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Combining Artificial Intelligence and Edge Computing to Reshape Distance Education (Case Study: K-12 Learners)

Chahrazed Labba¹, Rabie Ben Atitallah², and Anne Boyer¹

¹ University of Lorraine, Loria, France
{chahrazed.labba, anne.boyer}@loria.fr
² GSU - GalataSaray University, Turkey
{rabie.ben-atitallah}@expertisefrance.fr

Abstract. Nowadays, the use of distance learning is increasing, especially with the recent Covid-19 pandemic. To improve e-learning and maximise its effectiveness, artificial intelligence (AI) is used to analyse learning data stored in central repositories (e.g in cloud). However, this approach provides time-lagged feedback and can lead to a violation of user privacy. To overcome these challenges, a new distributed computing paradigm is emerging, known as *Edge Computing* (EC), which brings computing and data storage closer to where they are required. Combined with AI capabilities, it can reshape the online education by providing real-time assessments of learners to improve their performance while preserving their privacy. Such approach is leading to the convergence of *EC* and *AI* and promoting *AI at the Edge*. However, the main challenge is to maintain the quality of data analysis on devices with limited memory capacity, while preserving user data locally. In this paper, we propose an Edge-AI based approach for distance education that provides a generic operating architecture for an AI unit at the edge and a federated machine learning model to predict at real-time student failure. A real-world scenario of K-12 learners adopting 100% online education is presented to support the proposed approach.

Keywords: Real-time Feedback · Privacy · Federated learning

1 Introduction

In recent years, there has been a massive use of online courses, particularly with the current Covid-19 pandemic. Although the distance education helped in maintaining a certain continuity of the learning process, however it comes with several challenges related to the infrastructure cost and preserving learners privacy and security [6, 9–11]. Conventionally, data are collected and stored in centralised repositories to be later analyzed to fulfill various learning analytics objectives. However, with the excessive use of Internet of Things (IoT) technologies, there is an increasing amount of multi-source and heterogeneous data collected and analysed by educational institutions. This increase in data creates

a risk of bandwidth saturation, which increases latency and leads to overuse of computing resources. Recently, an alternative computing paradigm, Edge Computing (EC) is being proposed to solve the aforementioned issues. It consists in bringing computing and data storage closer to where they are required, which increase performance while reducing operating costs [13]. Combined with the use of AI, the Edge AI has multiple advantages such as bringing more security and confidentiality by allowing the filtering and the aggregation of data before sharing it at the network. The Edge AI can reshape the world of education today by offering the potential to preserve privacy and to improve student performance, confidence and mental well-being by delivering real-time feedback. The main idea is to use analytical models at the edge. These models as well as the way of their training on a distributed data and heterogeneous systems need to be redesigned. To meet this challenge, Federated Learning (FL) [7] is emerging as a promising technology. FL is a Machine Learning (ML) technology that enables collaborative learning of a common model by a number of entities (users, organizations) holding data locally. Unlike the traditional centralized ML approaches, FL does not require data to be uploaded to a central repository. This feature addresses our need for data privacy in online education.

In the frame of this work, we present how the Edge AI combined with FL can be used to reshape the distance education and ensure more data privacy while minimising the infrastructure usage. The proposed approach tackles at first the architecture of the AI unit to be used at the edge. An AI unit represents the device a learner can use in distance education. Secondly, we present a new scenario of using Edge AI with FL to predict k12-learners' failure. Indeed, the real case study consists of learning data collected and stored in a centralized repository within the National Center for Distance Learning (Cned³). To adapt the data to a federated use, we used the TensorFlow Federated (TFF)⁴ and the Artificial Neural Network (ANN) model to anticipate student failure as early as possible. The federated ANN was evaluated under different client sample selection strategies. The experimental results show that with proper selection of training samples in a federated setting, the federated model can be as good as the centralized model in anticipating students failure.

