An Innovative Low-cost IoT-Based Asthma Exacerbation Prediction System Using Federated Learning*

Amine Dahane[1,2,3,*], Rabaie Benameur[1,2], Kheireddine Abainia[4], Dalila Benatta[6], Souheila Meneceur[1,3], Chemseddine Brakna[1,3], Amin Bouamar[1,7], Ghalem Belalem[1,7], Abdelmajid Snouber[1,6] and Abdelhamid Mellouk[5]

[1]*University of Oran 1, Oran, Algeria*
[2]*Laboratory of Industrial Computing and Networks (RIIR), Oran, Algeria*
[3]*Institute of Applied Science and Technology ISTA, Oran, Algeria*
[4]*PI: MIS Laboratory University 8 Mai 1945, Guelma, Algeria*
[5]*Image, Signal and Intelligent Systems (LiSSi) Laboratory, TincNET Research Team, Univ. Paris-Est Creteil, France*
[6]*Pulmonology Department, Oran University Hospital, Oran, Algeria*
[7]*Oran Computer Science Laboratory (LIO), Oran, Algeria*

Abstract

This paper presents the design and development of a fog-IoT/AI asthma exacerbation system with full functionality. The system was developed using open-source platforms that monitor real-time medical data. Users administer the Asthma Control Test (ACT) to determine the likelihood of asthma exacerbations. The asthma data set comprises panel data from 10 individuals, with 1010 ACT scores as the desired output. ACT scores 19 reflect uncontrolled asthma; >19 reflect well controlled asthma. This paper proposes a federated learning-based asthma exacerbation prediction system named FELAE. Specifically, the FELAE system protects data privacy through local learning, in which devices benefit from the knowledge of their peers by sharing only updates from their model with an aggregation fog layer that produces an enhanced prediction model. The results demonstrate that the FL approach outperforms the classic or centralized versions of machine learning (non-federated learning). Moreover, using the essential performance indicators, namely, accuracy, precision, f1score, and recall, the proposed model detects asthma exacerbations with the highest accuracy of 97.02%.

Keywords

IoT, Asthma exacerbation, Federated learning, Centralized model, Low-cost

1. Introduction

Healthcare Internet of Things (HIoT) refers to the application of Internet of Things (IoT) devices and sensors in the healthcare area. Connected to the internet and able to collect, transmit, and analyze data in real time [1]. In addition, H-IoT devices enable healthcare providers to more efficiently monitor and manage patients' health conditions in an optimal manner. More specifically, it seeks to improve patient outcomes, the quality of care, and healthcare costs. Thus, healthcare applications include telemedicine, smart hospitals, remote patient monitoring, and medication management [2] [3]. Among the applications, we find the following (Figure 1):

ECG monitoring. records the heart's electrical activity over time, aiding in diagnosing cardiac conditions like arrhythmias and heart disease. It's utilized in hospitals, clinics, and with devices like Holter monitors, event monitors, and loop recorders.

Temperature monitoring. Health IoT devices like wearable sensors and smart thermometers offer real-time body temperature data, transmitted to healthcare systems. Analysis of this data detects temperature trends or abnormalities for early intervention, benefiting patients and caregivers. Additionally, these devices aid in monitoring the health of vulnerable individuals, notifying caregivers of potential health concerns.

BP monitoring. Blood pressure monitoring assesses arterial force during circulation, vital for cardiovascular health and detecting conditions like hypertension. A sphygmomanometer, with cuff, gauge, and stethoscope, measures systolic (during heartbeats) and diastolic (between beats) pressures. These two numbers reveal crucial information about an individual's blood pressure and overall well-being.

6th International Hybrid Conference On Informatics And Applied Mathematics, December 6-7, 2023 Guelma, Algeria
*Corresponding author.
dahane.amine@univ-oran1.dz (A. Dahane); benameurrabaie@gmail.com (R. Benameur); k.abainia@gmail.com (K. Abainia); dfbenatta@gmail.com (D. Benatta); sawsenmaneceur@gmail.com (S. Meneceur); chemseddinebrakna@gmail.coml (C. Brakna); aminbouamar97@gmail.com (A. Bouamar); ghalem1dz@gmail.com (G. Belalem); majidsnouber@gmail.com (A. Snouber); mellouk@u-pec.fr (A. Mellouk)
0000-0001-6998-208X (A. Dahane); 0009-0001-7617-9057 (R. Benameur); 0000-0002-8703-2480 (K. Abainia); 0000-0002-9694-7586 (G. Belalem); 0000-0001-7116-9338 (A. Snouber); 0000-0002-6886-7394 (A. Mellouk)

