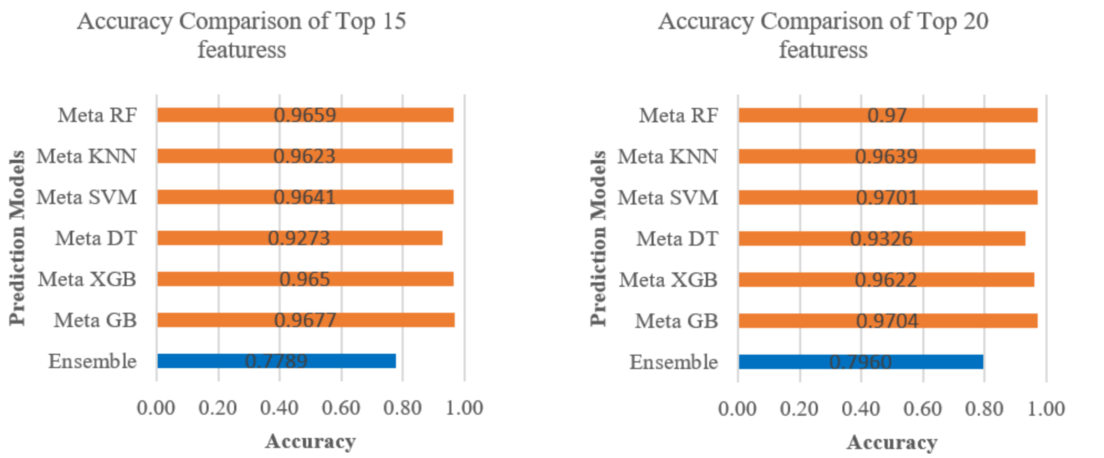


(a) (b)

Figure 4. Meta vs basic ensemble comparison (a) comparison of top 5 features and (b) comparison of top 10 features

Figure 5 depicts a comparison between meta and basic ensemble model for top '15' and '20' features. Figure 5(a) shows the case for top 15 parameters, the hybrid ensemble approach maintains its advantage, with the GB and RF hybrids achieving the most significant accuracy gains, reaching 96.77% and 96.59%, compared to 77.89% for the basic ensemble. As the parameter set increases to 20 as seen in Figure 5(b), the trend persists, with GB and SVM hybrids continuing to outperform the base ensemble, delivering accuracies of 97.04% and 97.01% versus 79.60%.

Figure 6 displays two comparisons between meta and basic ensemble model for top '23' and their execution time. As can be seen in Figure 6(a) for the full set of 23 parameters, the hybrid meta-learner models again outshine the basic ensemble approach. The GB and SVM hybrids stand out, achieving accuracies of 98.38%, compared to 86.68% for the basic ensemble. Overall, across all parameter sets, the hybrid meta-model consistently delivered far superior performance, highlighting its effectiveness in enhancing prediction accuracy compared to the basic ensemble model. The graph in Figure 6(b) illustrates how reducing the feature count through weighted feature selection significantly decreases computational time for all algorithms. For instance, the time drops from 37.65 seconds with 23 features to 29.35 seconds with 10 features, highlighting the efficiency of using fewer, more relevant parameters in accelerating the prediction process.



(a) (b)

Figure 5. Meta vs basic ensemble comparison (a) comparison of top 15 features and (b) comparison of top 20 features

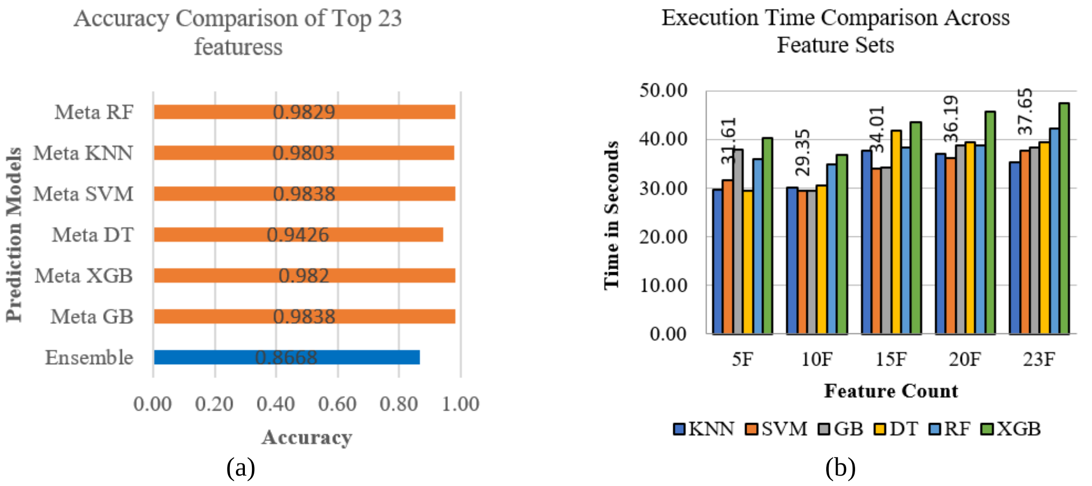


Figure 6. Performance and execution time comparison of meta and basic ensemble models (a) meta vs basic ensemble comparison for 23 features and (b) comparison of execution time