The rest of the paper is organized as follows: The section 2 presents the related works. Section 3 introduces our Edge AI based approach to reshape the distance education. In Section 4, we present the case study of K-12 learners enrolled within the Cned as well as the results of using a federated ANN model to predict student failure. Section 5 presents the conclusions, the threats to validity and the future works.

2 Related works

Techniques such as machine learning and data mining have been widely applied in the context of e-learning [5, 8, 14]. Despite the diversity of the AI techniques,

³ CNED: Centre national d'enseignement à distance

⁴ <https://www.tensorflow.org/federated?hl=fr>

the used methodology to apply them is common. It consists in collecting and cleaning the data, then extracting the features and applying the AI algorithms. Usually, the data is stored in central repositories (e.g Cloud), which may result in a breach of students privacy. According to [11], six distinct ethical concerns are identified within the context of big data and personalized learning, which are as follows: information privacy, anonymity, surveillance, autonomy, non-discrimination, and ownership of information. These concerns have been confirmed and discussed in numerous works [6, 9, 10]. Under the principle of data protection, in many fields such as healthcare and industry, data are not shared but stored and explored locally. Thus, in this case, we lose all the benefits brought by the use of big data technology. To address this problem, FL [7] is gaining momentum, especially with the emergence of the Edge AI paradigm. The principle of FL is that many entities collaboratively form a common model using their local learning data and communicate the updated model weights to a central server. No data is shared or exchanged between the different entities, thus reducing the risks related to privacy. An entity in FL can be a user (e.g IoT device) or an organization. Depending on the level of granulation of the FL application, we distinguish two types of research work. On one hand the works that focus on the inter-organisational FL such as in [2], The authors highlight the confidentiality issues that hinder data sharing between different industrial organizations. To address this challenge, they present how FL can be used to predict production line failures in different organizations. In [3], the authors proposed a FL-based education data analysis framework that can be used to build data analysis federations between many institutions. In [12, 15], FL based approaches have been proposed to address privacy issues and fully exploit the potential of AI in healthcare domain. On the other hand, other research works focus on the inter-devices (users) FL such as in [4], the authors used FL to predict the next word prediction in a virtual keyboard for smartphones. In [16, 17], FL is used to provide personalized recommendations to users.

In this work, we focus on the use of FL on Edge computing-based system for the distributed analytics in order to support real-time students' assessment. To our knowledge, we are the first to consider the application of FL at a fine-grained level to reshape online education. According to the literature review, FL in education [3] has only been addressed at the inter-institutional level.

3 Distributed Analytics and Edge Intelligence

In our work, we consider a generic distributed *EC*-based system composed of N AI units at the edge *EUs* and one Coordinator Server *CS* as illustrated in Fig.1. In such system, data analytics is distributed over all the nodes and conventionally only aggregated data or model parameters should be exchanged. However, if a raw data related to a given user is generated elsewhere, for example at the *CS* level, it can be transferred to the corresponding edge unit with a specific message. The *EUs* can be homogeneous or heterogeneous (PC, mobile terminal,

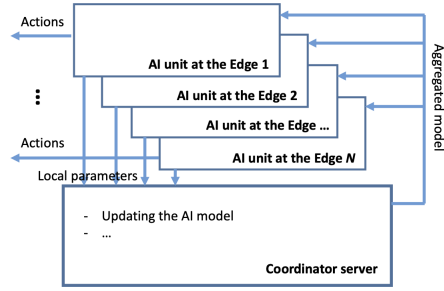


Fig. 1. Generic distributed EC-based system

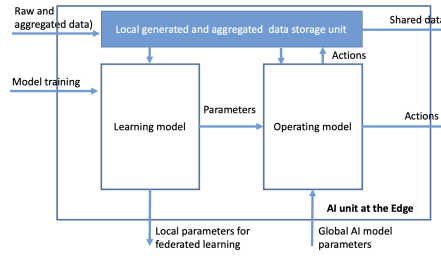


Fig. 2. AI-Edge unit architecture

industrial computer, IoT device, etc.) connected to the CS with a communication infrastructure (Ethernet, WIFI, LTE, etc.).

