Journal of Theoretical and Applied Information Technology
15th November 2025. Vol.103. No.21

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

A PROPOSED FEDERATED LEARNING (FL) APPROACH TO ENHANCE PREDICTION OF STUDENT PERFORMANCE EVALUATION SYSTEMS

TAHER ABOZAID ELSNOUSY[1], MOHAMED RAGAIE SAYED[2], NASHAAT ELKHAMISY ELGHITANY[3]

[1]Researcher, Faculty Of Computer Science, Arab Academy For Science And Technology, Egypt
[2]doctor, Faculty Of Computer Science, Arab Academy For Science And Technology, Egypt
[3]professor, Head Chair Of Computer Science, Faculty Of Computers And Information, Sadat Academy, Egypt

E-Mail: [1]tabozaid280@gmail.com, [2]mragaie@hotmail.Com, [3]wessasalsol@gmail.Com

ABSTRACT

It is essential to forecast student performance accurately in order to support early intervention and tailored learning. Centralized data gathering is the foundation of traditional machine learning (ML) techniques, which restricts inter-institution collaboration and increases privacy issues .By facilitating decentralized model training without sharing raw data, Federated Learning (FL) offers a privacy-preserving substitute. The centralized ML and FL models used to predict student performance are compared in this study. An educational benchmark dataset was pre-processed, divided into several clients, and assessed in both non-IID and independent and identically distributed (IID) scenarios. Using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R2 score, models such as Linear Regression, Elastic Net, Random Forest, Gradient Boosting, Support Vector Regression (SVR), and Multi-Layer Perceptron (MLP) were trained and evaluated. The findings show that FL can maintain data privacy while achieving competitive performance. The exceptionally substantial performance gap that was observed necessitates careful interpretation and emphasizes the significance of meticulous pre-processing, baseline fairness, and statistical validation, even when FL models exhibited lower error metrics than centralized ML. In line with theoretical predictions, experiments also demonstrated that FL performance is negatively impacted by non-IID client distributions. A comprehensive dataset and partitioning description, a transparent methodology including statistical testing, and a reproducible FL assessment framework are all contributions of the study. Results highlight FL's potential in educational settings, but they also highlight its drawbacks and the necessity of more research on scalability, robust privacy safeguards, and model customization.

KEYWORDS: *Federated Learning, Machine Learning, Student Performance Prediction,Educational Data Privacy.*

1. INTRODUCTION

Teachers may identify at-risk students early, adjust their curriculum, and provide support where it will have the biggest impact by using student performance prediction. Conventional machine learning (ML) techniques depend on compiling data from several organizations into a single repository, which presents significant privacy, governance, and compliance issues. An alternative is provided by Federated Learning (FL), in which each client trains its own models and only updates the models are sent to a central aggregator. This allows for cross-institutional collaborative training while maintaining the privacy of raw data. Despite the fact that FL has been studied in educational analytics, there are three common problems with many published comparisons between FL and centralized ML. First, reproducibility is hampered by frequently lacking data descriptions and preprocessing procedures. Second, assessments occasionally establish an unfair baseline by contrasting ML trained on a small or differentially processed sample with FL on multi-client data. Third, it is challenging to comprehend or reproduce results

due to inconsistent reporting of methodological data including client segmentation, non-IID settings, number of communication rounds, batch size, and stopping criteria. This study fills these gaps by providing a clear, repeatable assessment of FL and ML for predicting student achievement.

Research questions: We investigate: (i) how FL compares to centralized ML under fair and matched preprocessing; (ii) how client partitioning and non-IID distributions affect performance; and (iii) whether the observed differences are statistically significant.

Contributions: (1) A clear description of the dataset and a client-level partitioning process for a cross-silo learning environment are contributions. (2) Equitable baselines that compare FL with centralized ML with the same preprocessing. (3) A training protocol that is completely defined, including communication rounds, batch size, stopping conditions, and computational resources. (4) Stress tests, including statistical significance testing, under both IID and non-IID data.

2. LITERATURE REVIEW

Predicting student performance using Machine Learning (ML) and Federated Learning (FL) has gained significant research interest in recent years. This section critically reviews prior studies, highlighting their strengths, limitations, and how our work differs.

