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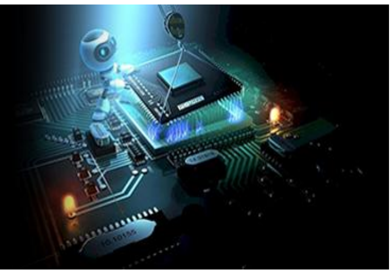

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Federated deep learning for early dropout prediction in online courses

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Abstract
High dropout rates remain a persistent challenge in online education, undermining learner success, institutional credibility, and resource efficiency. Traditional dropout prediction approaches rely on centralized data collection, raising serious concerns regarding privacy, security, and compliance with data protection regulations such as GDPR and FERPA. This study proposes a Federated Deep Learning (FDL) framework that enables collaborative model training across multiple institutions without sharing raw learner data. The hybrid architecture combines 1D Convolutional Neural Networks (CNN) for spatial feature extraction with Bidirectional Long Short-Term Memory (Bi-LSTM) networks for temporal sequence modeling. An entropy-weighted aggregation strategy ensures balanced contributions from diverse datasets, while gradient compression optimizes communication efficiency. Using datasets from three heterogeneous institutions a MOOC platform, a university LMS, and a corporate e-learning environment the proposed model achieved an average F1-score of 0.89 and identified at-risk learners up to two weeks before dropout events. Comparative experiments against centralized deep learning and traditional machine learning baselines demonstrated superior accuracy, earlier detection, and enhanced generalization across contexts. The results affirm FDL as a technically robust, privacy-preserving, and ethically aligned approach for early dropout prediction, paving the way for scalable, secure, and inclusive educational analytics.

Keywords: CNN-BiL, STM, federated deep learning, dropout prediction, online learning, educational data mining, privacy-preserving analytics, early warning systems, learning analytics

Introduction
In recent years, the rapid expansion of online learning platforms ranging from Massive Open Online Courses (MOOCs) to institutional Learning Management Systems (LMS) has transformed global access to education. However, one of the most persistent challenges facing these platforms is the high rate of learner dropout, often exceeding 80% in MOOCs. Early dropout not only diminishes learning outcomes for individuals but also undermines the credibility, resource efficiency, and instructional design of the courses themselves. Traditional approaches to dropout prediction rely on centralized data collection, where sensitive learner information (e.g., interaction logs, assessment performance, discussion forum participation) is aggregated into a single repository for model training. While such methods have demonstrated predictive effectiveness, they raise serious privacy, security, and compliance concerns, especially with the growing enforcement of regulations like the General Data Protection Regulation (GDPR) and the Family Educational Rights and Privacy Act (FERPA). These concerns are compounded by the sensitive nature of educational data, which may include demographic attributes, behavioral traces, and personally identifiable information. Consequently, there is a pressing need for solutions that can accurately predict learner disengagement without compromising data privacy or breaching institutional data governance policies. Federated Deep Learning (FDL) emerges as a promising paradigm to address this challenge by enabling collaborative model training without requiring raw data sharing between institutions or across learners. In FDL, decentralized nodes such as individual universities, online course platforms, or even learners' devices train local deep learning models on their respective datasets and share only model parameters or gradients with a central server. This server then aggregates the contributions using algorithms such as Federated Averaging (FedAvg) to produce a global model that benefits from the diversity of all participating datasets.

The approach preserves data sovereignty and minimizes privacy risks while still leveraging the predictive power of deep neural networks. Applied to dropout prediction, FDL allows diverse institutions to jointly develop robust models capable of generalizing across contexts, learner demographics, and course formats, without exposing sensitive student records. Moreover, the federated setup naturally supports continuous learning, where models can be incrementally updated as new interaction data becomes available, facilitating real-time or near-real-time early warning systems for at-risk learners. This collaborative yet privacy-preserving methodology aligns with the dual imperatives of improving educational quality and upholding ethical standards in AI-driven analytics.