3.1 AI-Edge unit architecture

The key architectural feature of the distributed system is the EU. Let us consider \mathcal{U} the set of EUs. Each unit EU_i is characterized with a memory storage capacity M_i , a processing power P_i , and a communication bandwidth B_i with the CS. It incorporates three main functions: the operating model, the data storage unit, and the learning model as shown in Fig.2.

The operating model (OM): Depending on the application objective, this model can perform different type of actions recommendation, alerting, prediction, decision making, etc. In the literature, a multitude of techniques and algorithms are developed for each type of action regarding the size of the available data (*SAD*) as well as respecting some functional and non-functional constraints (e.g. real-time and energy consumption). In the Edge computing paradigm, the limited hardware resources lead rule-setting for the appropriate choice taking into consideration the computation cost of the algorithm and the *SAD*. These two parameters should fit respectively to the P_i and M_i of the corresponding EU_i . The execution of the operating model can be synchronised with a clock frequency f , the arrival of a new data, or the user request.

The operating model can be performed using the global AI model parameters collaboratively extracted on the CS or using the local parameters extracted from the learning model function. This last case is quite pertinent while considering specific user profile (e.g. disabled person).

After running the operating model, the generated actions will be communicated to the user as well as saved on the data storage unit for the next model training process (see Fig.2).

The data storage unit (DSU): It contains four data categories: raw data, aggregated data, previous actions, and the operating model parameters. At the edge, we have to deal with the challenge of the limited storage capacity. In order to achieve better AI model accuracy, data replacement policies should be defined

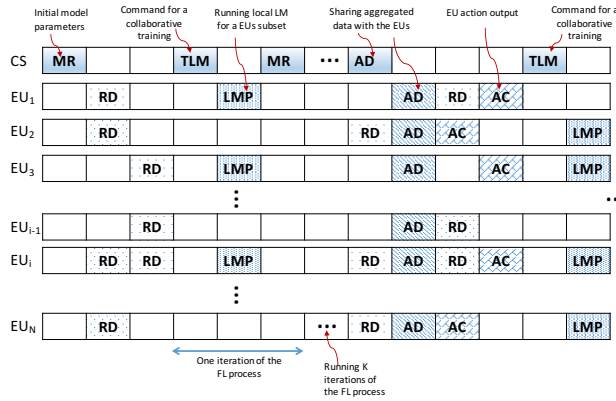


Fig. 3. Operating scenario with frame settings

to keep the most pertinent data for the operating and learning models. Referring to the cache memory replacement policies such as First in first out (FIFO), Most recently used (MRU), or Least recently used (LRU), these techniques can be adapted for our context. However in our knowledge, there is no specific research focusing on this aspect. As future work, we are planning to consider a cost function for each data and to evaluate its impact on the AI model accuracy. Indeed, we think that the data replacement at the Edge is an application-oriented challenge and it should be resolved according to the use case scenario.

The learning model (LM): It covers a large spectrum of learning techniques : symbolic (e.g. production rules) and machine learning (e.g. ANN, random forest, SVM). As same for the OM, the LM algorithm should 1) be adequate to the execution support characteristics (operating frequency, P_i and M_i), 2) satisfy non-functional constraints (e.g. energy consumption and thermal dissipation) while considering embedded devices (tracking static and dynamic obstacles for autonomous car), and 3) take into consideration the available small data (e.g. no sufficient data for running a deep learning algorithm).

As our main objective is to keep data closer to where they are generated, we propose a federated learning model well-traced on the distributed analytics EC-based system in order to respect the privacy of data and to train the AI model collaboratively with a subset of EUs $A \subset \mathcal{U} \rightarrow A \in \mathcal{P}(\mathcal{U})$. The M EUs samples of A can be selected randomly among the N EUs of \mathcal{U} or according to a guided strategy of sampling ($M \ll N$).