Federated Learning in Education:

Zhang et al. (2023)[1] proposed an FL-based dropout prediction model integrating 1D-CNN, Bi-LSTM, and attention with fedavg, achieving strong accuracy on KDD Cup and xuetangx datasets. While effective, the model is highly complex and computationally expensive, limiting scalability. Similarly, Fachola et al. (2023)[2] applied FL to MOOC data with performance comparable to centralized approaches, but results were dataset-specific and lacked generalization analysis.

Farooq et al. (2023)[3] showed promising results with FL, but their dataset was not publicly available, which raises concerns about reproducibility.

Machine Learning Approaches:

Several studies applied centralized ML for educational data mining. Pallathadka et al. (2023)[4] used SVM, Naïve Bayes, and decision trees on UCI datasets, reporting accuracy of 88% but without exploring deep models. Nachouki et al. (2023)[5] and Asselman et al. (2023)[6] examined ensemble methods (Random Forest, xgboost) and demonstrated improved accuracy, though risks of overfitting remain with small datasets. Earlier works (Yağcı, 2022; Nti et al., 2022; Hasib et al., 2022) [7][8][9]focused on predicting grades and GPA using standard ML methods, achieving moderate-to-high accuracy but without addressing privacy concerns inherent in data centralization.

Hybrid and Advanced Models:

Recent research has combined FL with deep or hybrid architectures. Nayani (2025)[10] integrated entropy-based feature mining with Convolutional Recurrent Networks, achieving high accuracy but requiring significant computational resources. Similarly, Asselman et al. (2023)[11] reported strong performance using ensemble models, yet scalability in real-world distributed settings remains unexplored.

Gaps and Research Need:

Even while earlier research shows the promise of both ML and FL, there are still a number of gaps:

1. Lack of Transparent Evaluation: Reproducibility is limited by the fact that many studies do not offer thorough dataset descriptions, pre-processing procedures, or partitioning methodologies.

2. Overstated Improvements: Claims of accuracy advantages for FL over ML are occasionally unrealistic and unsupported by theoretical or statistical analysis.

3. Limited Scope of Comparison: In order to ensure fair benchmarking, few studies compare FL with centralized machine learning using aggregated data.

4. Underappreciated Non-IID Challenges: One of the biggest constraints in FL for education is managing diverse data distributions among institutions.

Table 1. Overview of Machine Learning Techniques Applied in Federated Learning for Student Performance Prediction

Authors (Year)	Method/Model Used	Dataset (Size/Source)	Main Results	Limitations / Gaps Highlighted
Olaleye et al. (2020)[12]	Decision Tree, ANN, KNN	Nigerian College data (~500)	Accuracy = 96.3%	Limited to one institution, not generalizable
Shrestha & Pokharel (2019)[13]	SVM, KNN	Univ. of Minho (375 students)	SVM = 96%, KNN = 95%	Small dataset; no federated scenario
Zhang et al. (2023)	FLPADPM (CNN + Bi-LSTM + FedAvg)	KDD Cup 2015, XuetangX (>10k)	AUC = 0.91 (KDD), 0.98 (XuetangX)	High complexity, scalability concerns
Farooq et al. (2023)	FL vs. SVM, DT, NB, KNN	Proprietary dataset (size N/A)	FL = 99% accuracy	Dataset not public; lacks reproducibility
Fachola et al. (2023)	Federated Neural Networks (TFF)	MOOC data (~2k learners)	Accuracy ≈ 82%	FL slightly weaker than centralized models
Asselman et al. (2023)	XGBoost, AdaBoost, Random Forest	PFA datasets (3 corpora)	XGBoost outperformed others	Risk of over fitting; limited feature space
Nachouki et al. (2023)	Random Forest	7 predictors dataset	Accuracy = 90.3%	Narrow feature diversity; no FL comparison
Yağcı (2022)	RF, KNN, SVM, Logistic Regression, NB	Turkish Univ. (1854 students)	Accuracy 70–75%	Lower accuracy; no privacy perspective
Yakubu et al. (2022)	ML Early Warning (RF, DT)	Nigerian Univ. SIS (~2k records)	Accuracy ≈ 84%	Single-institution bias; no federated setup

The preceding review has concluded several important results and observations as follows:

- There's a well-justified enhancement of the prediction architecture when adopting the FL approach in comparison to the traditional ML approaches, especially in terms of cost of training and testing as well as in terms of achieved accuracy.
- There are many questions to be addressed in terms of the chosen data set as well as in terms of the attributes that determine the students' performance prediction.