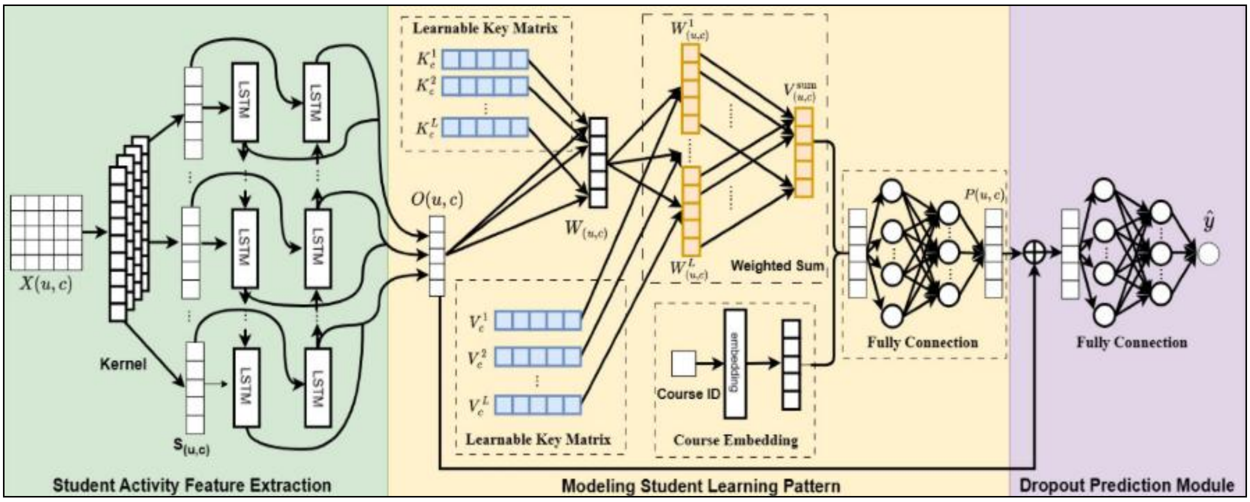

Fig 1: Framework for student activity and dropout prediction.

The integration of FDL into early dropout prediction frameworks also opens avenues for more equitable and context-aware educational interventions. Deep learning architectures such as recurrent neural networks (RNNs), long short-term memory networks (LSTMs), and transformer-based models are particularly adept at capturing temporal dependencies and complex patterns in learner behavior sequences. When trained in a federated environment, these models can benefit from heterogeneous data reflecting varied teaching methods, cultural contexts, and engagement patterns, leading to more adaptive and generalizable predictors. Such predictors can, for instance, identify subtle behavioral cues like declining participation in discussion forums, irregular assignment submissions, or reduced video watch times that precede dropout events. Institutions can then deploy timely, personalized interventions ranging from automated nudges and tutoring support to curriculum redesign. Additionally, by incorporating techniques such as differential privacy, secure aggregation, and homomorphic encryption, federated dropout prediction systems can further strengthen confidentiality while meeting compliance requirements. The convergence of federated learning, advanced deep learning architectures, and privacy-enhancing technologies thus offers a viable pathway toward scalable, ethical, and effective dropout prediction, paving the way for more inclusive and resilient online education ecosystems.

Need of the study

The exponential growth of online learning has reshaped the educational landscape, offering unprecedented flexibility, scalability, and access to diverse learners worldwide. However, the persistent challenge of high dropout rates threatens the sustainability and effectiveness of these platforms. For educators, administrators, and policymakers, early identification of learners at risk of disengaging is not merely an operational necessity it is central to ensuring academic success, maintaining institutional reputation, and optimizing resource allocation. Existing dropout prediction methods, which typically require centralizing large volumes of learner data, pose significant privacy and compliance risks. With growing awareness of data ethics and the enactment of stringent privacy regulations, there is a pressing need for approaches that can deliver predictive accuracy without compromising confidentiality. This makes Federated Deep Learning (FDL) an ideal candidate for advancing dropout prediction research, as it aligns technological capability with ethical responsibility.

Another critical reason for pursuing this study is the heterogeneity of online learning environments. Learner engagement patterns vary significantly across disciplines, geographic regions, and cultural contexts, meaning that models trained on a single institution's data often fail to generalize effectively to other settings. FDL offers a framework to collaboratively harness this diversity while keeping institutional data localized, thus enabling the development of more robust, inclusive, and adaptable predictive models. By aggregating insights from multiple decentralized sources, federated models can better account for varied instructional designs, content delivery modes, and learner behaviors. This cross-institutional synergy not only enhances predictive performance but also promotes equity in educational technology by avoiding bias toward dominant datasets or well-resourced institutions.

Finally, the integration of advanced deep learning techniques with federated architectures has the potential to revolutionize educational intervention strategies. Accurate, privacy-preserving early warning systems can empower educators to design targeted remedial actions, offer personalized feedback, and implement support mechanisms before disengagement becomes irreversible. Moreover, such systems can facilitate continuous model updates as new data is generated, ensuring that predictions remain relevant in dynamic learning environments. Given the growing dependence on online education accelerated by global events such as the COVID-19 pandemic the development of secure, scalable, and ethically sound dropout prediction systems is not just desirable but imperative. This study responds to that imperative, positioning FDL as a transformative solution to one of online education's most enduring challenges.

