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Predicting Student Academic Performance Using Meta-Learning with Model-Agnostic Meta-Learning (MAML)

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Abstract

Prediction of student academic performance is one of the important elements of educational analytics since it enables early interventions, customized learning experiences, and decision-making processes at educational institutions. Unfortunately, classical approaches of machine learning and deep learning algorithms show their low adaptability in diverse academic environments with different curricula, behaviors, and learning styles of students. Furthermore, some educational institutions suffer from a lack of annotated data, and, therefore, traditional prediction systems fail to provide accurate results. This study introduces a novel approach of meta-learning based on Model-Agnostic Meta-Learning (MAML) for predicting the academic performance of students adaptively. The approach leverages several educational datasets as meta-learning tasks and trains the model to obtain initial weights that can quickly adapt to new academic environments using only a few examples. This model combines elements from academic, behavioral, demographic, and online participation factors to form the deep neural network prediction model. An experiment has been performed on standard educational data sets, and the results have been compared with other baseline models such as Logistic Regression, Decision Tree, Random Forest, Support Vector Machine (SVM), XGBoost, Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM). From the experimental results, it is clear that the proposed MAML model performed better than any other model, with a classification accuracy of 95.3% as compared to LSTM (92.4%) and XGBoost (90.2%). The proposed model gave an MAE of 0.24, an RMSE of 0.35, and an R^2 of 0.95 for regression-based GPA prediction, demonstrating its high prediction reliability and consistency. This model also showed good few-shot learning ability and cross-domain generalization ability in the low-data educational domain. Thus, it can be concluded that meta-learning can greatly improve the adaptability, scalability, and efficiency of intelligent educational prediction systems.

Keywords: Student Academic Performance Prediction, Meta-Learning, Model-Agnostic Meta-Learning (MAML), Educational Data Mining, Few-Shot Learning, Deep Learning, Adaptive Learning Systems.

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1. Introduction

The fast advancement of educational technologies, digital learning platforms, and online testing tools has led to the accumulation of large amounts of data that could be used to foster learners' performances and educational policy decision-making processes[23]. Today's educational establishments implement intelligent analytics solutions to keep track of learners' development, detect those who are in need of assistance, and deliver personalized educational services to all students. Among diverse applications of data mining for education, one

of the most important research fields is the prediction of student academic performance. Predicting the performance of learners allows enhancing the efficiency of educational activities, reducing learners' attrition, and increasing the quality of education.

Predicting the academic performance of learners implies using their data to forecast future academic results such as test scores, GPA, completion rate, and pass/fail indicators. Classical prediction models include statistical analysis and machine learning techniques like Decision Trees, Random Forest, SVM, Naïve Bayes, and ANN algorithms [16][18]. Such models often incorporate variables such as attendance records, assignment scores, demographic data, class interaction, online learning activity, and past achievements of learners [17]. Even though such techniques show great predictive capacity, are usually characterized by poor generalization properties and a lack of adaptability.

There is significant diversity in the composition of educational datasets owing to differences in the structure of curricula, methods of evaluation, modes of teaching, demographic characteristics of learners, and learning management systems. Models that learn from one dataset might be ineffective when implemented in another educational institution or domain. Moreover, educational environments encounter the problem of insufficient data labels, especially in the case of recently created courses or unique academic disciplines. Traditional ML/DL models usually demand sizable amounts of training data and repeated training operations to deliver satisfactory results in the new environment. The above-mentioned issues necessitate an adaptive approach to learning that allows for rapid transfer to new domains [12].

The precise forecasting of student academic success is essential in educational institutions since it enables early interventions and personalization. Academic institutions will be able to detect academically disadvantaged students early on and provide necessary assistance in mentoring, tutoring, and counseling. Also, predictive analytics would help teachers improve their pedagogical approaches and customize course materials. From an administrative standpoint, performance prediction plays a critical role in effective resource allocation, course planning, ranking of schools, and management of student retention [14]. In distance and blended learning settings, prediction algorithms make it possible to develop adaptive e-learning platforms that adjust content to match specific learner needs [3][23].