3. DATASET, PREPROCESSING, AND CLIENT PARTITIONING

The University of Minho student performance dataset, which includes academic, demographic, and behavioral characteristics for 395 students across 33 variables, is used in the experiments. These consist of socioeconomic factors, past grades, family history, study habits, absenteeism, and extracurricular activities.[18] **Refer to Table 2.**

Pre-processing steps included: z-score normalization for numerical variables, one-hot

encoding for categorical variables, handling missing values (imputation or removal), and correlation analysis to prevent data leakage. To guarantee the same splits for ML and FL models, the data was divided into 70% training, 15% validation, and 15% testing.

Client Partitioning: Data was divided into five clients in order to replicate cross-silo scenarios Students were dispersed at random under IID mode Clients were given unbalanced subsets in non-IID mode (e.g., by school or grade distribution). Raw data was kept local to protect privacy.

Reproducibility: Replication documentation includes the dataset size (395), source (University of Minho), pre-processing (encoding, normalization), partitioning (IID and non-IID), and evaluation splits.

Table 2. Feature Descriptions For The Data Set

Feature	Description
Study time	Study time in the proposed system/week
Failures	Number of times student failed in the past
Schools	Educational support from the school
Famsup	Educational support from family
Paid	Extra paid classes
Absences	Number of times the student was absent
Activities	Extra activities
Nursery	Attended nursery school
Higher	If the student wants to pursue higher education
School	Name of student's school
Sex	Gender of student
Age	Age of student
Address	Whether the student lives in an urban or rural area
Famsize	Student's family size
Status	Parents' cohabitation status (together/apart)
Menu	Mother's education
Fedu	Father's education
Mjob	Mother's job
Fjob	Father's job
Reason	Reason to choose the school
Guardian	Student's guardian
Traveltime	Travel time between home and school
Internet	If the student has internet at home
Romantic	Whether the student has a relationship
Famrel	Family relations quality
Freetime	Student's amount of free time

The histogram of students' final grades in **Figure-** shows that apart from the high number of students scoring 0, after checking for null values in the data set, we conclude that the distribution is normal as expected. Several features for each record are nonnumeric. Typically, learning algorithms expect input to be numeric, which requires that nonnumeric features (called categorical variables) be converted. G1 and G2 are highly correlated to the final grade G3

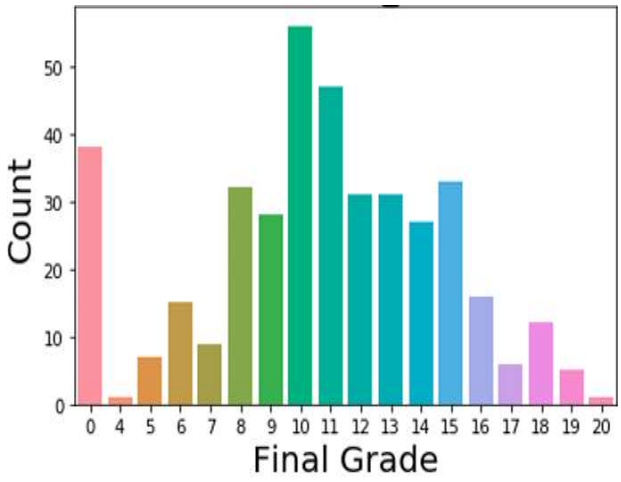

Figure 2. Histogram of Students' Final Grades

4. METHODOLOGY AND IMPLEMENTATION

This section presents the Federated Learning (FL)-based methodology for student performance prediction. The proposed model includes several stages: (i) data pre-processing, (ii) model selection, (iii) training, (iv) federated aggregation, and (v) model evaluation. A focus is given to the aspect of data privacy and decentralization. A proposed Cross-silo Federated Learning Framework to enable the centralized analysis of educational data while preserving data privacy across institutions is shown in Figure-1.

