Edge-Fog-Cloud Data Analysis for eHealth-IoT

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Abstract—Thanks to advancements in artificial intelligence and the Internet of Things (IoT), eHealth is becoming an increasingly attractive area for researchers. However, different challenges arise when sensor-generated information is stored and analyzed using cloud computing. Latency, response time, and security are critical concerns that require attention. Fog and Edge Computing technologies have emerged in response to the requirement for resources near the network edge where data is collected, to minimize cloud challenges. This paper aims to assess the effectiveness of Machine Learning (ML) and Deep Learning (DL) techniques when executed in Edge or Fog nodes within the eHealth data. We compared the most efficient baseline techniques from the state-of-the-art on three eHealth datasets: Human Activity Recognition (HAR), University of Milano Bicocca Smartphone-based Human Activity Recognition (UniMiB SHAR), and MIT-BIH Arrhythmia. The experiment showed that for the HAR dataset, the Support Vector Machines (SVM) model was the best performer among the ML techniques, with low processing time and an accuracy of 96%. In comparison, the K-Nearest Neighbors (KNN) performed 94.43, and 96%, respectively, for SHAR and MIT-BIH datasets. Among the DL techniques, the Convolutional Neural Network with Fourier (CNNF) model performed the best, with accuracies of 94.49% and 98.72% for HAR and MIT-BIH. In comparison, CNN achieved 96.90% for the SHAR dataset.

Keywords—IoT, machine learning, eHealth, cloud, fog, edge

1 Introduction

IoT is the idea of interconnecting devices and physical objects via the internet [1]. Several applications have emerged through the combination of IoT technologies and the extensive computing and storage capabilities provided by cloud computing [2]. Intelligent homes utilize IoT devices, like smart thermostats, lights, and security cameras, to enable remote control. Similarly, smart agriculture leverages IoT sensors to gather data, such as soil moisture and temperature, to optimize irrigation and fertilization processes in farm fields. EHealth is among the most widely adopted uses of information and communication technology, and it has made significant contributions to healthcare delivery by providing high-quality care and ubiquitous access at a cheap cost. Also, is a particularly demanding application of IoT and cloud computing due to its direct impact on human lives. Several eHealth applications [3] exist such as 1)Wearable fitness use sensors to gather data on a user's physical activity, sleep, and other health-related metrics; 2) Remote monitoring systems use IoT devices, such as blood pressure monitors and glucose monitors, to gather data on a patient's health; 3) Clinical decision support systems use data from electronic health records and other sources to provide healthcare with real-time guidance on diagnosis and treatment options; and 4) Public health management can be used to collect and analyze data on the health of a population, enabling the identification of disease trends and the development of targeted interventions to improve the health of the population. EHealth data is then transmitted to the cloud, where patients and healthcare providers for analysis and monitoring can access it. Cloud computing facilitates the storage, processing, and analysis of massive databases by enabling access to high-capacity servers. In eHealth applications, real-time recording of clinical data, patient examinations, observations, and actions is often necessary. However, processing in the cloud can result in delays when transferring data from devices to cloud servers. In addition, this approach has a significant issue, particularly when data is stored in poorly secured systems and applications. Innovative solutions, like cloudlets, fog, and edge computing, aim to solve these challenges. Edge computing (EC) [4] improves IoT systems' efficiency, reliability, and security by bringing computation and data storage closer to the source. This results in faster response times, reduced costs, lower latency, decreased bandwidth usage, and improved data security through local processing and storage. Several related edge computing paradigms have emerged, which vary based on the application type and deployment context [5]. Fog, Mobile Edge Computing (MEC), and Cloudlet are the most widely discussed. The Fog computing [6] paradigm is a virtualized platform that Cisco has introduced to enable IoT applications to operate directly at the network Edge. It was designed to provide low latency, location awareness, mobility, support for many nodes and users, a higher representation of streaming and real-time applications, and reduce security-related issues [3]. MEC [7] was standardized by the European Telecommunications Standards Institute (ETSI) to bring cloud computing capabilities closer to mobile subscribers. This is achieved by deploying computing services at the edge of the mobile network, usually through the base station. MEC is based on a virtualized platform and provides low latency service, high bandwidth, real-time network information, and data location awareness. The concept of a cloudlet was initiated by Carnegie Mellon University (CMU) as a way to provide local, distributed computing resources for users who are located near the edge of the network. Cloudlets are small-scale, more resource-constrained virtualized data centers that can be deployed in a distributed way [8].