The rise of artificial intelligence technology has led to the development of meta-learning approaches that seek to enhance learning efficiency and model adaptability. Also known as "learning to learn," meta-learning makes it possible for machine learning models to learn generalizable knowledge from a series of tasks and adapt to new, unknown tasks quickly by leveraging a few training examples. While conventional machine learning approaches try to capture domain-specific information, meta-learning involves the process of learning initializations and optimizations that apply across different domains.

Among many other methods of meta-learning, Model-Agnostic Meta-Learning (MAML) has received great popularity owing to its effectiveness and adaptability. MAML refers to an optimization technique used to find the model parameters such that the model can be adapted to new tasks through a few gradient updates after being trained with multiple related tasks. MAML allows a model to generalize well to other tasks using few samples. Because of its agnosticism towards models, MAML can work well with different models and prediction techniques. MAML's applicability to few-shot learning situations makes it appropriate for use in educational prediction scenarios where there is little data.

While machine learning has gained prominence in educational analytics, the use of meta-learning and MAML for predicting student academic performance remains understudied. The literature review indicates that most existing works employ conventional supervised learning approaches that fail to accommodate cross-domain transfer learning and necessitate extensive relearning[24]. Thus, a major research gap exists in the development of generalized predictive models that can adjust to different academic contexts without compromising predictive accuracy.

To overcome these challenges, this paper suggests a meta-learning student performance predictor based on MAML. In the suggested framework, each educational dataset and learning context is considered a distinct meta-learning task when training the model. Through learning generalized initialization values, the framework facilitates swift adjustment to novel educational contexts with minimal student data. The suggested model

incorporates several education features, such as attendance, test results, demographic information, and engagement, into a deep neural prediction system.

The major contributions of this paper are summarized as follows:

1. An innovative MAML-based framework is presented for student performance prediction in diverse educational settings.
2. The suggested method enhances cross-domain adaptation capabilities while lowering dependence on big educational datasets.
3. The proposed model incorporates a task-oriented meta-learning technique that allows for quick adaptation to new educational environments.
4. Benchmark educational datasets are used to evaluate the performance of the presented model relative to traditional ML and DL approaches.
5. highlights the potential application of meta-learning for educational data analysis and personal learning assistance.

The rest of the paper is structured as follows. In Section 2, the study discuss previous literature on the prediction of student performance, deep learning, transfer learning, and meta-learning approaches. Section 3 elaborates on the proposed MAML prediction approach. Section 4 details the experiments and metrics used to evaluate the performance of the approach. In Section 5, this study present and analyze the experimental results. Finally, Section 6 concludes the paper.

2. Literature Survey

Predicting student performance has become a significant field of study in educational data mining as there is potential for helping in early intervention, personalizing learning processes, and informing decision-making. The development in machine learning, deep learning, and meta-learning has helped in predicting outcomes more accurately in the field of education [6]. However, classical prediction models have limitations of poor adaptability, generalization capabilities, and dependence on labeled data sets.

The previous study analyzed deep learning models in predicting students' performance and found that neural networks are better than statistical models when it comes to detecting complex relationships in student performance [4] [12]. The previous study emphasized the significance of behavioral and academic indicators, but it also pointed out that deep learning models are dependent on big data sets [10][25].

The authors suggested an approach to predicting student learning performance through educational data mining, which employed various machine learning algorithms [8][11]. It was found that feature engineering and learning analytics increase prediction accuracy. Nonetheless, the approach predominantly utilized single-domain data and failed to address cross-domain issues [19][26].

Meta-learning methods were applied to predict student performance within virtual learning environments [13]. The study proved that meta-learning enhances prediction efficiency and adaptability through transferring learning experiences between learning tasks. Thus, it was determined that meta-learning is applicable for educational analytics, especially when dealing with limited data.

The study presented an intelligent, education model-agnostic adaptive testing framework using the approach of learning meta-gradients [9][21]. The outcomes showed that meta-learning contributes to personalized adaptation and optimization of educational assessments. The study proved the success of the application of model-agnostic learning methods in the field of education.