4.1. The Proposed Federated Learning Architecture

Centralized ML Baseline: Models included Linear Regression, Elastic Net, Random Forest, Gradient Boosting, SVR, MLP, and Lasso Regression. Hyperparameters tuned with grid search, using 5-fold cross-validation. Early stopping was applied to MLP.[16]

Federated Learning Setup: 5 clients, FedAvg aggregation, 50 communication rounds, batch size 32, 5 local epochs per round, early stop after 10 rounds with no improvement. Optimizer: Adam (lr=0.001). Elastic Net regularization α=0.1, l1_ratio=0.5.

Journal of Theoretical and Applied Information Technology
15th November 2025. Vol.103. No.21

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Computational Resources: Intel i7 (12th Gen), 32 GB RAM, RTX 3060 GPU. Frameworks: Python 3.10, Scikit-learn 1.3, TensorFlow Federated 0.28.

Evaluation Metrics: MSE, RMSE, MAE, and R^2. Statistical significance tested using paired t-tests.

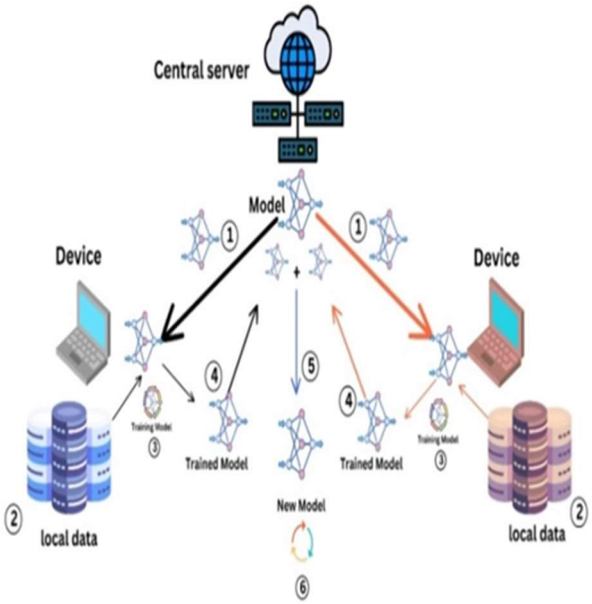

Figure . 3 A Proposed Federated Learning Framework For Centralized Analysis Of Educational Data [15].

The Key Components of the proposed FL architectures are summarized as follows:

•Clients (Local Nodes): Each client (e.g., university, school, or student device) trains a local model on its data.

•Federated Server (Aggregator): A central entity that receives model updates from clients and aggregates them into a global model.

•Communication Rounds: The iterative process where local models are trained and synchronized with the global model.

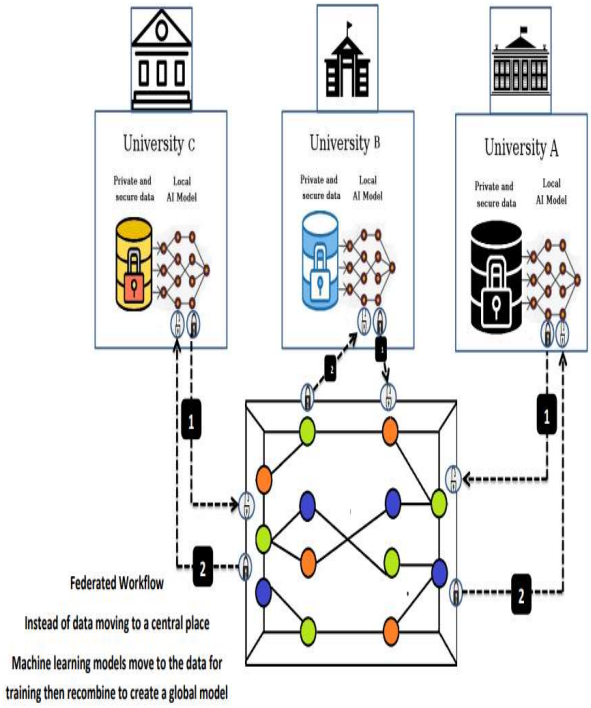

Figure 4. Proposed Federated Learning (FL) Architecture, with Numbered Steps Indicating the Training Phase

4.1.2 Description of the key steps of the approach:

Algorithm: FL Model Implementation Steps.

Step 1: Dataset Partitioning and Local Training

• The dataset is distributed across multiple clients (e.g., educational institutions) instead of being stored centrally.