3.2 Communication protocol and high level system reconfiguration

In order to ensure data transmission between the CS and the EUs, we propose a generic and open communication protocol dedicated to the distributed Edge computing-based system. It is conceived at a high level of abstraction to be transport technologies-independent, thus allowing easy integration of emerg-

ing technologies. The encapsulation of the protocol in software components will guarantee the evolutionary as well as the scalability of the system according to the number of EUs. Communication between nodes is provided by high-level frames consisting of a sequence of fields that indicate:

- **Header:** The beginning of a new frame.
- **Type:** There are different types of frame: 1) *RD* (Raw Data), 2) *AD* for sharing Aggregated Data with EUs as it respects users’ privacy, 3) *TLM* is a command for a collaborative training of the learning model on a subset of the EUs, 4) *LMP* Local Model Parameters from an EU, 5) *MR* (Model Reconfiguration) is a broadcast of the global learning model to the EUs, and 6) *AC* (Action) corresponds to EU output.
- **Sender:** can be an EU or the CS.
- **Receiver:** that can be: 1) a specific EU (e.g. related raw data generated on the CS), 2) a subset of EUs (for the collaborative training process), 3) all EUs (updating the parameters of OM), or 4) the CS (receiving the local model parameters from an EU). We highlight that when a generated data should be stored locally the Sender and Receiver fields should have the same value.
- **Data:** According to the Type field, the transmitted information can be a raw data, aggregated data, actions (OM output), the global OM parameters, or the local extracted parameters from an EU.
- **Time:** All the generated and transmitted data are performed with time annotation for functional verification and the overall system synchronisation. For that reason, a Data Distribution Service (DDS) can be used in the distributed analytics system for better real-time performance.
- **Security:** allows encrypted data for an enhanced security.
- **Footer:** The end of the frame.

Fig.3 offers an operating scenario with frame settings covering the initialisation, the federated learning, and the operating model phases. At the beginning, the CS initiates a frame of Type *MR* that allows the EUs to download the initial OM parameters. After that, all the nodes start generating raw data through the users activities. Having enough data distributed on the system will trigger the frame *TLM* allowing several iterations of the FL process. In each iteration, the EUs share their local parameters (frame *LMP*) and receive the global extracted model (frame *MR*) from the CS. Over the time, the accuracy of the LM will be improved with the incremental process of learning and with sharing aggregated data (frame *AD*).

4 A Real Case Study: K-12 learners

As a proof of concept, this section presents how we can apply our Edge-AI based approach to the Cned context. In addition, it presents the results of experiments conducted to compare federated and centralized ANN models for predicting failure of K-12 learners enrolled at Cned. The data are initially centralized on

the cloud. To adapt them to our federated context, we used TFF, which is an open source framework developed by google for ML on decentralized data.

4.1 Context Description

The Cned provides a wide range of courses entirely online to k-12 learners who are geographically dispersed around the world. These learners have different demographic profiles and are unable to attend regular schools for many reasons. The Cned offers the courses through a Learning Management System (LMS) and provides with it a set of applications such as the education management system GAEL that allows administrative tracking of the students. All data are stored in a central repository and then analysed using ML techniques. For example, one of the main concerns of the Cned is to reduce the high failure rate among K-12 learners [1]. The Cned online teaching system has many limitations. First, as learners are physically dispersed around 173 countries, they do not make profit from the same quality of internet connection. Second, given the number of learners and the range of levels offered by the Cned, there is a huge amount of data generated on daily basis which has to be sent to a central repository without being filtered. For such a process, a powerful infrastructure in terms of bandwidth and storage resources is required. Third, sending user data containing sensitive information to a central repository may be exposed to security issues that could result in a breach of user privacy. Given all of these challenges, we believe that using our Edge-AI based approach is appropriate for reshaping distance learning at Cned.