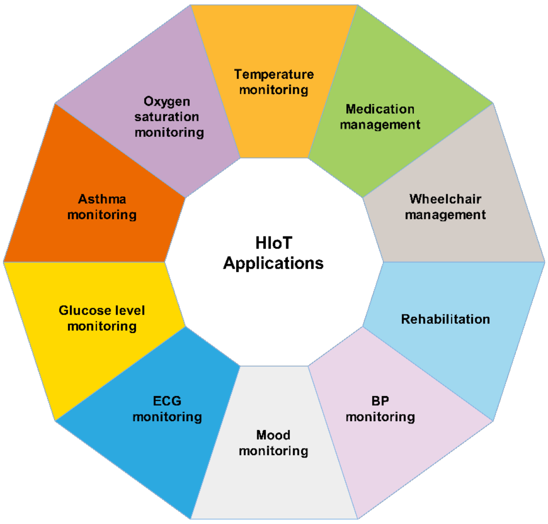

Figure 1: The classification of HIoT applications.

Oxygen saturation monitoring. Achieved through non-invasive devices like pulse oximeters, assesses the oxygen levels carried by red blood cells, aiding in respiratory function evaluation. This crucial process helps detect issues like hypoxia or respiratory failure by measuring SpO2, expressed as a percentage. Using light absorption, sensors on the fingertip or earlobe accurately determine peripheral oxygen saturation, making it a valuable health assessment tool.
Medication management. Encompasses safe and effective medication use, including prescribing, patient education, and monitoring for side effects. It plays a crucial role in optimizing patient health outcomes and minimizing adverse drug events. Effective medication management is essential for patient well-being.
Glucose level monitoring. is vital for diabetes management through various methods like blood glucose meters, CGM systems, or lab tests. Frequency and targets depend on individual needs. Mood monitoring. Utilizing tools like mood diaries or apps, aids in tracking and recording emotional states. It assists those with mental health conditions by revealing patterns, identifying triggers, and guiding treatment decisions, commonly used for depression, anxiety, or bipolar disorder.
Wheelchair management. Encompasses assessing mobility needs, choosing the right wheelchair, and ensuring its safe and effective utilization. It enhances independence and well-being while preventing complications and improving functional outcomes for those with mobility impairments.
Asthma monitoring. Asthma control tests, peak flow meters, spirometry, and electronic health records are used to track an individual's asthma symptom diaries, night waking up, activity limitation, lung function, and medication usage over time. It is a critical tool for asthma management, changing treatment programs, and lowering the risk of asthma exacerbations. Individuals who have effective asthma monitoring may attain optimum asthma management and enhance their quality of life. The symptoms of asthma can vary in severity and may include:

- Wheezing: A whistling sound when breathing out;
- Wheezing: A whistling sound when breathing out;
- Chest tightness: A feeling of tightness or pressure in the chest;
- Shortness of breath: Difficult breathing, especially during physical activity [4].

In this paper, we discuss the latest achievements in the tackled field by focusing on different asthma care approaches as well as describing some relevant healthcare applications to our system. The impact of meteorological conditions on people with asthma is characterized by distinct and unique patterns, which may be attributed to the intrinsic diversity in lung function found among asthmatic patients. The extent of this diversity is dependent on demographic characteristics, such as age and gender. In addition, the geographic location adds an additional level of complication since the connection between meteorological conditions and the symptoms of asthma demonstrates inconsistency across various climatic zones. Moreover, asthma systems are data-hungry, and data is scattered over several hospitals with privacy limitations in place. Traditional ML solutions need centralized data collection and processing, which is becoming more impractical due to efficiency challenges and growing data privacy concerns [5]. As an outcome of these limitations, in 2017, Google introduced the federated learning (FL) approach, where the objective is to train a high-quality centralized model using training data dispersed over a large number of clients, each with unreliable and generally sluggish network connections. As a result of these features and inspiration from the previous federated systems, FL is a hot research topic in smart HIoT. For example, the data of several hospitals is segregated and forms "data islands." Due to each data island's size and approximation constraints, a single hospital may not be able to train a high-quality model with excellent prediction accuracy for a particular application. In addition, regulations cannot force hospitals to provide data in many cases. However, hospitals participating in FL can benefit from it, e.g., with higher model accuracy. A challenging problem is designing a fair incentive mechanism to allow the contributing entity to benefit from FL. The rest of the paper is organized as follows: Section 2 briefly surveys the related works. Sections 3 and 4 provide the materials and methods used in this study, as well as the results of the comparative study and the performance evaluation. Finally, Section 5 concludes the paper and outlines the perspectives for future work.