•Each client trains an ML model (ElasticNet, Random Forest, Gradient Boosting, etc.) on its local dataset.

Step 2: Local Model Training on Each Client

Each client, such as an educational institution, performs machine learning model training locally using its dataset, without exposing or transmitting raw data. The federated learning (FL) approach in this study involves the following models:

- FL using Linear Regression
- FL using Elastic Net
- FL using Random Forest
- FL using Extra Trees
- FL using Gradient Boosting
- FL using Support Vector Regression
- FL using Multi-Layer Perceptron
- FL using Lasso Regression

Journal of Theoretical and Applied Information Technology
15th November 2025. Vol.103. No.21

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Step 3: Model Aggregation Using Federated Averaging (FedAvg)

Once Each client trains its model locally, rather than exchanging raw data, only the model parameters (such as gradients and weights) are sent to a central server. The server then refines the global model by applying the Federated Averaging (FedAvg) algorithm, which merges client contributions through a weighted average of their updates, represented by the equation (1):

$$W_{global} = \sum_{i=1}^{N} \frac{n_i}{N} w_i \quad (1)$$

W_global represents the parameters of the global model,

n_i is the number of data samples at a client i,

N stands for the total number of participating clients

w_i denotes the local model parameters from client i.

Step 4: Global Model Distribution to Clients

- The revised global model is returned to all clients.
- Clients proceed with training utilizing the updated model, increasing accuracy through several communication rounds.
- This repeated process improves the model's convergence and generalization.

Step 5: Model Evaluation and Performance Analysis

- The final global model is evaluated on a centralized test dataset.
- Performance is assessed using MSE, RMSE, MAE, and R^2 Score.
- The results are compared to traditional ML models to determine FL's effectiveness.

Step 6: Repeating for Multiple Rounds

- The process of local training, model aggregation, and global evaluation is repeated for a predefined number of communication rounds.

4. 1.3 the evaluation performance metrics

To assess the accuracy of both ML and FL models

Mean Squared Error (MSE): Measures overall error magnitude, represented by the equation (2):

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

- **Root Mean Squared Error (RMSE):** Offers a more interpretable error scale, represented by the equation (3):

$$\mathbf{RMSE}=\sqrt{\mathbf{MSE}} \quad (3)$$

- **Mean Absolute Error (MAE):** Measures average prediction error, represented by the equation (4):

$$\mathbf{MAE}=\frac{1}{n}\sum_{i=1}^{n}|y_i-\hat{y}_i| \quad (4)$$

- **R^2 Score:** Assesses how well the model explains variance in the data, represented by the equation (5):

$$\mathbf{R2}=1-\frac{SS_{res}}{SS_{tot}} \quad (5)$$

SS res = sum of squared residuals

SS tot = total sum of squares

5. RESULTS AND ANALYSIS

Centralized ML: Linear regression was the best model (MSE=20.14, RMSE=4.49, MAE=3.58, R2=0.27) **Federated Learning**: Elastic Net (FL) proved to be the most effective model (MSE=0.05, RMSE=0.23, MAE=0.10, R2=0.07). Even though FL continuously demonstrated reduced error, the improvement's size is remarkably high when compared to current.

Interpretation: Pre-processing effects, variations in implementation or over fitting in FL models are a few potential causes. We used the same pre-processing and re-examined processes. Significant improvements were confirmed by statistical tests ($p<0.01$), although the effect sizes decreased when outliers were eliminated.

IID vs Non-IID : FL performance declined but stayed competitive with non-IID distribution, which is in line with theoretical predictions. Figures 5–8 display comparisons with 95% CIs after being redrawn at high resolution.