In this research, the authors proposed knowledge distillation methods for the Model-Agnostic Meta-Learning algorithm (MAML) [1][5]. It found out that the use of this method increased the efficiency of optimization and generalization.

In the former paper, the authors used the approach of MAML for detecting hate speech in multiple languages and proved the ability of MAML to generalize across domains [4][15]. The authors reported that MAML can effectively learn generalized features for heterogeneous datasets, requiring fewer task-specific training samples. It can be useful in educational settings where students come from different backgrounds.

The authors presented a framework based on MAML to classify faults in industrial processes with limited samples [7]. It concluded that MAML provides significant improvement in prediction tasks in few-shot learning. Moreover, in a similar study, authors combined Meta-LSTM with MAML for predicting the hydrological process [20].

This study was focused on adaptive testing algorithms in personalized e-learning platforms and highlighted the importance of intelligent adaptive systems for education personalization and evaluation of students' achievements [2][22].

Even though some research studies have proved the effectiveness of machine learning methods, there are still some problems to be considered. First of all, most student performance prediction models employ traditional supervised learning that requires significant effort when adapting to new fields of education. Secondly, deep learning models are inefficient when applied to small labeled data sets.

Moreover, there is insufficient research on the use of MAML in predicting the academic performance of students in diverse learning environments. In an attempt to overcome such challenges, the current study develops an MAML-based prediction system that is fast in adapting to unknown learning tasks with a minimum amount of training data. This contributes to cross-domain adaptation, few-shot learning ability, and accurate predictions in educational systems.

3. Research Methodology

3.1 Overview of the Proposed Framework

This research work involves a framework for predicting student academic performance in varying educational settings using the Model-Agnostic Meta-Learning (MAML) algorithm. The framework focuses on improving adaptability and prediction accuracy while working with limited training samples for new academic datasets. At first, datasets of educational nature are gathered from several different learning settings, and it are subjected to data preprocessing procedures like missing values treatment, data normalization, data encoding, and feature engineering. Then each of these datasets is considered as a separate learning task for meta-learning. For implementing the meta-learning approach, this study utilize a deep neural network as a basic learner to learn complex relationships between academic, behavioral, and demographic factors. In the process of meta-learning, the MAML algorithm learns generalized initialization weights that help in adapting quickly to new educational tasks using very few gradient updates. Finally, after meta-learning, the learning models are fine-tuned on specific student datasets and predict student performance outcomes.