2. Related works

In this section, we present and review recent research works on IoT-based asthma exacerbation prediction systems that investigate the most recent developments and challenges in this field. By analyzing these studies, we hope to provide insights and recommendations for future IoT-based asthma prediction system research directions. Raherison-Semjen et. al [6] addressed asthma management during pregnancy and the influence of environmental factors on asthma. It emphasizes the significance of taking risk factors and prospective comorbidities into account in asthma management and individualized management plans for asthma patients. Oletic and Bilas [7] described a method for detecting asthmatic wheezing noises using compressive sensing and machine learning techniques to analyze respiratory sound spectra. Using a digital stethoscope, the authors acquired respiratory sound data from asthmatic and non-asthmatic subjects. The proposed method detects asthmatic wheezing sounds with high accuracy and has potential applications in portable and non-invasive asthma monitoring devices. Using computer science (CS) and ML techniques, the study presents a promising strategy for the development of an automated and accurate asthmatic wheezing detection system. Anan et. al [8] described the creation of an IoT-based remote health monitoring system for asthmatic patients. The system consists of an Android application, a website, and multiple sensors to collect health-related data and facilitate communication between physicians and patients. The system was determined to be accurate and affordable for low-income asthma patients after being tested on actual human subjects. Tsang et. al [9] reviewed the use of machine learning algorithms in mobile health for asthma management. The review highlighted the potential of machine learning to improve asthma management but also noted the need for larger sample sizes and external validation of algorithms before they can be used in clinical practice. The article discussed various studies on the use of machine learning algorithms for asthma management, including activity detection and breathing monitoring. A fog-driven IoT e-Health surveillance and control framework for asthma exacerbations is proposed by Maach et al. [10]. The framework gathers physiological data from asthma patients using ubiquitous sensors, then processes the data using fog nodes and cloud computation. By providing personalized and timely interventions, the proposed framework is scalable and has the potential to enhance asthma patients' quality of life. The effectiveness of the proposed framework for monitoring and regulating asthma exacerbations is demonstrated through a case study. The previous discussion made it evident that there are some gaps in the literature, including privacy concerns, computational issues, and accuracy limitations for centralized models, all of which must be successfully addressed to secure smart HIoT data. This paper presents the FELAE framework to solve these challenges. Sharing patient electronic health information across hospitals may not be possible due to the sensitive nature of healthcare data. In such cases, FELAE offers a viable approach, enabling the creation of a collaborative learning model for asthma data. The main contributions of this paper are as follows:

- The design and development of a low-cost IoT/AI asthma exacerbation system.
- We investigate the implementation of three deep learning classifiers: deep neural networks (DNNs), convolutional neural networks (CNNs), and long short-term memory recurrent networks (LSTMs) architectures.
- In addition, we present a comprehensive performance evaluation and comparison between the FL approach and centralized learning models.

3. Materials and methods

The IoT platform architecture, as shown in Figure 2, has been proposed to collect, transmit, and process the physical parameters (temperature, humidity, O2, air flow) of patients along with the weather forecast information to manage the decision of asthma exacerbation. In our study, it is necessary to transform pressure readings into airflow. We convert the values obtained from the MPX5010 sensor to kilopascals (kPa), utilizing a scale ranging from 0 to 40 kPa. As depicted in Figure 2, the network component of our platform is supplied via multi-hop communication between box A (the data collection layer) and box B (the gateway node or fog layer) in order to deploy classification and prediction models. We have used the NRF24L01+ (i.e., 2.4Ghz radio) module for wireless communication and the Atmega328P (with Arduino bootloader) as microcontrollers, as well as Raspberry Pi 3 B+ as a fog layer. Data is stored closely in the fog layer, so doctors can rapidly access data during interventions. In addition, asthma data is accessible even if the internet connection is temporarily lost. Processing and validating data at the fog level reduces the data transmitted to the cloud and conserves the energy consumption and global network bandwidth. In a centralized learning configuration, as illustrated in Figure 3, every client uploads his data to a centralized deep learning server to train the prediction model. In contrast, with the FELAE framework, the entire process is adapted from the basic and widely used

Table 1
Summary of Studies on Asthma Monitoring

Ref.	Studies	Measurements	Sensors Used	CL	FL	Low Cost
[6]	This study covers the diagnosis and management of asthma...	Several measurements including FeNO, PEFR, FEV1, etc.	Various diagnostic tests, Spirometry, Chemiluminescence or Electrochemical Analyzer, Peak flow meter	No	No	No
[7]	The article describes a method for detecting asthmatic wheezing sounds...	Respiratory sound measurements using auscultation, STFT for spectrograms	Wearable wireless acoustic sensor and smartphone system	Yes	No	No
[8]	The paper describes the development of an IoT-based remote health monitoring system...	Tested on real human test subjects, sensors include MAX30100, MLX90614, DHT11, MQ-135	Body temperature, Pulse rate, Humidity, Temperature, Air quality, Blood pressure	No	No	No
[9]	This paper reviews the use of machine learning algorithms in mobile health for asthma management...	Use of machine learning algorithms for monitoring breathing sounds, lung function, activity, etc.	Various wearable sensors, smartwatches, portable sleep diagnostic devices, electronic nose, peak flow meters, spirometers	Yes	No	No
[10]	Authors propose a fog-driven IoT e-Health framework for monitoring and controlling asthma exacerbation...	Air temperature, air pollution measurements using wireless sensors	Wireless sensors	Yes	No	No
Our Study	The study presents the design and development of a low-cost and full-featured fog-IoT/AI asthma exacerbation system...	Air temperature, Air humidity, Airflow, Heart rate, Oxygen saturation	DHT22, Max30100, MPX5010	Yes	Yes	Yes