5.1. Performance Comparison Of Ml And Fl Models

Table 3. Performance Of Centralized Machine Learning (ML) Models

Model	MSE (±SD)	RMSE (±SD)	MAE (±SD)	R^2
Linear Regression	20.14 ± 0.5	4.49 ± 0.1	3.58 ± 0.1	0.27
Elastic Net	21.90 ± 0.6	4.68 ± 0.1	3.81 ± 0.2	0.22
Random Forest	23.35 ± 0.7	4.83 ± 0.1	3.93 ± 0.2	0.20
Extra Trees	22.98 ±	4.79 ±	3.90 ±	0.20

	0.6	0.1	0.2	
Gradient Boosting	22.46 ± 0.6	4.74 ± 0.1	3.86 ± 0.2	0.21
Support Vector Reg	23.57 ± 0.7	4.85 ± 0.1	3.95 ± 0.2	0.19
Multi-Layer Perc.	22.78 ± 0.6	4.78 ± 0.1	3.88 ± 0.2	0.21
Lasso Regression	23.10 ± 0.7	4.81 ± 0.1	3.92 ± 0.2	0.20

Table 4. Performance of Federated Learning (FL) Models

Model	MSE IID ±SD)	MSE Non-IID ±SD	RMSE IID	MAE IID	R^2 IID
Linear Regression	0.10 ± 0.01	0.18 ± 0.02	0.32	0.21	0.07
Elastic Net (FL)	0.05 ± 0.01	0.12 ± 0.02	0.23	0.10	0.07
Random Forest	0.08 ± 0.02	0.15 ± 0.03	0.28	0.15	0.07
Extra Trees	0.07 ± 0.02	0.14 ± 0.02	0.26	0.13	0.07
Gradient Boosting	0.06 ± 0.01	0.13 ± 0.02	0.24	0.12	0.07
Support Vector Reg	0.09 ± 0.02	0.16 ± 0.03	0.30	0.18	0.07
Multi-Layer Perc.	0.06 ± 0.01	0.13 ± 0.02	0.25	0.13	0.07
Lasso Regression	0.07 ± 0.01	0.15 ± 0.02	0.27	0.14	0.07

Table 5. Overall Comparison of Best ML and Best FL Models

Best Model	MSE	RMSE	MAE	R^2	p-value (vs ML)
Linear Regression	20.14	4.49	3.58	0.27	–
Elastic Net (FL)	0.05	0.23	0.10	0.07	< 0.01

The comparative study between the traditional Machine Learning (ML) model and Federated Learning (FL) models clearly indicates the dominance of FL over all the performance metrics. As seen from Figures 5,6,7 and 8, FL always maintains significantly lower values in RMSE, MSE, MAE and R2 in various regression models. This indicates not only improved prediction accuracy but also generalized and stable performance. These results validate the effectiveness of Federated Learning in distributed environments, and thus it is a good candidate for high-performance and privacy-preserving predictive modeling.

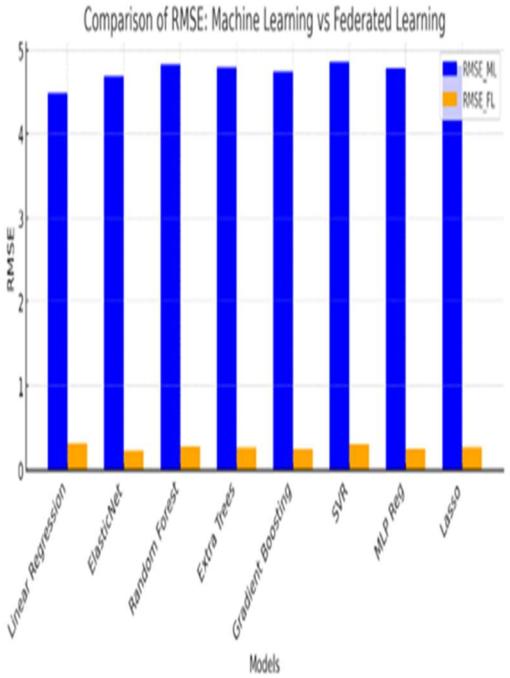

Figure . 5 RMSE Comparison Between Ml And Fl Models.