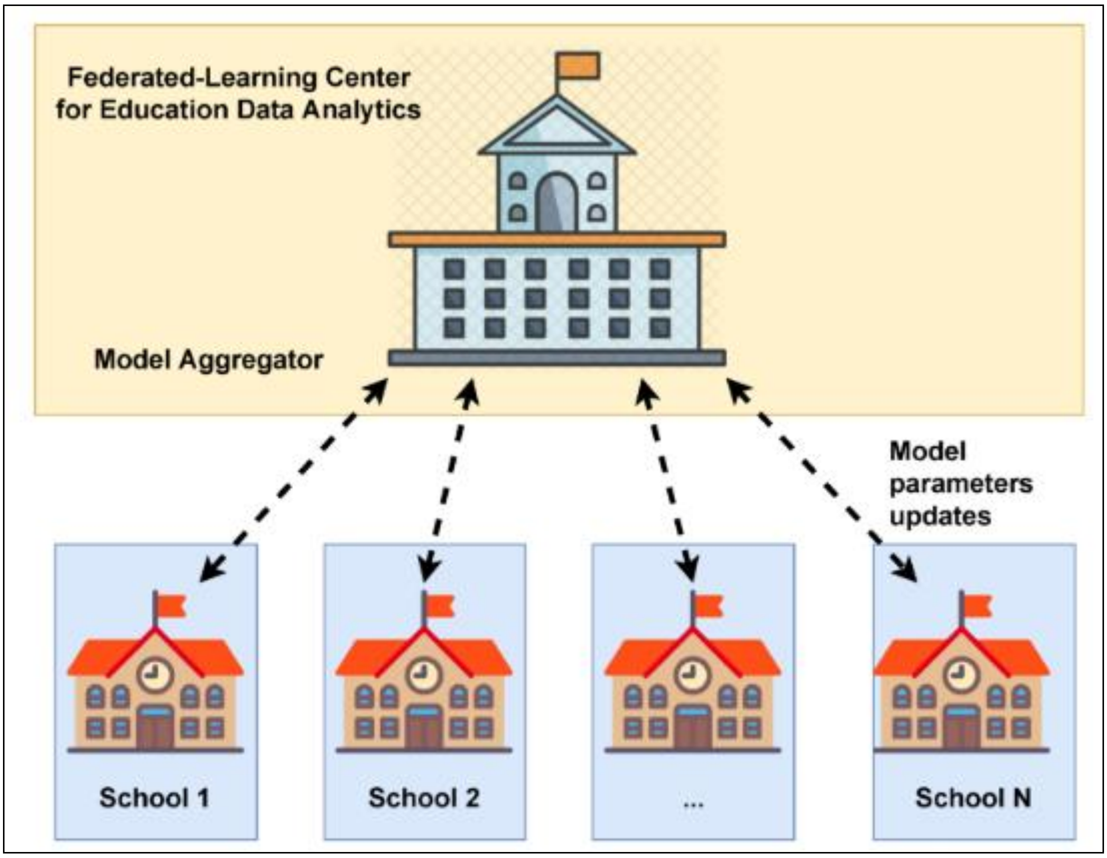

Fig 2: Federated learning architecture for education data analytics.