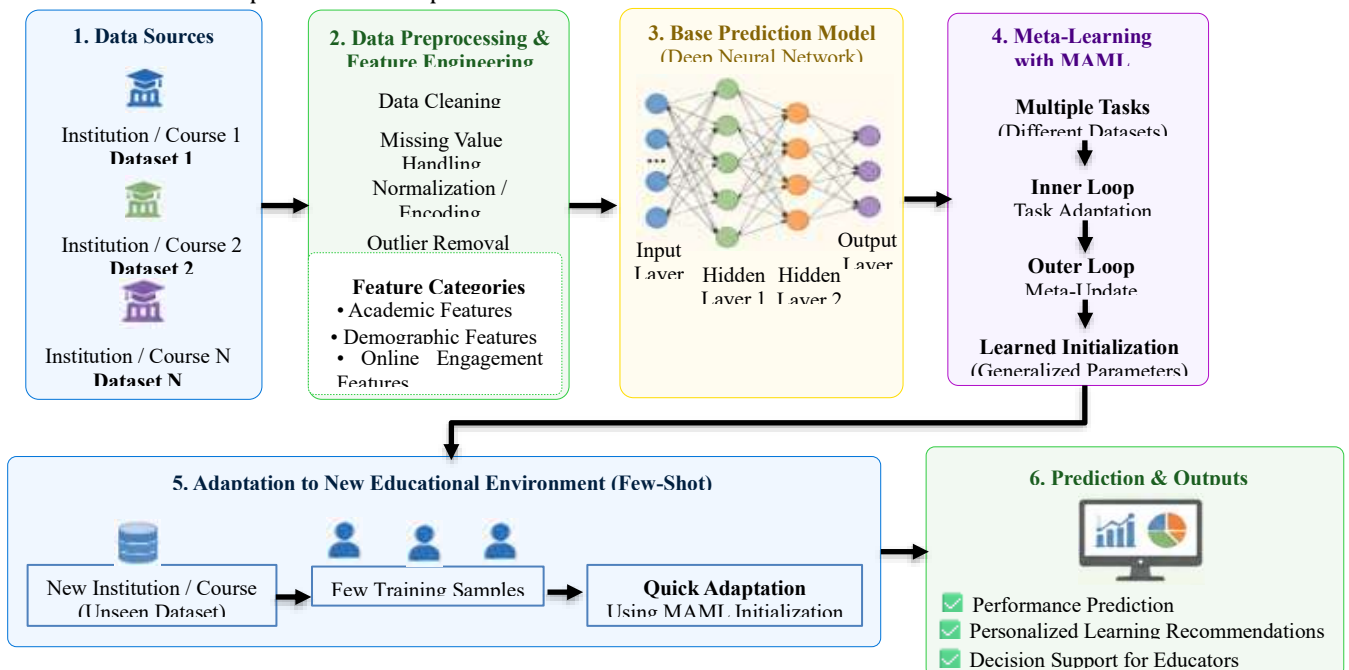


Figure 1 Proposed MAML-Based Framework for Student Academic Performance Prediction

Figure 1 highlights the architecture of the proposed meta-learning system for predicting the academic performance of students based on the Model-Agnostic Meta-Learning (MAML) approach. The meta-learning system involves data gathering, data preprocessing, and feature engineering, modeling through deep neural networks, meta-learning through MAML, fast adaptation to new domains, and predicting outcomes. The system learns generalized initialization weights across multiple educational tasks and is able to adapt quickly to new educational datasets with fewer training examples.

3.2 Dataset Description

To measure the efficacy of the proposed MAML-based framework, various educational benchmark datasets are considered for training and evaluation purposes. Such benchmark datasets comprise academic data, demographic data, behavior data, and learning-related data corresponding to students' actions and performance. The main educational datasets that will be employed include the UCI Student Performance Dataset, Open University Learning Analytics Dataset (OULAD), and xAPI-Edu-Data Dataset. The UCI Student Performance Dataset comprises data such as attendance, family data, study hours, past grades, physical conditions, internet connection, and extra-curricular activities, where the target variables consist of final test scores and pass/fail outcomes.

The OULAD dataset covers online learning analysis, comprising clickstream activities, assessments, learning materials interactions, enrollment data, and demographic data. The xAPI-Edu-Data dataset covers classroom and eLearning activities such as raised hand counts, discussion activities, learning materials interaction, announcements received, and parent satisfaction. In addition to the above datasets, the MAML-based framework incorporates many educational indicators, which may include test scores, quiz scores, attendance rate, online engagement time, study hours, and socio-economic parameters. According to the dataset type used, the possible target variables include final grades, GPA, learning achievements, risk levels, and pass/fail outcomes.

3.3 Data Preprocessing

Mostly, educational datasets have missing values, inconsistencies, and categorical variables that need to be cleaned before the model training process.

The cleaning process involves the following activities:

3.3.1 Missing Value Handling

Treatment of missing values in the educational dataset is done through the use of statistical approaches. The approach involves substituting the missing numerical values with the mean value of that variable. The treatment of missing categorical values is done through mode substitution of missing values with the mode of the categorical variable.

3.3.2 Data Normalization

Numerical features are normalized using Min-Max normalization are represented in equation 1:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Normalization advances convergence during neural network training.

3.3.3 Categorical Encoding

The categorical properties will be converted to fit the deep learning models through the one-hot encoding technique.