framework of Federated Averaging (FedAvg) [5] [11]. In particular, instead of training and assessing the model on a single machine, all the clients train their local models sharing the same structure, but with distinct and individual datasets. Subsequently, the trained local models are submitted to the aggregation server that combines all the models to produce a single global model with optimized parameters. This method allows the participants (typically the hospitals) to share knowledge while protecting the confidentiality of their sensitive information. Importantly, this collaborative approach eliminates the need for a high-authorization third party, a requirement frequently associated with high levels of trust and sturdiness. Such a requirement may impose financial restrictions that inhibit broader participation in FL-related initiatives. The current version of our system uses four floating values to transmit, as well as the user's ID code. Each floating value is encoded in 4 bytes, while the user's ID code is encoded in 8 bytes. Overall, we have 32 bytes to transmit from the emitter to the receiver. NRF24L01+ modules are configured to transmit and receive 32 bytes at a rate of 2 Mbps for real-time monitoring. However, due to the collisions and connections lost, we have implemented a mechanism for auto-restarting the module after finishing each transmission. This feature causes a minor delay, but it ensures the stability of the transmission over time.

4. Results and discussion

In this section, we first detail the dataset and experimental settings used in this work before assessing our proof-of-concept FELAE scheme implementation.

4.1. Experimental setup

Our experiments were carried out using Google Colaboratory [12], where Python 3 served as the primary programming language. The implementation of Convolutional Neural Networks (CNNs), Deep Neural Networks (DNNs), Long Short-Term Memory networks (LSTMs), and FL models leveraged widely recognized libraries. Specifically, we utilized NumPy for the manipulation of multidimensional arrays and matrices, as well as Pandas for the manipulation of data structures and the utilization of rich analytical tools.

4.2. Dataset preprocessing

Data preprocessing is the first stage in which the unprocessed input data is filled, digitized, and normalized. Fortunately, the chosen dataset has no missing NaN values, and the corresponding numerical data are all digitized. In this study, we used existing datasets in the context of the asthma dataset with the target variable ACT score.

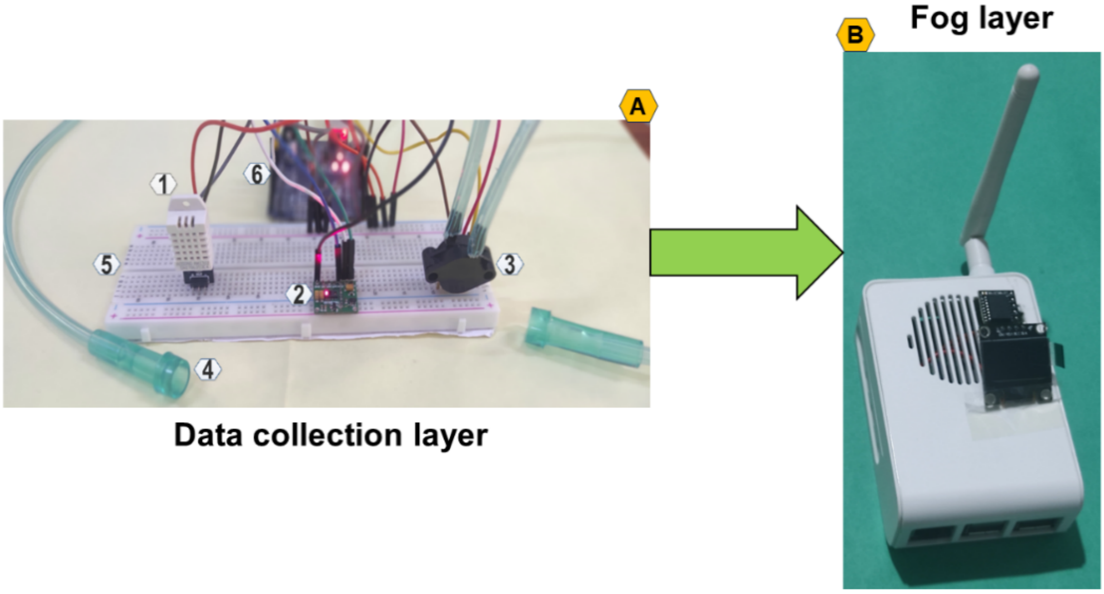

Figure 2: Hardware components involved on the prototype experiment, Data collection: [Legends 1: DHT22 Sensor, 2: max30100, 3: MPX5010 differential Pressure sensor, 4: Pipe attached to the MPX5010 sensor, 5: Breadboard, 6: Arduino uno board]; Fog layer: [Raspberry pi3, Small Oled displays], NRF24L01 module for the transmission.