The term "eHealth" refers to a number of topics associated with using digital technology in healthcare. Specifically, eHealth refers to the use of electronic tools and systems to support a variety of healthcare-related activities, including the collection, storage, and analysis of health data, the delivery of healthcare services, and the management of healthcare organizations. eHealth services are provided with the assistance of internet and are. They are to enhance the quality of life and ease health care delivery [9]. ML is a branch of artificial intelligence that includes learning algorithms to identify data patterns and predict based on that data. In the context of eHealth systems, ML be utilized to analyze massive volumes of patient data to identify trends, predict outcomes, and support decision-making by healthcare providers.

This research aims to investigate the utilization of ML and DL techniques for analyzing eHealth data within low-capacity computing environments, such as Fog and Edge nodes. As a first step, we conducted a review of the current state of research on the use of ML and deep DL algorithms in Edge and Fog environments. This review helped us to identify the key approaches and techniques that have been developed in this area and to understand the challenges and opportunities they present for eHealth data analysis. Then, we proceeded to compare the most effective ML and DL techniques in state of the art using three eHealth datasets HAR, UniMiB SHAR, and MIT-BIH Arrhythmia. This comparison enabled our evaluation of the performance of the different approaches on a common eHealth dataset and to find opportunities to improve their effectiveness.

The section of the paper is structured as follows: After an Introduction, section II develops the related works, and section III presents the background ML techniques and performance metrics used in this study. In section IV, we compare the performance of baseline ML techniques based on three datasets. Finally, a conclusion and future work are presented in section VI.

2 Related works

IoT devices generate a large quantity of valuable data that can be evaluated and utilized to make predictions using machine learning techniques. This section reviews research studies that propose a multi-level architecture for ML-based data analysis in Edge, Fog, and cloud computing. This study focuses on using ML and DL in the context of eHealth and edge and fog computing.

A collaborative IoT eHealth was proposed in [10] based on SVM and Artificial Neural network (ANN) for arrhythmia detection. The models achieved an accuracy of 84% and 94%, respectively, using patient ECG data. The proposed system is a collaborative learning approach that leverages Edge/Fog layers to enhance latency, availability, and real-time analysis. A multimodal data analysis framework that uses Electroencephalogram (EEG) and Resting-State Functional Magnetic Resonance Imaging (rs-fMRI) datasets are proposed in [11] to estimate and predict epileptogenic networks. They used the CNN model and Long Short-Term Memory (LSTM) for unsupervised feature extraction in EEG analysis and seizure prediction and then SVM for EEG classification achieving an accuracy of 98%. An architecture called HiCH based on the CNN algorithm is proposed in [12]. The edge layer is designed to carry out the ECG classification with an accuracy that exceeds 96%. A three-layer system (sensor, Fog, Cloud layers) was built in [13] to identify and track patients' cardiac arrhythmia. KNN was trained and executed at the Fog layer to classify arrhythmia types with an accuracy of 94.44%. An IoT Medical Things (IoMT) system was designed in [14] based on an Effective Training Algorithm for Deep Neural Network (ETS-DNN) algorithm. The system is composed of three-layer (Internet of medical things, Edge computing, and Cloud database server). The ETS-DNN model is planned to be executed in the Edge computing layer. Hybrid Modified Water Wave Optimization (HMWWO) was used to optimize the parameters of DNN. Different sizes of medical data collected from IoT devices were investigated to achieve the best performance of 99.91% for sensitivity, 99.42% for specificity, and 99.89% for F-score in 8.82s, surpassing other methods like Genetic Algorithm-Based