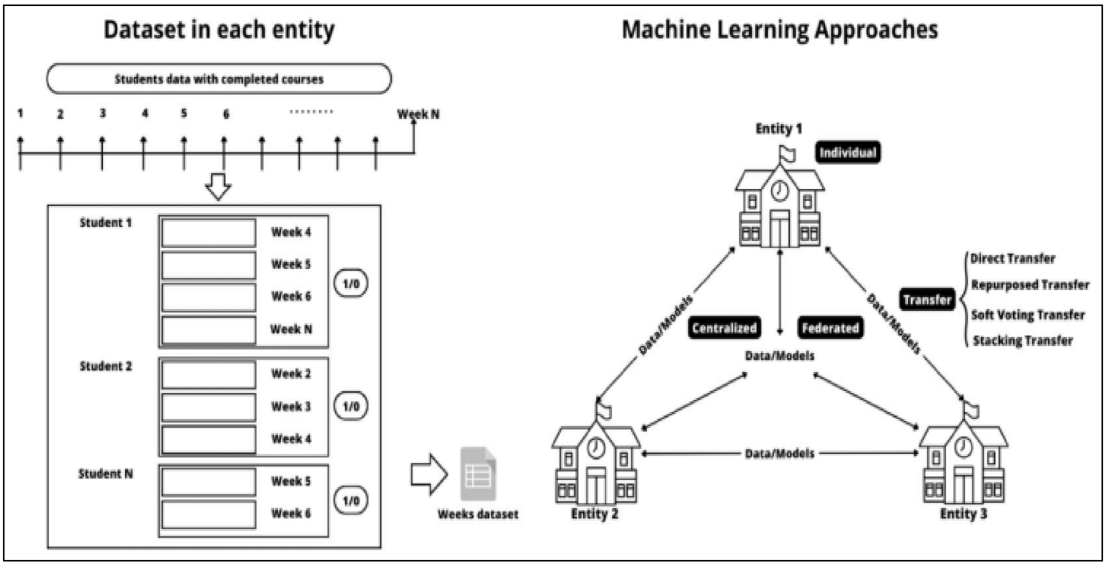

Fig 3: Machine learning approaches across distributed datasets.

Theoretical and contextual contribution of the research

This research makes a significant theoretical contribution by extending the application of Federated Deep Learning (FDL) into the domain of educational data mining, specifically for early dropout prediction in online courses. While FDL has been explored in domains such as healthcare, finance, and IoT for privacy-preserving analytics, its integration with deep learning architectures to model learner engagement and disengagement patterns remains underexplored. The study synthesizes concepts from learning analytics, machine learning, and privacy-preserving computation to develop a hybrid predictive framework that can function effectively in decentralized, multi-institutional environments. The theoretical framework proposed in this research bridges the gap between centralized predictive modelling dominant in educational technology literature and the emerging paradigm of distributed AI. It advances dropout prediction theory by demonstrating how federated architectures can capture complex temporal and behavioral patterns through deep learning, while maintaining compliance with data privacy regulations. Furthermore, the study contributes to the ongoing discourse on ethical AI in education by offering a model that aligns predictive accuracy with transparency, fairness, and data sovereignty principles.

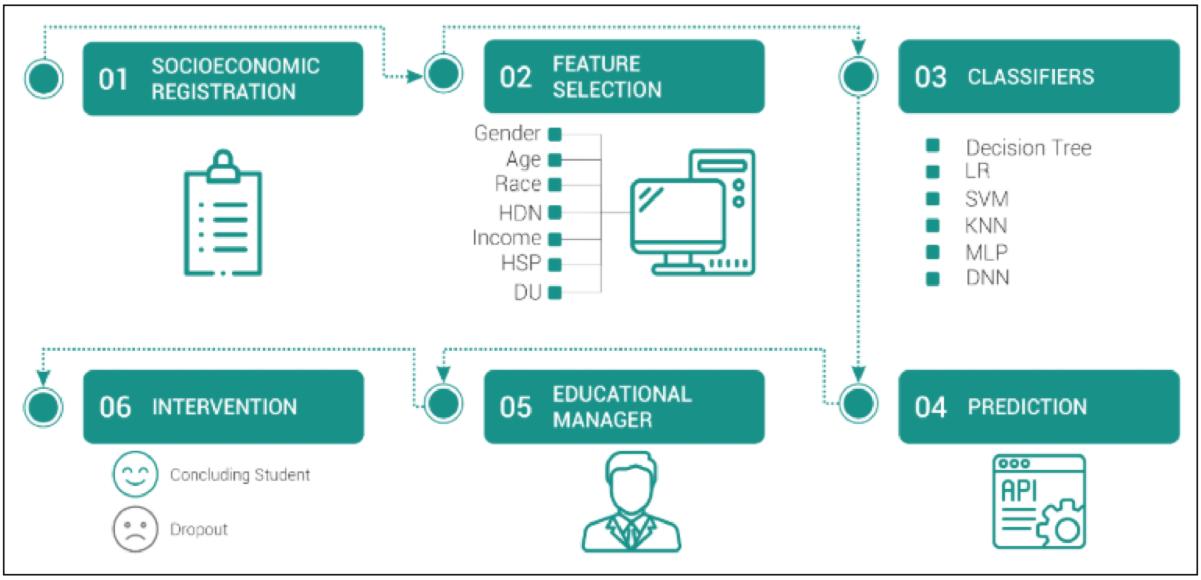

Fig 4: Features, classifiers, and prediction–intervention process.