3.2. Discussions

The weighted parameter approach employed in this study provided a substantial improvement over the traditional non-weighted ensemble models. This is clearly evident with the non-weighted ensemble model's accuracy of 86.68% compared to with the weighted ensemble's accuracy of 92.91%. Building on the foundation of weighted parameters, the integration of hybrid meta-learners further boosted the model's performance as compared to the basic ensemble approach. For instance, when utilizing the top 5 parameters, the hybrid model showed a considerable accuracy increase, with RF and KNN hybrids achieving 92.73%, compared to the basic ensemble's 73.71%. This trend persists even with larger parameter sets, such as 23 parameters, where hybrid models reached an impressive 98.38%, further reinforcing the superior performance of the hybrid ensemble. Another notable benefit of assigning weights to features is the ability to reduce the execution time by prioritizing the key features. For instance, as seen in Figure 6(b), SVM takes 29.35 seconds for execution under 10 feature sets, whereas the same model takes 37.65 seconds for a full feature set of 23 parameters. When we look at the accuracy point of view, the SVM model gives an accuracy of 97.13% for the 10-feature set which marginally increases to 98.38% for 23- feature set. But there is 21.24% increase in execution time with no significant gain in accuracy levels.

When compared to prior studies, this research presents notable improvements. For example, researchers in [17], [21] explored ensemble techniques for academic performance prediction, yet their approaches did not fully integrate the meta-learning layer. This study's hybrid method with both base and meta learners enhances model accuracy beyond these traditional ensembles. Moreover, Niyogisubizo *et al.* [20] introduced a two-layer ensemble for dropout prediction, which aligns with the stacked generalization used in this study. However, the inclusion of parameter weighting, as in this research, adds an additional layer of precision, reducing computational costs while maintaining high accuracy, making it a more efficient and scalable solution. Despite these strengths, a limitation of the study lies in the absence of longitudinal data, which could further validate the model’s performance over multiple academic years.

The purpose of this work was to improve the predictive power of ML models for student performance by integrating weighted parameters and a hybrid ensemble with meta-learners. The results of this study clearly demonstrate the effectiveness of employing weighted features in improving prediction accuracy. By assigning weights to features based on their importance, the model focused more on the parameters that had the most significant impact on student performance. This approach reduced noise from less relevant features, resulting in enhanced accuracy across all models. Moreover, the use of weighted features not only improved predictive performance but also allowed for more computational efficiency. By reducing the feature set from 23 to smaller, high-impact subsets (such as the top 5 or 10 features), the computational time was significantly reduced while maintaining high accuracy. The hybrid ensemble approach, which incorporates meta-learners provided an additional layer of improvement over traditional ensemble models. This method benefited from the diversity and complementary strengths of multiple base learners, improving the model's generalization and predictive power. Hybrid ensembles with weighted features consistently outperformed basic ensembles, demonstrating their superiority in tackling complex, non-linear relationships within the data.

4. CONCLUSION AND FUTURE SCOPE

Our research introduces a multifaceted approach to learner performance anticipation through the innovative application of ML techniques. The proposed hybrid model, crafted using an ensemble with meta-learners, demonstrates exceptional accuracy, particularly when leveraging academic data. The incorporation of parameter weighting and ensemble algorithm fusion contributes to the model's robustness and precision. The study underscores the significance of early prediction in facilitating timely support for at-risk students, providing educators with valuable insights to tailor interventions effectively. The architecture, validated across various features, achieved an impressive accuracy range of 97.13% to 98.38%, showcasing the efficacy of the proposed methodology.

The future scope of this work extends to exploring advanced ML and deep learning techniques for a more in-depth analysis of educational datasets. Further research could delve into the integration of emerging technologies, such as generative adversarial networks and deep reinforcement learning, to enhance predictive modeling capabilities. Additionally, investigating the impact of external factors, such as socio-economic variables, on learner performance prediction could provide a more comprehensive understanding. Continuous refinement of the hybrid model through ongoing evaluation and adaptation to evolving educational landscapes remains a crucial avenue for future exploration.

This research holds significant implications for educational institutions, educators, and policymakers. The accurate anticipation of learner performance enables targeted interventions, fostering a supportive environment for students at risk of underperformance. Educators can utilize the insights gained to tailor instructional strategies, allocate resources effectively, and implement proactive measures to enhance student success. Policymakers can benefit from evidence-based decision-making, leading to the formulation of interventions that address systemic challenges in education. Ultimately, the implications extend to the continuous improvement of educational practices, promoting a holistic approach to student well-being and success.

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