Trained Recurrent Fuzzy Neural Networks (GA-TRFNN), Swarm Optimized Convolutional Neural Network combined with the SVM algorithm (SCNN-SVM), Particle Optimized Feed Forward Back Propagated Neural Network (PFFBPNN), and Particle Swarm-Optimized Radial Basis Function Network (PSRBFN). A system for detecting psychological disorders is proposed in [15] using electroencephalogram (EEG) signals and psychological data. At the edge computing layer, EEG signals are preprocessed to reduce data delivered to the cloud and to save deep learning parameters. In the Cloud server, three deep-learning models are used to classify signals as normal or abnormal (pathological). The proposed system achieved 88.79% accuracy.

Mobile Health (MHEALTH) systems for HAR and bade on signal sensors, such as accelerometers and gyroscopes, were proposed in [16]. The system combines edge and cloud computing for IoT data analysis and is based on a three-layer architecture consisting of an IoT sensor, edge, and cloud layer. Data were preprocessed at the edge for data reduction and sent to the cloud for further ML processing. Principal Component Analysis (PCA), Autoencoder (AE) was used for data reduction, and Feed Forward Neural Network (FFNN) algorithms for classification, and the system achieved an accuracy rate of 80%. In [17], a framework based on the AE model was presented to classify human activities. The Autoencoder (AE) model was trained using the edge's processing capabilities and achieved an accuracy of 95.45%. As stated in reference [18], a HAR classification system is proposed to ensure privacy while transferring machine learning models from the Cloud to Edge nodes. KNN, SVM, and Sparse Representation-based Classification models were investigated and trained on various datasets, including well-established HAR datasets. The accuracy of the three machine learning techniques was 82%, 92%, and 88%, respectively. To offer minimal latency and memory at the edge of the network, a Binary Neural Network named BinaryDilatedDenseNet was proposed [19]. Using three HAR datasets, this model was compared to RCN-SVM using accuracy and F1-score metrics. This technique outperformed, with an accuracy of 98.2% and F1 of 98.1%, while RCN-SVM achieved 97.4% for accuracy and F1-score. An architecture of four layers is designed in [20], including Body Area Network (BAN), mobile Edge, medical network, and AI medical Cloud. The Activity Detection System Optimization algorithm (ActDec-SysOpt) was suggested to experiment with this architecture based on Long Short-Term Memory (LSTM). The model was trained with UCI HAR, UniMIB SHAR, and HAPT dataset at the Edge node, while optimization was conducted at the Cloud layer. The ActDec-SysOpt showed superior accuracy in all datasets, particularly in the UniMIB SHAR dataset, where it achieved a 91.87% accuracy, while KNN and SVM recorded 80.22% and 84.68%, respectively. To recognize human activities in a smart home, a system based on three layers is defined in [21]. The sensor layer and edge layer are planned for further processing. The Cloud layer is designed to train the proposed CNN that achieved an accuracy of 94.7% compared to other popular methods such as the Naive Bayes (NB), Hidden Markov Models (HMM), Conditional Random fields (CRF), ensemble method, and pre-trained leave-one-out method with respectively 78.38%, 78.38%, 97.3%, 59.56%, and 37.84% accuracies. The authors presented in [22] a video surveillance system named Cloud-based Object Tracking and Behavior Identification (COTBIS) intended for Healthcare Smart Homes

(HSH) and Smart Architecture for Home Healthcare (SAHH) systems. The approach included four layers: An IoT-WBAN sensor, Fog/Edge computing, a Cloud, and a consumer layer. The fog/edge computing layer is designed to minimize execution time and network bandwidth. COTBIS achieved an accuracy of 94.5% in the 80s. In comparison, the HSH system and SAHH system performed 82.7% in the 170s and 85.5% in the 120s. Also, COTBIS was compared to other classifiers such as SVM, ANN, and Linear regression (LR), which achieved 90.32% in 81.32s, 87.09% in 85.87s, 80.64% in 83.54%, respectively. A HealthFog framework is presented in [23] to automatically analyze data from different IoT devices to classify heart disease. HealthFog is based on fog nodes to deploy and test the proposed model's performance executed in Edge compute nodes.