ACT scores 19 reflect uncontrolled asthma; >19 reflect well controlled asthma [4]. The provided dataset [13] [14] is divided in half at an 80:20 ratio. In other words, 80% of the data is utilized for training, while the remaining 20% is used for testing. Additionally, 80% of the data from the training step is divided into K=4 clients, each representing a hospital's data in our example. For the data distribution among the various clients, we employed independent and identically distributed (IID): Each FL client's data distribution aligns with the distribution of all the dataset's data.

4.3. Performance evaluation metrics

The metrics used for evaluating the models include precision, recall, F1 score, and accuracy. They are calculated as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + FP + TN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{F1-score} = \frac{2 \cdot (Precision \cdot Recall)}{Precision + Recall} \tag{4}$$

- True Positive (TP): reports the number of ACT scores samples that are correctly classified as well controlled asthma.
- False Positive (FP): reports the number of ACT scores samples that are wrongly classified as well controlled asthma.
- True Negative (TN): reports the number of ACT scores samples that are correctly classified as uncontrolled asthma.
- False Negative (FN): reports the number of ACT scores samples that are wrongly classified as uncontrolled asthma.
- Accuracy: reports the proportion of properly categorized samples to all other samples in the testing set.
- Precision: reports the percentage of samples properly categorized for all TP and FP in the testing set.
- Recall: the ratio of TP samples to the total number of TP and FN samples is known as recall.
- The F1-score reports the harmonic mean between precision and recall.

4.4. Severity of asthma classification through centralized learning

Table 2 displays the precision, recall, accuracy, and F1-score for binary-class classification for the centralized

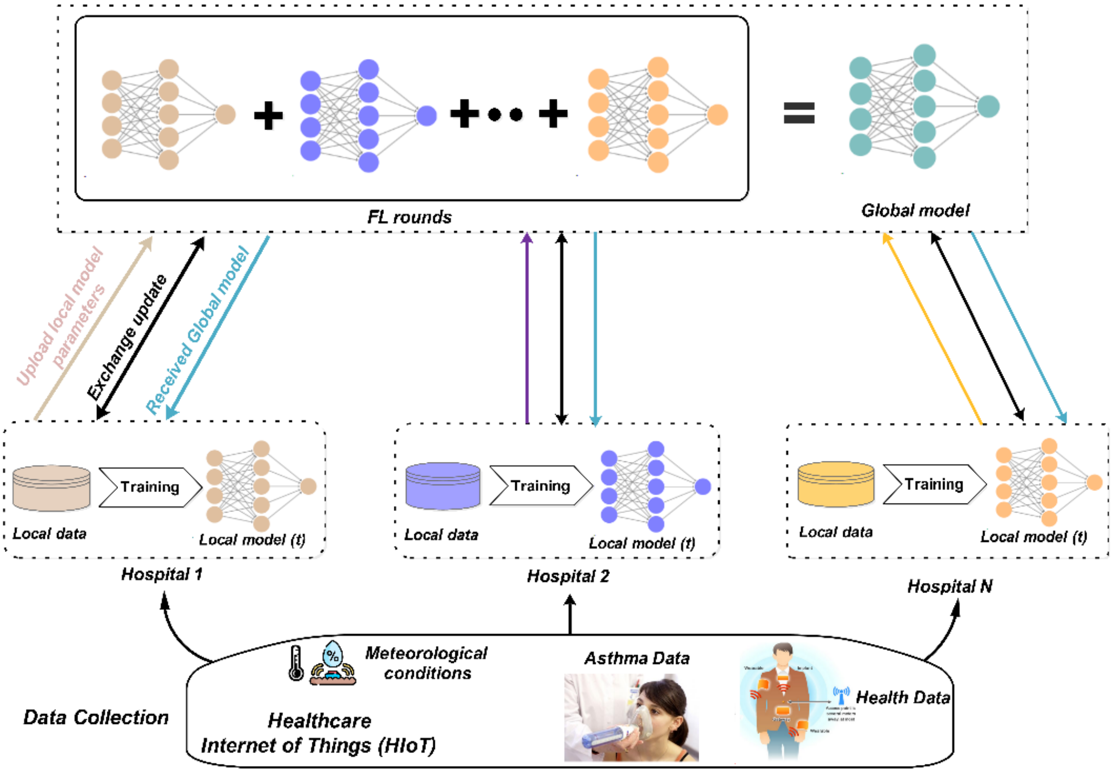

Figure 3: Centralized vs. federated learning approaches.

model that used deep learning methods. It shows how well the model performs in predicting the severity of asthma for specific asthmatic patients (well controlled asthma, uncontrolled asthma). In this analysis, we employed three distinct neural network architectures, CNN, LSTM, and DNN, to forecast the severity of asthma for specific patients in four different clients. We evaluated the outcomes using various performance metrics, including accuracy, F1-score, recall, and precision. To begin, we assessed accuracy, a measure of overall correctness.