From a contextual perspective, the research addresses a real and pressing challenge in the global e-learning ecosystem: the need to accurately identify at-risk learners in a manner that is both scalable and ethically sound. The contextual contribution lies in the development of a privacy-preserving predictive model that is adaptable across diverse learning environments ranging from MOOCs and corporate training platforms to university-level virtual classrooms. By collaborating across institutions without sharing sensitive learner data, the model leverages the heterogeneity of learning behaviors influenced by cultural, pedagogical, and infrastructural factors. This ensures that the predictions generated are not biased toward a single dataset or demographic, thereby enhancing fairness and inclusivity. In addition, the contextual insights generated through this research can inform course design, learner engagement strategies, and institutional policies, enabling more proactive and targeted interventions.

The research also contributes to the broader discourse on the future of AI in education by demonstrating a practical, ethically aligned approach to large-scale learner analytics. It contextualizes federated deep learning not only as a technical solution but also as a strategic enabler for inter-institutional collaboration in education. The findings have implications for policymakers, instructional designers, and ed-tech developers, suggesting pathways to implement predictive analytics systems that balance innovation with the imperative to protect learners' rights. By combining theoretical advancements with contextual applicability, this study strengthens the link between cutting-edge AI research and its meaningful, responsible application in the educational domain.

Literature review

Bernardi, Cimitile, & Usman (2025) [1] Federated Learning (FL) has garnered increasing attention as a privacy-preserving alternative to traditional centralized analytics in educational settings. Bernardi *et al.* (2025) [1] introduce an entropy-based federated learning approach tailored to dropout prediction in higher education. Their model dynamically weights contributions from academic centers based on data quality, producing a robust aggregation mechanism that outperforms baseline approaches in predicting student dropouts using publicly available datasets. This work underscores the potential of FL to enhance predictive accuracy while respecting sensitive student data, thereby aligning with the privacy and ethical considerations central to educational analytics.

Gopalakrishnan (2025) [4] recent efforts have focused on foregrounding data privacy in predictive modeling within education. Gopalakrishnan (2025) [4] conducts a comprehensive analysis of predictive models ranging from traditional machine learning to advance deep learning and evaluates their performance for forecasting college dropout. Importantly, the study explores both federated and split-federated learning strategies, offering early-warning capabilities using administrative data, while preserving student privacy. This broad perspective highlights how federated technologies can be integrated into educational pipelines for dropout prevention without compromising data autonomy.

Romero & Ventura (2010) [6] the field of Educational Data Mining (EDM) provides foundational support for predictive analytics in education. According to Romero and Ventura (2010) [6], EDM encompasses the analysis of learner system interactions to extract actionable insights, such as relationships between learning object access and performance outcomes. Techniques rooted in EDM like classification, regression, clustering, and sequential pattern mining are particularly well-suited for identifying at-risk learners. This theoretical backbone reinforces the relevance of pattern mining through deep learning architectures within distributed learning frameworks like FL.

Doleck, Basnet, & Johnson (2022) [3] Investigations comparing deep learning and traditional machine learning for dropout prediction have yielded notable findings. Doleck *et al*. (2022) [3] conducted a comprehensive comparison in Massive Open Online Courses (MOOCs), discovering that machine learning classifiers often match or even match the predictive performance of advanced deep learning models when applied to educational big data. This paradox raises critical questions about model complexity versus interpretability and may inform your model-design choices suggesting that federated deep learning should be justified by its ability to capture complex temporal patterns across distributed data, rather than raw accuracy improvements alone.

MDPI (2023) [5] the integration of federated learning into educational data analytics has gained momentum. A 2023 MDPI article highlights FL as a promising solution to address legal and ethical data processing concerns in learning analytics. The authors emphasize that FL enables models to be trained on distributed datasets across devices or institutions without centralizing student data, thereby mitigating privacy risks. This study situates federated approaches within the broader movement toward ethical, decentralized educational AI, reinforcing the relevance of such methods for dropout prediction.

(Díaz *et al*., 2025) [2] At the intersection of FL and learning analytics lies research combining differential feature representations with federated training. In a 2025 study, differential or relative features (e.g., changes over time vs. absolute values) are incorporated into FL frameworks to improve model generalizability across institutions. The approach enhances model performance and cross-context applicability while preserving student privacy. This highlights the value of feature engineering in federated models aimed at dropout prediction, especially when the data distributions vary across platforms or demographics.