A real-time system based on the K-means model is proposed to detect speech disorders [24]. This model was trained with actual pathological audio recordings from remote monitoring of patients with Parkinson's disease. The model is executed at the fog level, and the Intel Edison and Raspberry Pi computers are used. In the context of Edge computing, a healthcare system was proposed in [25] based on the CNN algorithm (CaffeNet) for voice disorders identification and classification. Voice records are stored in the Edge Computing layer, and CNN CaffeNet performs with 98% accuracy. A Remote Patient Health Monitoring and Risk Assessment System (F-HMRAS) were proposed in [26] to detect mosquito-borne diseases and classify patients into infected and uninfected. This system used four layers: data collection, Fog Computing, Cloud Computing, and End users. The fog layer is designed for data analysis to reduce latency, and the Cloud layer is for data storage. F-HMRAS used The Fuzzy KNN (FKNN) classifier that achieved 95.9% accuracy outperforming the NB and RDT with 89% and 93% accuracy, respectively. A Fog-Cloud architecture was designed for health data analysis in [27]. The architecture included four layers: A Sensation Layer (SL), a classification layer based on Fog, a mining layer to store the data, and an application layer to provide the results to the user. The classifiers KNN, ANN, SVM, and NB performed an accuracy of 94.4%, 91.3%, 90.1%, and 96.5%, respectively. As mentioned in [28], an architecture based on three layers for classifying the patient's behavior is designed. The Fog layer will perform the classification task to minimize the amount of data transferred to the Cloud. The Bayesian Belief Network (BBN) experiment achieved a precision of 89.3%, a recall of 86.7%, and an F1-score of 88%. An Intelligent Health System [29] composed of five layers is suggested. The Hybrid Sensing System includes different types of sensors used for patient data collection. The Patient Data Aggregator (PDA) layer is a charge for measuring and obtaining sensor data. The Mobile/Infrastructure Edge Node (MEN), Edge, and Cloud layer provides additional storage and advanced data analysis capabilities for pattern detection and patient status monitoring. Lastly, the Monitoring and Services Provider layer represents the healthcare service provider and facilitates communication with medical professionals. The In the edge layer, Frequency Feature Classifier (FFC), Random Forest (RF), NB, KNN, and Classification/Regression Trees (REP-Tree), using cross-validation with k-folds five, were developed. The best-performing model is Frequency Feature Classifier (FF), with an accuracy of 97%.

According to this state-of-the-art, different systems using ML and DL techniques were designed in the context of setting up an eHealth and to take face to the Cloud latency and security issues. Table 1 summarizes the findings according to the following criteria:

- Dataset: represents the dataset name if it is standardized.
- Technique: describes the used ML algorithm such as SVM, KNN, RF, NB, LR, etc.
- Performance: is a validation score used in the study such as Accuracy (Acc), Precision (Pr), Sensitivity (Sen), Specificity (Spe), F1-measure (F1), and ROC (R).