Table 2 shows that the CNN architecture consistently achieved the highest accuracy across the clients, ranging from 84.15% to 88.11%. The DNN architecture also demonstrated respectable accuracy, ranging from 78.71% to 90.59%. In contrast, the LSTM architecture consistently exhibited the lowest accuracy, ranging from 72.27% to 88.61%. Next, we considered the F1-score, which balances precision and recall. The analysis revealed that the DNN architecture consistently had the highest F1 score across all clients, indicating its effectiveness in classification. The CNN architecture also displayed robust F1 scores, while the LSTM architecture needed to catch up, suggesting difficulties in achieving high precision and high recall. Turning to recall, a measure of the model's ability to identify positive instances, both the CNN and DNN architectures generally outperformed the LSTM. This indicated their superior capability in identifying patients with severe asthma, which is especially noteworthy given the absence of sequential data patterns in this context. Lastly, precision, which measures the model's ability to classify positive instances accurately, illustrated that the DNN architecture consistently maintained higher precision in most clients, implying a lower rate of false positives. Conversely, the LSTM architecture produced more false positives, resulting in lower precision scores. In summary, the DNN architecture emerged as the most effective choice for predicting asthma severity across the clients, consistently excelling in accuracy, F1 score, and precision. The CNN architecture also performed admirably, particularly in identifying cases of severe asthma. The DNN architecture emerged as the most effective choice for predicting asthma severity across hospitals, consistently excelling in accuracy, F1 score, and precision. The CNN architecture also performed admirably, particularly in identifying cases of severe asthma.

Table 2
Performance Metrics of Different Models on Various Clients

Models	Clients	Accuracy	F1-score	Recall	Precision
CNN	Client 1	0.8415	0.8457	0.8415	0.8777
	Client 2	0.8514	0.8554	0.8514	0.8874
	Client 3	0.8762	0.8789	0.8762	0.8941
	Client 4	0.8811	0.8826	0.8811	0.8870
LSTM	Client 1	0.7772	0.7820	0.7772	0.7978
	Client 2	0.7227	0.7269	0.7227	0.7328
	Client 3	0.8861	0.8844	0.8861	0.8852
	Client 4	0.7970	0.7843	0.7970	0.7974
DNN	Client 1	0.7871	0.7929	0.7871	0.8355
	Client 2	0.7821	0.7602	0.7821	0.7920
	Client 3	0.8712	0.8746	0.8712	0.9024
	Client 4	0.9059	0.9067	0.9059	0.9086

4.5. Severity of asthma classification through federated learning

In this experiment, we demonstrate the feasibility of a FELAE framework. This method requires the participation of multiple clients, specifically hospitals, to share knowledge while protecting the confidentiality of their sensitive information. Importantly, this collaborative approach eliminates the need for a high-authorization third party, a requirement frequently associated with high levels of trust and sturdiness. Such a requirement may impose financial restrictions that inhibit broader participation in FL-related initiatives. To evaluate our proposed FELAE scheme, we have conducted a series of tests. These investigations involved the construction of a controlled FL environment in which deep learning models (i.e., CNN, DNN, and LSTM) were implemented on a Raspberry Pi 3 board. The figures 4, 5, and 6 show how well all four global models worked over 10 rounds, with three different deep-learning classifiers used for each client (hospitals). It is worth mentioning that the FL training process is done over 10 rounds, where each model is saved after every round to avoid overfitting after a long period of training. The primary conclusion drawn from this study is the discernible improvement in precision as a function over iterative rounds across all FL global models. This improvement signifies the concurrent progress and mutual benefits realized by all the participants due to their participation in the global model. A notable corollary observation is that, in certain instances, global models have demonstrated the ability to approach or closely rival the performance levels attained by the centralized model. In the evaluation, we ran the FL training process for 10 rounds. However, we save the global model at each round to avoid overfitting issues after a long training period. Table 3 shows a full analysis of how well three different neural network architectures CNN, DNN, and LSTM can predict the severity levels of asthma in a dataset of patients. The CNN classifier exhibits notable proficiency in accurately discerning patients as either 'well controlled' or 'uncontrolled, boasting many true positives in these categories.

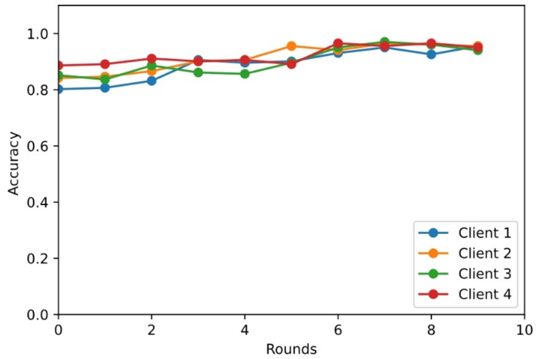

Figure 4: Learning performances using a FedAvg-based CNN-model.