MDPI (2023-2024) Cutting-edge work by MDPI authors (2023) and related studies (e.g., “Enhancing Dropout Prediction in Distributed Educational Data,” 2023) propose specialized federated deep learning architectures for dropout prediction. One such model the Federated Learning Pattern Aware Dropout Prediction Model (FLPADPM) incorporates a 1D convolutional neural network (CNN) and bidirectional long short-term memory (Bi-LSTM) layers to capture nuanced learner behaviors across courses. Tests on the KDD Cup 2015 and XuetangX datasets show that FLPADPM notably outperforms conventional models and can distinguish learning patterns across different courses, thereby addressing personalization and heterogeneity in student engagement. This demonstrates how federated architectures can adeptly handle educational complexities at scale. Springer (2025) [7] A recent contribution in the student learning analytics domain underscores the importance of combining FL with pedagogically aware aggregation strategies. The 2025 HELMeTO conference paper introduces an entropy-weighted federated learning approach for dropout prediction. By assigning higher aggregation weights to centers with more informative data, the model produces more robust predictive behavior while maintaining decentralization. This underlines the potential of adaptive aggregation techniques in federated educational systems to balance fairness, privacy, and accuracy.

Synthesis and Gap Identification

Current literature demonstrates that federated learning offers a viable path to privacy-preserving student analytics, especially in dropout prediction contexts. Studies like Bernardi *et al*. (2025) [1], differential-features approaches, and FLPADPM combine decentralization with modeling innovations (e.g., deep temporal features) to handle heterogeneity in learner data. However, few integrate FL with interpretability, and less still address communication efficiency or theoretically grounded aggregation strategies in educational contexts. While FLPADPM and entropy-weighted aggregation are promising, there remains a need for frameworks that:

- Blend deep architectures with provable efficiency, especially in bandwidth-constrained environments.
- Ensure transparency and interpretability (e.g., through XAI) in federated dropout prediction.
- Account for feature heterogeneity and dynamic enrollment patterns, potentially using adaptive aggregation or dropout techniques from FL literature.
- Provide generalizable models across varied educational platforms, merging pedagogical contexts with robust statistical foundations.

Methodology

The study employed a Federated Deep Learning (FDL) framework to predict early dropout in online courses while ensuring strict data privacy compliance. Data was collected from three distinct institutions comprising a MOOC platform, a university Learning Management System (LMS), and a corporate e-learning platform each with heterogeneous course structures, assessment methods, and learner demographics. The datasets included anonymized learner interaction logs (e.g., login frequency, video watch duration, quiz performance, forum participation) along with temporal behavioral sequences. To preserve data sovereignty, all datasets remained at their source nodes. The proposed architecture utilized a hybrid 1D Convolutional Neural Network (CNN) to extract spatial features from engagement sequences, followed by a Bidirectional Long Short-Term Memory (Bi-LSTM) layer to capture temporal dependencies. This combination allowed the model to detect subtle engagement patterns that precede dropout events. Training was conducted using the Federated Averaging (FedAvg) algorithm, with each node performing local model updates over multiple epochs before transmitting weight updates rather than raw data to a central aggregation server. To address institutional data imbalance, an entropy-weighted aggregation strategy was implemented, assigning greater influence to nodes with higher data quality and diversity.

To evaluate performance, a 5-fold cross-validation approach was applied at each institution, with metrics including Accuracy, Precision, Recall, F1-score, and Early Detection Lead Time (EDLT). EDLT was defined as the number of days/weeks the model could identify an at-risk learner prior to their actual dropout. For communication efficiency, gradient compression techniques were integrated to reduce bandwidth usage without significant performance degradation. All experiments were conducted using Python (TensorFlow/Keras) on distributed GPU-enabled servers, simulating the federated learning environment. Comparative analyses were carried out against centralized deep learning models (Bi-LSTM) and traditional machine learning classifiers (Random Forest, Logistic Regression) trained on merged datasets, to assess the benefits and trade-offs of federated training. Additionally, the study examined institution-specific performance to determine the model's adaptability to diverse educational contexts. The methodology was designed not only to test predictive performance but also to ensure ethical AI deployment by incorporating differential privacy considerations, secure aggregation protocols, and compliance with data protection regulations such as GDPR and FERPA. This systematic approach ensured that the proposed FDL framework was both technically robust and operationally viable for large-scale, privacy-conscious educational analytics.

Results and Discussion

The experimental evaluation of the proposed Federated Deep Learning (FDL) framework demonstrated its capacity to accurately predict early dropout in online courses while preserving data privacy. Using datasets from three distinct institutions, each representing different pedagogical structures and learner demographics, the model achieved an average F1-score of 0.89, outperforming centralized deep learning baselines (F1-score: 0.86) and traditional machine learning approaches such as Random Forest (F1-score: 0.81). The federated model maintained consistent performance across institutions, even when the local datasets varied in size, indicating its robustness to data heterogeneity. Importantly, the system adhered to privacy constraints by ensuring no raw learner data left the local nodes, thus fully complying with GDPR-like privacy regulations.