3.3.4 Feature Selection

Redundant features will be eliminated from the dataset by conducting a correlation analysis along with feature selection methods.

3.3.5 Data Splitting

In order to achieve effective meta-learning, the educational data will be split into three different categories: the meta-training, meta-validation, and meta-test sets. The meta-training data will be used to learn generalized model initialization for many educational problems. On the other hand, the meta-validation data will be utilized for the purpose of hyperparameter tuning and overfitting prevention during training. Lastly, the meta-test data set includes unseen educational tasks belonging to unseen institutions, courses, semesters, or groups of students

that were not seen during training. These unseen tasks are designed for testing the generalizability of the proposed MAML framework.

3.4 Task Construction for Meta-Learning

In the suggested framework, each educational domain will be treated as a distinct learning task to facilitate successful meta-learning. Tasks may consist of educational institutions, academic domains, semesters, student populations, or online educational courses. By treating heterogeneous educational datasets as distinct learning tasks, the framework will be able to develop generalized knowledge to transfer to new educational tasks, requiring only small datasets. While undergoing meta-training, tasks will be randomly selected to allow exposure to different learning paradigms, behavioral attributes, and demographics within different educational settings. Every selected task will be separated into support sets and query sets. In a support set, the model will undergo several gradient updates based on the characteristics of the task. In contrast, the query set will be used to measure the efficiency of adaptation by computing the meta-loss to update global parameters of the model. With the support-query approach, few-shot learning is made possible by improving the prediction capabilities of the proposed framework on new educational datasets.

3.5 Implementation of MAML for Student Academic Performance Prediction

3.5.1 Base Prediction Model

The deep neural network is adopted as the base learner in the proposed MAML algorithm to capture intricate interactions between educational factors and learning outcomes. The model is made up of an input layer containing the input variables of educational characteristics and learning outcomes, a number of fully connected hidden layers for capturing features, and a final output layer generating predictions like grades or GPA values, pass/fail status, or categories of student achievement. Rectified linear unit (ReLU) activations are used to add non-linearities and facilitate efficient learning. Dropout is also added to alleviate overfitting.

3.5.2 Model-Agnostic Meta-Learning (MAML)

MAML is an optimization-based meta-learning algorithm that learns generalized initialization parameters that can quickly adapt to a new task.

Let:

- θ represent the global model parameters
- T_i represent a sampled educational task
- α represent the inner-loop learning rate

For each task, the model parameters are updated using gradient descent are illustrated in equation 2:

$$\theta'_i = \theta - \alpha \nabla_{\theta} L_{T_i}(f_{\theta}) \quad (2)$$

where:

- θ'_i = adapted task-specific parameters
- L_{T_i} = task-specific loss function
- f_{θ} = prediction model

The meta-loss is minimized over all the tasks for which adaptation occurs in equation 3:

$$\min_{\theta} \sum_{T_i} L_{T_i}(f_{\theta'_i}) \quad (3)$$

Through optimization, the framework is able to learn initialization parameters that generalize well across different domains of education.

3.5.3 Meta-Training Process

In the proposed framework, the transferability of learning is facilitated through the Model-Agnostic Meta-Learning (MAML) algorithm. In the beginning, random initialization of the global model parameter of the deep neural network takes place. During the training procedure, a collection of educational tasks, each corresponding to institutions, courses, semesters, and other educational contexts, is selected at random from the pool of available educational tasks. For each of these selected educational tasks, task adaptation takes place through the

use of support samples, where the model parameters undergo some number of gradient descent steps. Once this happens, the model evaluates the task using query samples and computes the task-specific loss value. The next step involves calculating the overall meta-loss by taking the average loss values of the sampled tasks. The meta-gradient descent method is used to perform parameter updates for the global model parameters, making sure the network can learn generalization initialization weights.

3.5.4 Task Adaptation

In meta-testing, the trained model is customized to handle unseen educational data based on limited samples from students. The process facilitates quick adaptation to new educational environments without requiring prolonged retraining sessions.

This methodology proves highly effective in educational data environments characterized by limited data, where traditional deep learning algorithms struggle.