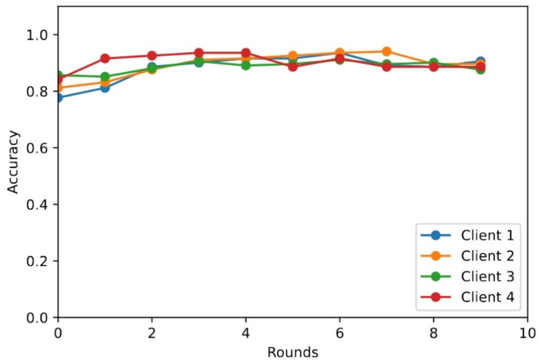

Figure 5: Learning performances using a FedAvg-based DNN-model.

Conversely, the DNN classifier accurately identifies patients at the extremes of well-controlled and uncon-

Table 3
Comparative study performance evaluation of federated models.

Models	TP	TN	FP	FN	Accuracy	F1-score	Recall	Precision
CNN	132	64	4	2	0.9702	0.9701	0.9702	0.9702
LSTM	128	52	16	6	0.8910	0.8887	0.8910	0.8914
DNN	130	60	8	4	0.9405	0.9401	0.94059	0.9405

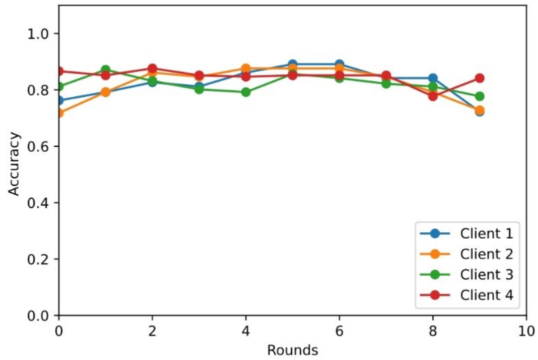

Figure 6: Learning performances using a FedAvg-based LSTM-model.

trolled asthma, achieving high true positive rates. Nevertheless, it also needs help classifying 'partially controlled' cases, as it tends to make false predictions of 'well controlled' and 'uncontrolled'. The LSTM classifier accurately distinguishes between well-controlled and uncontrolled asthma cases, with notable true positives in these extreme categories. According to Table 3, the CNN model stands out as the top performer among the three evaluated deep learning models, with a substantial accuracy of 97.02%. It excels at accurately categorizing patients with varied levels of asthma severity and a substantial number of true positives and true negatives. Notably, the F1-score, a metric balancing precision and recall, reaches an impressive score (i.e., 97.01%), highlighting the model's effectiveness in minimizing false positives while capturing true positives. In contrast, the LSTM model, although reasonably accurate with an 89.10% accuracy rate, grapples more with false positives and negatives. As a result, its F1-score and precision are lower than those of CNN, indicating difficulties in striking the ideal balance between precision and recall. Finally, DNN reports good performances with 94.05% accuracy. Like CNN, it maintains an effective equilibrium between precision and recall, leading to a high F1 score (i.e., 94.01%). Furthermore, its precision slightly outperforms CNN, which lowers the number of false positives. As presented in Table 3, CNN can perform better with 97.02%, 94.05% for DNN, and 89.10% for LSTM, respectively. Overall, through these experiments, we can highlight that CNN is the more reliable and ranked first due to the strengths of extracting the category features.

5. Conclusions and future trends

This research paper proposes an innovative, low-cost, IoT-based asthma exacerbation prediction system using the FL approach. Our proposed system aims to provide asthma patients a user-friendly solution for monitoring their symptoms and anticipating potential crises. The three phases of data collection, analysis, and treatment serve as a road map for the system's ongoing development. It is essential to acknowledge that there are several perspectives for the future enhancement of this project. As we continue our work, we plan to explore additional features and functionalities to improve the system's effectiveness. The following recommendations summarize the research challenges that could enhance the performance of the proposed asthma exacerbation system:

- Using the proposed low-cost IoT/AI asthma exacerbation system in order to generate our dataset for the pulmonology department at the university hospital in Oran.
- Use teacher and student networks and knowledge distillation (KD) techniques to make models smaller, faster, and more efficient.
- Include the most specific asthmatic symptom in respiratory sounds, such as wheezing, in our dataset.

Acknowledgments

The mixed team IA-Respir, approved in January 2022 under "Respiratory pathologies via artificial intelligence," supports this work. The authors would like to acknowledge the medical team of the pulmonology department, Oran University Hospital, and the Thematic Research Agency in Health and Life Sciences (ATRSSV).