The proposed approach (Section 3) can be easily transposed to the Cned context. Indeed, students connect to the LMS and other applications via their terminals (e.g smartphone, tablet, personal computer), which represent the EUs. Whereas the Cned storage infrastructure is considered as the CS. The number of EUs is equal to the number of students. An open question is whether the use of FL on EC-based systems allows building a reliable alert system that predicts student performance on a weekly-basis. Data is collected from two sources: the LMS platform and the education management system GAEL. In the frame of this work, our case study consists of K-12 learners enrolled in the physics-chemistry course during the 2017-2018 school year. In total, there are 46 weeks in the school year and 671 enrolled students that represents the number of EUs in our system.

4.2 Our approach to predict students performance per week

To predict students performances on weekly-basis, the problem is formalized as a n-classification problem. We adopted the same classification as well as features introduced in [1]. The classification consists of three classes: high failure risk, medium failure risk and success. On each week w_i , a student is defined by a tuple $X = (f_1, \dots, f_m, y)$ where f_1, \dots, f_m are the features and y is the class to predict. The student class may vary from one week to another. The selected features are extracted from the two data sources including the LMS and GAEL (the selected

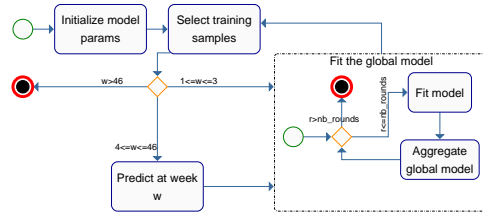


Fig. 4. Federated approach

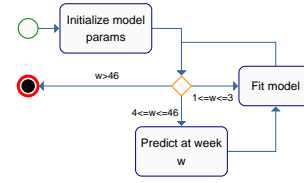


Fig. 5. Centralized approach

features are out of the scope of this work). For the reader information, the same features have been used to train and test both centralized and federated ANN models. Our main goal is to build an incremental ML model to predict student performance over time. To mimic a real situation, two approaches have been proposed: i) the centralized approach: as shown in Fig.5, we first initialize the model parameters, then we fit the model to the first three weeks of data. The choice of this number is not arbitrary and was set based on experimentation. Indeed, from week 4 on, the model starts to make good predictions. Each week, the model is tested on the current week’s dataset and then trained on it. At the end of each week, the model is updated and used to make predictions for the following week. ii) the federated approach: as shown in Fig.4, we adopt the same principle of weekly validation and training. The main differences with the centralised approach are: the use of federated data to train and validate the model as well as the way the model is built through the communication of model updates between the clients (EUs) and the server (CS). The process starts with the initialization of the model parameters (CS) and then selects the set of clients (EUs) that will participate in the model training phase. During the first three weeks, the model is simply adjusted to the data. from week 4 on, the model is tested to make predictions on the current week’s data, and then it is trained on the local data of the selected EUs. Each EU fits the model on its own data and then sends the model updates to the CS. The CS aggregates all the updates and sends the model back to the clients participating in the training phase. The training phase can last several rounds that are set on the basis of experimentation. The number of selected EUs for the training phase may vary from round to round as well as from week to week.

4.3 Experiment Results

Different configurations have been used to build and evaluate the federated incremental ANN model. A set of experiments have been conducted to find the best parameters for our model, including defining the optimizer, the learning rate and the number of rounds. Due to space limitations, the suitable parameters are directly presented in the Table.1 and will not be discussed. The configurations differ mainly in terms of the number of selected EUs (80, 100, 150, 186) to be

| | nb_clients (EU) | optimizer | nb_rounds | LR |
|----------|-----------------|-----------|-----------|----------|
| Config.1 | 80 | SGD-SGD | 15 | 0.02-1.0 |
| Config.2 | 100 | | | |
| Config.3 | 150 | | | |
| Config.4 | 186 | | | |