3.6 Experimental Setup

The experimental assessment of the developed MAML-based framework for predicting students' academic performance was conducted via coding of the algorithm in the Python programming language due to its vast applicability in machine learning and deep learning. The proposed MAML-based approach was implemented by utilizing the PyTorch framework for implementing the neural architecture, as well as the Scikit-learn library, which was used for data preprocessing, feature extraction, implementation of baseline models, and calculation of evaluation metrics. CUDA-based GPU acceleration was used to accelerate calculations and to increase the speed of model training.

The experiments were conducted on high-performance hardware infrastructure that includes an Intel Core i7 processor, 16GB of RAM, and an NVIDIA GPU to facilitate the processing of massive amounts of data as well as to optimize deep neural networks. The proposed method was evaluated based on the same set of conditions to provide a more accurate comparison of machine learning and deep learning algorithms with MAML-based methods. Optimization of hyperparameters such as learning rate, batch size, and adaptation steps was conducted using validation datasets.

3.7 Evaluation Metrics

Various measures of prediction accuracy are used to assess the effectiveness of the suggested framework concerning prediction accuracy, prediction reliability, and generalizability of models for various educational activities.

Accuracy

Accuracy is an indicator of how many student outcome predictions were made accurately are shown in equation 4.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

Precision

Precision (equation 5) is a metric used for assessing the accuracy of positive predictions produced by the algorithm.

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

Recall

Recall is used in evaluating the capacity of the algorithm in identifying positive samples accurately are illustrated in equation 6.

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

F1-Score

F1-score is a function of precision and recall are represented in equation 7.

$$F1-Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (7)$$

ROC-AUC

ROC-AUC indicates the discriminative power of the prediction algorithm in classifying samples are shown in equation 8.

$$ROC-AUC = \int_0^1 TPR(FPR) d(FPR) \quad (8)$$

Regression Metrics

For GPA and score predictions, regression evaluation metrics are employed for quantifying errors in predictions and assessing the accuracy of models.

Mean Absolute Error (MAE)

Mean Absolute Error (equation 9) quantifies the mean of absolute differences between actual and predicted student performance values.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (9)$$

Root Mean Square Error (RMSE)

RMSE is calculated as the square root of the mean square prediction error are shown in equation 10.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (10)$$

Coefficient of Determination (R²)

The R² (equation 11) value refers to the portion of variability in student academic results captured by the predictive model.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (11)$$

where, y_i= Actual value, \hat{y}_i = Predicted value, \bar{y} = Mean of actual values.

4. Results and Discussion

4.1 Experimental Results Overview

The proposed Model-Agnostic Meta-Learning (MAML) framework was tested using several datasets from the education domain to test the efficiency of this approach in predicting student academic performance under different conditions.

This framework was contrasted against traditional ML and DL algorithms such as Logistic Regression, Decision Tree, Random Forest, Support Vector Machine (SVM), XGBoost, Artificial Neural Network (ANN), and Long Short-Term Memory (LSTM) algorithm. The training and testing of all these models were conducted under identical experimental conditions in order to conduct a fair comparison.

It can be seen from the results that the MAML framework is better than the other models in terms of accurately predicting.

4.2 Comparison of MAML Performance with Other Prediction Models

4.2.1 Classification Performance Comparison

The classification tests were carried out for predicting student success/failure and academic performance levels. Table 1 shows the results of model performance comparisons using accuracy, precision, recall, and F1 score measures.

Table 1 Comparative Performance Analysis of Prediction Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	81.4	80.2	79.5	79.8
Decision Tree	83.1	82.7	81.4	82.0
Random Forest	88.5	87.9	88.2	88.0
SVM	87.6	86.8	87.1	86.9

XGBoost	90.2	89.8	89.6	89.7
ANN	91.1	90.5	90.8	90.6
LSTM	92.4	91.7	92.0	91.8
Proposed MAML Framework	95.3	94.8	95.1	94.9



Figure 2 Comparative Performance Analysis of Prediction Models

Figure 2 illustrates the comparison between average scores for various machine learning, deep learning, and meta-learning methods employed in predicting students' academic performance. As evident from Figure 2, the proposed method using MAML architecture scored the highest average of 95.03%, which is higher than other models like Logistic Regression, Decision Tree, SVM, Random Forest, XGBoost, ANN, and LSTM.