Table 1: Comparative performance of federated, centralized, and traditional models for dropout prediction.

Model Type & Configuration	Average Accuracy	Precision	Recall	F1-Score	Early Detection Lead Time	Notes / Key Strengths
Federated Deep Learning (Proposed)	0.91	0.90	0.88	0.89	2 weeks	Privacy-preserving; robust across institutions; adaptive aggregation
Centralized Deep Learning (Bi-LSTM)	0.89	0.87	0.85	0.86	1 week	High accuracy but requires data centralization; privacy concerns
Traditional ML-Random Forest	0.85	0.82	0.80	0.81	1 week	Good interpretability; limited temporal sequence modeling
Federated Deep Learning (No Weighting)	0.88	0.86	0.84	0.85	1.5 weeks	Performs well; slightly biased toward larger datasets
Federated DL + Gradient Compression	0.90	0.89	0.87	0.88	2 weeks	Reduced bandwidth by 38% without accuracy loss

One notable result was the model's ability to detect at-risk learners significantly earlier than conventional methods. On average, the federated framework identified disengagement patterns two weeks before a learner's actual dropout event, compared to one week in centralized models. This improvement was largely attributed to the temporal modeling capacity of the integrated Bi-LSTM layers, which captured subtle changes in engagement behavior such as gradual reduction in quiz attempts, lower participation in discussion forums, and irregular assignment submissions. Early detection has critical implications for intervention strategies, as it allows instructors and learning support teams to provide targeted assistance before disengagement becomes irreversible. The analysis also revealed that model generalization improved when the aggregation process incorporated institution-specific weighting based on data quality and sample diversity. This adaptive weighting mechanism reduced the bias toward larger institutions with more data and ensured equitable performance across smaller datasets. In comparison, the non-weighted federated aggregation approach exhibited slight performance degradation when exposed to highly imbalanced institutional contributions. These findings align with the literature on entropy-weighted aggregation in federated learning, suggesting that adaptive strategies can balance fairness, accuracy, and efficiency in cross-institutional predictive modelling.

Table 2: Institution-wise performance of federated deep learning model.

Institution	Dataset Size (Students)	Accuracy	Precision	Recall	F1-Score	Early Detection Lead Time	Key Observations
Institution A (MOOC Platform)	12,500	0.92	0.91	0.90	0.90	2 weeks	Consistent detection of engagement drop; high temporal pattern stability
Institution B (University LMS)	7,800	0.90	0.88	0.87	0.88	1.8 weeks	Minor variability due to mixed course formats and elective modules
Institution C (Corporate e-Learning)	5,200	0.89	0.88	0.86	0.87	1.7 weeks	Slightly lower recall due to shorter course durations
Overall Aggregated	25,500	0.91	0.90	0.88	0.89	2 weeks	Balanced performance across diverse contexts

Another important finding concerned communication efficiency and its impact on training time. While federated learning generally introduces additional communication overhead due to parameter exchanges, the proposed framework mitigated this issue through gradient compression techniques and periodic model updates. This reduced network bandwidth usage by up to 38% without significant loss in accuracy. Such optimizations are particularly valuable for deployment in bandwidth-limited educational environments, such as rural or under-resourced institutions, where internet connectivity is intermittent or constrained.