Table 1. Federated Configurations

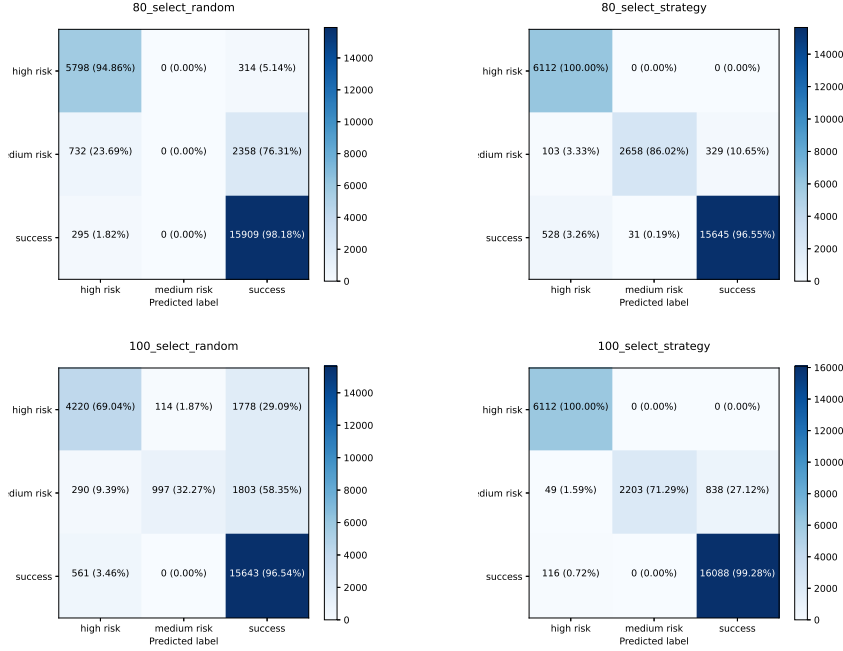


Fig. 6. confusion matrix

used during the training phase. In a federated context, this number is dynamic and may vary during the training sessions, since EUs can connect/disconnect at any time.

Impact of the client selection strategy on the quality of the predictions: The used data present imbalances with respect to the "medium risk failure" class. Consequently, this class is not well detected, especially when EUs participating in the training phase are randomly selected. First, we compared the accuracy of the federated model using different numbers of EUs (80 and 100) with two selection strategies. The first strategy consists in randomly taking a set of client samples, for the training, without checking the proportions of the 3 classes taken in it. The second strategy consists in selecting a set of clients with 30% of the samples belonging to the high-risk of failure class, 30% to the medium-risk of failure class and the rest to the success class. The Fig.7 represents the federated models accuracy on the test data. We note that models with