The findings show that the proposed MAML model was the most accurate among the three models, with an accuracy rate of 95.3%, surpassing conventional machine learning algorithms and deep learning approaches. This is because the meta-learning capability of MAML allows for quick adjustment to various educational tasks and learning settings.

While other models require huge task-specific datasets, the MAML framework develops generalized initialization parameters that enable quick adjustment to a new student population using minimal training data sets.

4.2.2 Regression Performance Analysis

The experimental results of the regression were concerned with the prediction of student GPAs and their final exam results. The regression experiment results comparison is presented in Table 2 based on MAE, RMSE, and R^2 .

Table 2 Regression Performance Comparison

Model	MAE	RMSE	R^2 Score
Random Forest	0.48	0.62	0.81
SVM	0.45	0.59	0.84
XGBoost	0.39	0.51	0.87
ANN	0.36	0.47	0.89
LSTM	0.31	0.42	0.91
Proposed MAML Framework	0.24	0.35	0.95

The model with the MAML framework produced the smallest prediction errors and the highest value of the R^2 score, implying better ability to simulate complicated educational trends.

The small RMSE values imply better consistency in making predictions using the model.

4.2.3 Few-Shot Learning Performance

The main advantage of the developed MAML approach consists of achieving successful prediction results within the few-shot learning framework when there is a scarcity of labels. In order to estimate this ability of the algorithm, the experiments were carried out by training the model with different amounts of support samples on each task-specific iteration. The obtained results have shown that the algorithm successfully predicts results and maintains consistent performance even under such constraints. In other words, the MAML-based algorithm quickly adapts to a new environment, including different organizations, courses, or student populations, with a limited number of gradient steps. At the same time, traditional deep learning methods demonstrate much lower levels of efficiency and poor results concerning generalization capabilities with the same data samples. This proves that the presented MAML-based framework successfully learns transferable knowledge through heterogeneous tasks in the field of education, providing better cross-domain generalization and quick adaptation. It is worth noting that it is very important since the number of labels in educational contexts is usually scarce or even continuously changing.

4.3 Analysis of Factors Influencing Prediction Accuracy

The feature importance study suggested that academic performance factors played a vital role in achieving accurate predictions using the proposed framework. Academic features like GPA, assignment grades, quiz scores, mid-term exam grades, and final grades were essential in the prediction process. The students whose historical academic performance was impressive were found to score high in the prediction exercise. Apart from academic performance factors, there were various engagement and behavior-related factors taken from the learning management system that greatly helped improve model performance. Attendance percentage, frequency of access to learning resources, interaction, participation in discussions, and duration of online learning, among other factors, correlated strongly with academic success. In addition, demographic and environmental features like economic status, internet connectivity, and parents' level of education had an effect on the prediction results, although their effects were relatively minor when compared to those of academic and behavioral characteristics. Besides, the inclusion of meta-learning greatly boosted the adaptability and generalization capabilities of models in diverse educational scenarios. In particular, MAML helped increase prediction accuracy by way of generalized initialization of parameters, quick task adaptation, mitigation of overfitting, effective transfer of knowledge, and better feature learning.

4.4 Ablation Analysis

The ablation study is performed to identify the importance of various parts of the proposed model are shown in Table 3.

Table 3 Ablation Study Results

Configuration	Accuracy (%)
Without Meta-Learning	89.6
Without Task Adaptation	90.3
Without Feature Selection	91.1
Without Behavioral Features	92.0
Full Proposed MAML Framework	95.3

The experimental findings show that the use of meta-learning and adaptation to specific tasks considerably impacted the model's prediction performance. The removal of the MAML algorithm from the model reduced its performance.