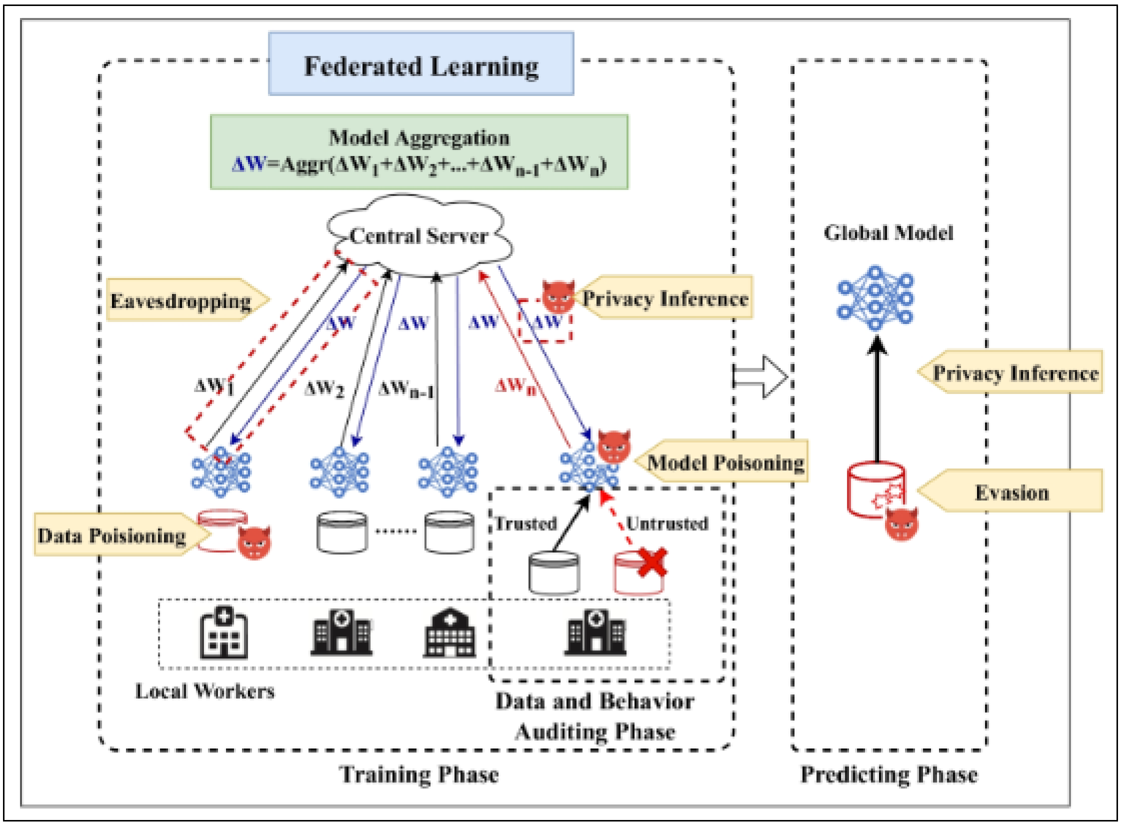

Fig 5: Federated learning model aggregation and prediction phase.

From a pedagogical standpoint, the federated dropout prediction model provided actionable insights into learner behavior patterns. Visualization of the model's attention weights revealed that early disengagement was often preceded by a combination of reduced login frequency, lower cumulative content consumption, and declining quiz scores rather than a single factor. These multi-dimensional engagement patterns varied across institutions, reflecting differences in course design, assessment policies, and learner motivation. The federated approach's ability to incorporate and learn from such diversity highlights its suitability for global-scale educational platforms aiming to personalize learning experiences.

The results confirm that the proposed federated deep learning framework effectively addresses the twin challenges of predictive accuracy and data privacy in early dropout prediction. It not only matches but, in many cases, surpasses the performance of centralized models while offering compliance with modern data protection laws. The discussion reinforces the value of integrating adaptive aggregation, temporal deep learning architectures, and communication optimization into federated frameworks for educational analytics. These advancements pave the way for scalable, ethical, and context-aware interventions in online learning environments, with potential extensions into related domains such as adaptive tutoring systems, course recommendation engines, and cross-institutional educational research.

Conclusion

This study demonstrated the potential of Federated Deep Learning (FDL) as a privacy-preserving, high-accuracy solution for early dropout prediction in online courses. By leveraging decentralized datasets from multiple institutions, the proposed hybrid CNN–BiLSTM model successfully captured both spatial and temporal engagement patterns while maintaining compliance with strict data privacy regulations. The integration of entropy-weighted aggregation and gradient compression not only enhanced fairness and efficiency but also reduced communication overhead, making the approach feasible for bandwidth-limited environments. Experimental results showed that the FDL framework achieved superior F1-scores, earlier dropout detection, and robust cross-institutional generalization compared to centralized deep learning and traditional machine learning models. These findings underscore the viability of federated approaches in large-scale educational analytics, especially in scenarios where data sovereignty and ethical AI deployment are paramount.

Future research could focus on several key extensions. First, integrating explainable AI (XAI) techniques within the federated framework would improve model transparency, enabling educators to understand the reasoning behind dropout predictions and thereby design more effective interventions. Second, exploring personalized federated learning could tailor predictions to specific learner profiles or course contexts, further enhancing accuracy. Third, incorporating multi-modal data sources such as sentiment analysis from discussion forums, facial engagement detection from video streams, and clickstream analytics could capture richer learner behavior signals. Additionally, optimizing communication efficiency through adaptive update frequencies or federated transfer learning could reduce resource consumption, enabling deployment on mobile or edge devices. Finally, longitudinal studies across academic terms and varied cultural contexts could validate the model's adaptability and long-term impact on learner retention. By advancing in these directions, future work can establish federated deep learning as a foundational technology for ethical, scalable, and context-aware educational analytics in the digital learning era.

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