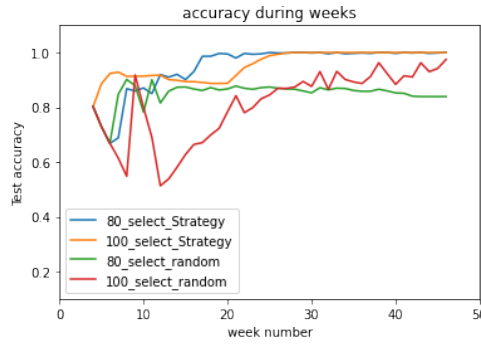


Fig. 7. Impact of clients selection strategy on accuracy

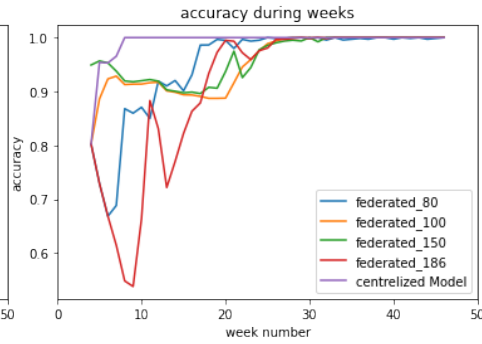


Fig. 8. Accuracy comparison: Centralized model VS Federated Ones

a guided strategy for selecting client(EU) samples for training perform better than this with random selection for both fixed numbers of samples (80 and 100). Since the accuracy measure does not distinguish between the number of correct labels from different classes, we present, in Fig.6, the confusion matrix for the four experiments. The matrices present the cumulative measures over all weeks. The main objective is to detect students at high and medium risk of failure in order to alert teachers about them and take the right action. We find that with a random selection strategy, there is a problem in classifying medium risk students and most of the time they are classified as successful. This classification is due to the fact that in the random sample, the medium-risk class is underrepresented compared to the rest of the classes. Therefore, we tried to guide the model during the learning phase by selecting samples that are balanced in terms of class representation. As shown in Fig.6, the medium risk class is better predicted under the guided selection strategy. In addition, we obtained 100% correct predictions for the high-failure risk.

Impact of the number of client samples on the quality of the predictions:

As shown in the Table. 1, we used four configurations (80,100,150,186). The guided selection strategy, presented above, is used for this experiment. As shown in Fig. 8, by varying the number of selected samples, the test accuracy over the weeks also changes. Indeed, we find that selecting more samples does not necessarily improve the accuracy of the model. For the performed experiments, training the model with 80 samples performs better, in terms of test accuracy, than training it with larger numbers of samples. Indeed, this may be a consequence of the used selection strategy. During the first weeks, some classes are poor in terms of the number of students that belong to them. Therefore, we cannot always have the total number of samples defined by the fixed rate (e.g. 30 % of the number of samples as medium-risk). However, with a smaller number of samples, during the learning phase, we can reach the full proportions of the different classes more quickly than by using a larger number of samples. The

rapidity is addressed in terms of the number of the week at which we begin to have a complete representation of all classes of students in the selected samples with respect to the predefined rate for each class. We believe it is important to determine the appropriate threshold that should be used as the number of EU samples to train the federated model.

Accuracy comparison: Centralized model vs Federated model

As shown in the Fig. 8 and as expected, the centralized model performs better than the federated models in terms of test accuracy. Each week, the centralized model is trained on all available data, while the federated models are trained on a subset of the data. However, the first thing to notice is that all the federated models eventually converge to reach an accuracy very close or even equal to that of the centralized model. In our context, the goal is to predict as early as possible when students are at high or medium risk of failure in order to take appropriate actions. Therefore, we need a federated model to achieve this goal. With the first three configurations 80, 100, and 150 respectively, the federated models have an accuracy that exceeds 85% as of the week 8 on. Thus, by selecting the appropriate number of EU samples, applying a good selection strategy and choosing the right parameters for training, the federated model can gradually approach the performance of the centralized model.

5 Conclusion, Threats to Validity and Future Work

Nowadays, distance learning presents multiple limitations including data privacy risks and high infrastructure costs in terms of bandwidth and computing resources to store big data. To overcome these challenges, we proposed to use an AI-based approach at the edge to perform distributed analytics while keeping the data stored where it is generated. Further, we presented a new scenario of using Edge AI with FL to predict k12-learners' failure. The experimental results are promising and show that with appropriate parameter settings in FL, we can still obtain good performance as the centralized approach.

The current work presents some limitations that we tried to mitigate when possible: i) As a proof of concept, one ML model (ANN) has been used. In the short term, we intend to apply other ML models such as decision trees. ii) The results presented are for the physics-chemistry course for the academic year 2017-2018. We plan to expand our work and consider students performance in different courses as well as across modules. iii) The results of the federated models are determined through the simulation environment TFF. The models need to be adapted for future use on IoT devices. Thus, a complexity study and encapsulation is required for future embedded implementation.

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