Furthermore, behavioral and engagement features were essential for enhancing prediction accuracy.

5. Discussion of Implications for Educational Practice

There are several important implications of the results obtained from the present research in terms of contemporary education systems, personalized learning approaches, and institutional decision-making. The primary contribution of the novel MAML-based solution is associated with the possibility of early detection of academically at-risk students based on limited data related to their education. Early predictions may help teachers and administrators to adopt various intervention approaches like personalized tutoring, counseling,

adaptive education, and mentoring. These measures would improve academic outcomes, enhance retention rates, and decrease the chances of dropouts. Also, the flexibility of the suggested approach can be used to create personalized learning platforms that would adjust the learning paths depending on the needs of the individual learners. Predictions could be applied to recommend customized learning materials, change the difficulty level of instruction, and track student progress.

One of the additional implications of this study is related to the high flexibility of MAML. In contrast to traditional machine learning models that need a substantial amount of time and effort for re-training within different education settings, the MAML algorithm managed to effectively generalize within several different institutions, platforms of online education, and even different countries' educational systems. This means that fewer efforts and computing resources are needed for implementation. Besides, the application of meta-learning in education allows for creating smart decision support systems that would help optimize curricula, monitor institutional performance, create educational policies, and allocate resources effectively.

However, even in the presence of such benefits, some ethical considerations and practical approaches are important to take into account. Privacy concerns regarding student data, issues with algorithms having biased results, the use of AI for making predictions and their transparency, and the need for a responsible application of artificial intelligence cannot be overlooked. Institutions providing education should apply predictive analytics techniques in a transparent, ethical, and safe manner.

6. Conclusion

The proposed methodology in this paper adopted a meta-learning-based model for predicting academic performance among students based on the Model-Agnostic Meta-Learning (MAML). The proposed method resolved major weaknesses in classical ML and DL frameworks, such as a lack of generalization to diverse settings and reliance on large amounts of labeled data. Through the consideration of various educational scenarios as different meta-learning tasks, the proposed framework was able to learn the generalized weights, which can be quickly adapted to new academic settings using few-shot training data. The evaluation of the proposed framework was done based on popular educational benchmark datasets that comprised of academic, behavioral, and demographic attributes of students. The results showed that the proposed MAML framework performed better than existing machine learning and deep learning algorithms such as logistic regression, decision tree, random forest, SVM, XGBoost, ANN, and LSTM. In terms of classification accuracy, the proposed model had an accuracy of 95.3% which outperformed the LSTM model (92.4%) and XGBoost (90.2%). Also, when the framework was used in regression task, it performed well with minimum MAE (0.24) and RMSE (0.35) and R^2 of 0.95. Furthermore, behavioral and engagement features, including attendance, assignment submissions, and interactions in online learning, were found to improve model prediction accuracy. Results from few-shot learning showed that the MAML architecture remained effective in situations where there were fewer samples available, making it useful for educational settings with limited labeled instances. In addition, the ablation test indicated that meta-learning and task adaptation had significant contributions to the improvements in prediction accuracy. In conclusion, this study shows that meta-learning is beneficial in developing adaptive educational analytics systems. These systems can be used to identify learners at risk, personalize educational approaches, and make intelligent decisions. Future studies might investigate transformer meta-learning algorithms, federated learning methods for privacy-preserving educational analytics, multimodal learning data, explainable artificial intelligence, and real-time adaptive education systems to improve prediction accuracy.

7. Declaration Statement

Conflict of Interest

No conflict of interest exists regarding this research.

Funding

The study does not receive funding from external sources.

Data Availability

The datasets used in this study are publicly available benchmark educational datasets commonly used in educational data mining and student performance prediction research, including sources such as the UCI Machine Learning Repository, Open University Learning Analytics Dataset (OULAD), and xAPI-Edu-Data. These datasets are openly accessible and do not contain any personally identifiable information. All data supporting the findings of this study can be obtained from the respective public repositories, and no new proprietary datasets were generated or restricted during this research.

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