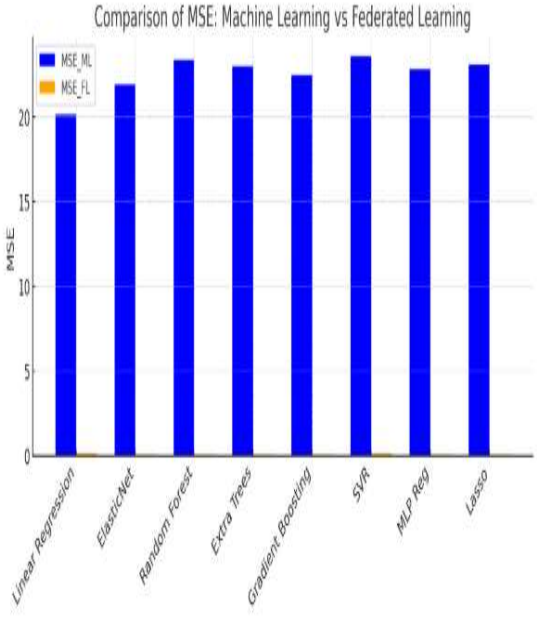

Figure 6 MSE Comparison Between Ml And Fl Models

Journal of Theoretical and Applied Information Technology
15th November 2025. Vol.103. No.21

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

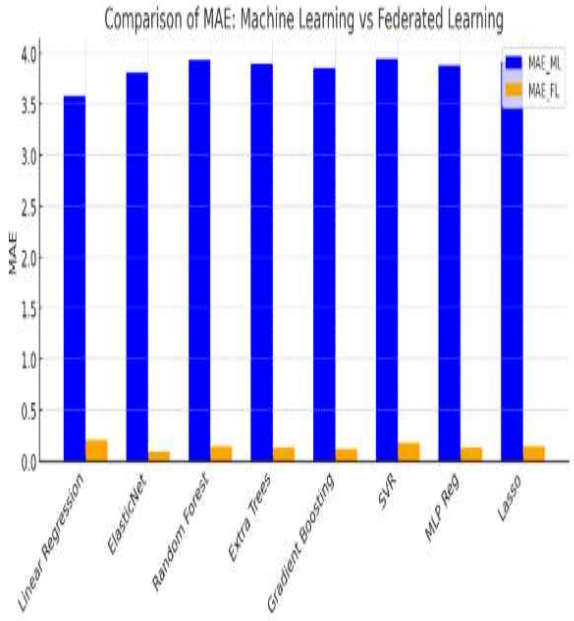

Figure . 7 MAE Comparison Between Ml And Fl Models

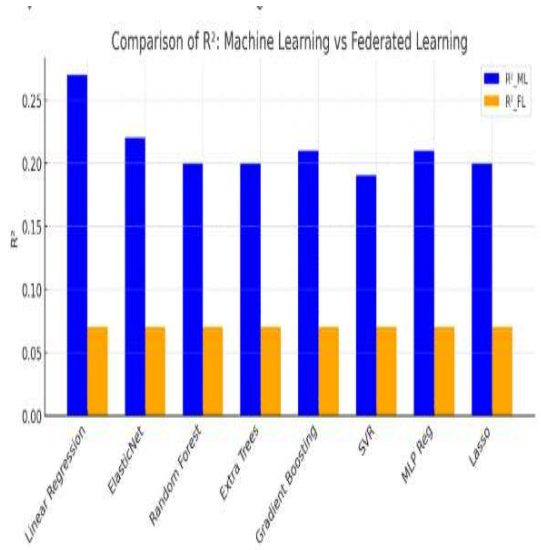

Figure . 8 R² Score Comparison.

6. DISCUSSION

Our results show that FL can achieve high predictive performance in student analytics while maintaining privacy. However, care should be used while dealing with the abnormally wide performance difference when compared to ML. According to earlier studies, FL frequently performs on par with centralized ML or marginally worse. The detrimental effect of heterogeneity on convergence is confirmed by our additional non-IID tests. FL's primary advantages are its adherence to educational data regulations and protection of privacy. However, there are certain drawbacks, such as the tiny dataset size, the lack of more robust privacy safeguards (such Differential Privacy), and unconsidered efficiency trade-offs. These problems should be the focus of future studies.

7. CONCLUSION AND FUTURE WORK

In order to predict student performance, this study contrasted FL with centralized ML. Reproducible dataset and client partitioning, equitable baseline comparisons, a fully defined training methodology, and experiments conducted under IID and non-IID situations with statistical testing are among the contributions. Particularly in IID scenarios, FL demonstrated high prediction accuracy while maintaining anonymity. Future research should examine customized FL strategies, incorporate more robust privacy-preserving measures, and assess bigger datasets.