References

[1] A. Dahane, N.-E. Berrached, Mobile, wireless and sensor networks: A clustering algorithm for energy efficiency and safety, 2019. URL: http://dx.doi.org/10.1201/9781351190756. doi:10.1201/9781351190756.

[2] A. Mwangi, E. Ndashimye, B. Karikumutima, S. K. Ray, An iot-alert system for chronic asthma patients, in: 2020 11th IEEE Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), IEEE, 2020. URL: http://dx.doi.org/10.1109/IEMCON51383.2020.9284816. doi:10.1109/iemcon51383.2020.9284816.

[3] G. S. Bhat, N. Shankar, D. Kim, D. J. Song, S. Seo, I. M. S. Panahi, L. Tamil, Machine learning-based asthma risk prediction using iot and smartphone applications, IEEE Access 9 (2021) 118708–118715. URL: http://dx.doi.org/10.1109/ACCESS.2021.3103897. doi:10.1109/access.2021.3103897.

[4] J. Davitte, B. DeBarmore, D. Hinds, S. Zhang, J. Chao, L. Sansbury, Asthma control among treated us asthma patients in practice fusion's electronic medical record research database, npj Primary Care Respiratory Medicine 33 (2023). URL: http://dx.doi.org/10.1038/s41533-023-00338-7. doi:10.1038/s41533-023-00338-7.

[5] Q. Li, Z. Wen, Z. Wu, S. Hu, N. Wang, Y. Li, X. Liu, B. He, A survey on federated learning systems: Vision, hype and reality for data privacy and protection, IEEE Transactions on Knowledge and Data Engineering 35 (2023) 3347–3366. URL: http://dx.doi.org/10.1109/TKDE.2021.3124599. doi:10.1109/tkde.2021.3124599.

[6] C. Raherison-Semjen, L. Guilleminault, I. Billiart, C. Chenivesse, A. De Oliveira, A. Izadifar, A. Lorenzo, C. Nocent, J. Oster, M. Padovani, T. Perez, M. Russier, M. Steinecker, A. Didier, Mise à jour des recommandations (2021) pour la prise en charge et le suivi des patients asthmatiques adultes sous l'égide de la société de pneumologie de langue française (splf) et de la société pédiatrique de pneumologie et allergologie (sp2a). version longue, Revue des Maladies Respiratoires 38 (2021) 1048–1083. URL: http://dx.doi.org/10.1016/j.rmr.2021.08.002. doi:10.1016/j.rmr.2021.08.002.

[7] D. Oletic, V. Bilas, Asthmatic wheeze detection from compressively sensed respiratory sound spectra, IEEE Journal of Biomedical and Health Informatics 22 (2018) 1406–1414. URL: http://dx.doi.org/10.1109/JBHI.2017.2781135. doi:10.1109/jbhi.2017.2781135.

[8] S. R. Anan, M. A. Hossain, M. Z. Milky, M. M. Khan, M. Masud, S. Aljahdali, Research and development of an iot-based remote asthma patient monitoring system, Journal of Healthcare Engineering 2021 (2021) 1–21. URL: http://dx.doi.org/10.1155/2021/2192913. doi:10.1155/2021/2192913.

[9] K. C. Tsang, H. Pinnock, A. M. Wilson, S. A. Shah, Application of machine learning algorithms for asthma management with mhealth: A clinical review, Journal of Asthma and Allergy Volume 15 (2022) 855–873. URL: http://dx.doi.org/10.2147/JAA.S285742. doi:10.2147/jaa.s285742.

[10] A. Maach, J. el Alami, E. H. el Mazoudi, A fog-driven iot e-health framework to monitor and control asthma exacerbation, in: 2019 International Conference on Wireless Networks and Mobile Communications (WINCOM), IEEE, 2019. URL: http://dx.doi.org/10.1109/WINCOM47513.2019.8942540. doi:10.1109/wincom47513.2019.8942540.

[11] H. B. McMahan, E. Moore, D. Ramage, S. Hampson, B. A. y. Arcas, Communication-efficient learning of deep networks from decentralized data (2016). URL: https://arxiv.org/abs/1602.05629. doi:10.48550/ARXIV.1602.05629.

[12] Google, Google Colaboratory, https://colab.research.google.com/, 06.01.2024.

[13] R. Haque, S.-B. Ho, I. Chai, A. Abdullah, Optimised deep neural network model to predict asthma exacerbation based on personalised weather triggers, F1000Research 10 (2021) 911. URL: http://dx.doi.org/10.12688/f1000research.73026.1. doi:10.12688/f1000research.73026.1.

[14] 1191402606, 1191402606/Optimised-deep-neural-network-model: Dataset and source code, 2021. URL: https://doi.org/10.5281/zenodo.5271780. doi:10.5281/zenodo.5271780.