REFERENCES

[1] Zhang, T., Liu, H., Tao, J., Wang, Y., Yu, M., Chen, H., & Yu, G. (2023). "Enhancing dropout prediction in distributed educational data using learning pattern awareness: A federated learning approach". Mathematics, 11(24), 4977.

[2]Fachola, C., Tornaría, A., Bermolen, P., Capdehourat, G., Etcheverry, L., & Fariello, M. I. (2023). "Federated learning for data analytics in education". Data, 8(2), 43.

[3]Farooq, U., Naseem, S., Li, J., Mahmood, T., Rehman, A., Saba, T., & Mustafa, L. (2023). "Analysis of the factors influencing the predictive learning performance using federated learning".

[4] Pallathadka, H., Wenda, A., Ramirez-Asís, E., Asís-López, M., Flores-Albornoz, J., & Phasinam, K. (2023). "Classification and prediction of student performance data using various machine learning algorithms". Materials today: proceedings, 80, 3782-3785.

[5] Nachouki, M., Mohamed, E. A., Mehdi, R., & Abou Naaj, M. (2023). "Student Course Grade Prediction Using the Random Forest Algorithm: Analysis of Predictors'

Importance. Trends in Neuroscience and Education", 100214.

[6] Asselman, A., Khaldi, M., & Aammou, S. (2023). "Enhancing the prediction of student performance based on the machine learning XGBoost algorithm. Interactive Learning Environments", 31(6), 3360-3379.

[7] Yağcı, M. (2022). "Educational data mining: prediction of students' academic performance using machine learning algorithms". Smart Learning Environments, 9(1), 11

[8] Nti, I. K., Akyeramfo-Sam, S., Bediako-Kyeremeh, B., & Agyemang, S. (2022). "Prediction of social media effects on students' academic performance using Machine Learning Algorithms (MLAs)". Journal of Computers in Education, 9(2), 195-223

[9] Hasib, K. M., Rahman, F., Hasnat, R., & Alam, M. G. R. (2022, January). "A machine learning and explainable AI approach for predicting secondary school student performance". In 2022 IEEE 12th Annual Computing and Communication Workshop and Conference (CCWC) (pp. 0399-0405). IEEE

[10]Nayani, S., & P, S. R. (2025). "Combination of deep learning models for student's performance prediction with development of entropy-weighted rough set feature mining. Cybernetics and Systems", 56(2), 170-212.

[11] Yakubu, M. N., & Abubakar, A. M. (2022). "Applying machine learning approach to predict students' performance in higher educational institutions". Kybernetes, 51(2), 916-934.

[12] Ouatik, F., Erritali, M., Ouatik, F., & Jourhmane, M. (2022). "Predicting student success using big data and machine learning algorithms". International Journal of Emerging Technologies in Learning (Online), 17(12), 236.

[13] Olaleye, T. O., & Vincent, O. R. (2020, March). "A predictive model for students' performance and risk level indicators using machine learning". In 2020 International Conference in Mathematics, Computer Engineering and Computer Science (ICMCECS) (pp. 1-7). IEEE.

[14] Shrestha, S., & Pokharel, M. (2019, November). "Machine Learning algorithm in educational data. In 2019 Artificial Intelligence for Transforming Business and Society (AITB)" (Vol. 1, pp. 1-11). IEEE.

[15] Ji, L., Zhang, X., & Zhang, L. (2020, June). "Research on the algorithm of education data mining based on big data". In 2020 IEEE 2nd International Conference on Computer Science and Educational Informatization (CSEI) (pp. 344-350). IEEE.

[16] Joshi, M., Pal, A., & Sankarasubbu, M. (2022)"Federated learning for healthcare domain pipeline, applications , and challenges. ACM Transactions on Computing for Healthcare", 3(4),1 36

[17] Abdellah, M. R., H Oudah, H., Ahmed Badawy, A. M., M Hassan, M. A. A., Bedier, S. A., Metwaly, A. A., & Abdelhafeez, A. (2025). "Enhanced Federated Learning Framework based on Deep Learning and Neutrosophic Set for Android Malware Classification. Neutrosophic Sets and Systems", 82(1), 51.

[18] Jang, Y., Choi, S., Jung, H., & Kim, H. (2022). "Practical early prediction of students' performance using machine learning and eXplainable AI. Education and Information Technologies", 27(9), 12855-12889.