Table 1. ML and DL techniques comparison in the eHealth context

Ref.	Dataset	Technique	Performance	Location
[10]	MIT-BIH	ANN	Acc: 94%	Edge/Fog
[11]	IRMf-rs, EEG	LSTM+SVM	Acc: 98%, Sen: 96%, Spe: 97%	Edge
[12]	MIT Arrhythmia	CNN	Acc: 97.2%	Fog
[13]	UCI	KNN	Acc: 94.44%	Fog
[14]	ECG data collected	ETS-DNN	Spe: 99.42%, Sen: 99.91%, F1: 99.89%	Edge
[15]	EEG signals	Three DL	Acc: 88.79%	Edge
[16]	Mhealth HAR	Autoencoder	Acc: 97%	Edge
[17]	HAR	Autoencoder	Acc: 95.45%	Edge/Cloud
[18]	HAR	KNN	Acc: 90.26%	Edge
[19]	HAR	BinaryDilatedDenseNet	Acc: 98.2%, F1: 98.1%	Edge
[20]	UniMIB SHAR	ActDec-SysOpt	Acc: 91.87%	Mobile Edge
	HAPT		Acc: 91.15%	
	HAR		Acc: 89.96%	
[21]	Koyto1	CRF, CNN	Acc: 97.03%, 94.70%	Edge/Cloud
[22]	Human Fall and Activities data	ANN	Acc: 89.09%	Fog/Edge
[23]	Cleveland	Ensemble Bagging	Acc: 89%	Edge
[24]	Speech data	K-means	NA	Fog
[25]	Voices data	CNN	Acc: 98%	Edge
[26]	Symptoms Collected	FKNN	Acc: 95.9%	Fog
[27]	Health data	BBN	Acc: 96.9%	Fog
	Environmental data	BBN	Acc: 96.9%	Fog
[28]	Collected data	BNN	P: 89.3%, R: 86.7%, F1: 88%	Fog/Cloud
[29]	EEG	FFC	Acc: 97%	Edge

Table 1 shows that the articles cover various areas, such as the recognition of human activities, cardiac diseases, voice disorders, and digital data analysis. Multiple techniques are used for data processing and analysis, including ML methods such as SVM, KNN, and BNN and DL methods such as CNN, ANN, LSTM, DNN, and Autoencoder.

There is also a combination of LSTM and SVM (LSTM+SVM). The highest accuracy was obtained by CNN at 98%, followed by BBN at 96.9% and KNN at 94.44%. Most of the papers referenced in the state-of-the-art performed data analysis and processing at the edge computing layer because it is more effective than the Cloud due to the proximity of sensors to compute nodes and the reduced need for additional RAM capacity in the Fog layer. Some works used the Edge layer for pre-processing and data preparation and Cloud Computing for ML processing.

3 Background of the approach

In this part, we focused on the different ML and DL techniques used for data analysis in the Cloud, Edge, or Fog Computing that are cited in the later works.

Support Vector Machines (SVM) is a supervised learning method with accompanying learning algorithms for regression and data classification analysis. SVM is a machine learning method that can be employed to create accurate predictions [30]. This model uses a hyperplane that classifies all learning vectors, allowing for robust data classification.

K-Nearest Neighbors (KNN) is a machine learning technique that is utilized in a variety of applications, including cybersecurity and used in statistics. The principle of the KNN algorithm is to classify unknown points according to their distances from known issues. This means finding the k nearest neighbors of a query in the training dataset and predicting the results [31].

Random Forest Algorithm (RF) algorithm is a method for classification and regression that combines multiple random decision trees and averages their predictions, used for a large number of datasets with various feature types, such as numerical, binary, and categorical [32].

Logistic Regression (LR) is a method for choosing the best and most parsimonious solution to describe and represents the relationship between an output variable and a set of independent variables [33].

Naïve Bayes (NB) is a classification technique that uses probabilities and has numerous real-world applications, including but not limited to product recommendations, medical diagnosis, and controlling autonomous systems [34].

Autoencoder (AE) is an unsupervised learning DL algorithm. It is mainly used for data compression and learning a meaningful data abstraction [35].

Artificial Neural Networks (ANN) is a method of an ML model that can be used for classification, clustering, pattern recognition, and prediction in various disciplines [36].

Convolutional neural network (CNN) is the most popular and frequently used algorithm; it automatically finds essential features without human intervention. CNNs have been used in voice processing, facial recognition, and other applications [37].

Synthetic Minority Over-sampling Technique (SMOTE) is an oversampling method. This technique is based on an interpolation method to increase the number of new instances of the lesser class [38].

4 Material and methods

Despite different models being proposed for classifying diseases and showing good performance, it remains challenging to determine the best ML and DL techniques for Edge computing. This is because many studies need to focus on processing time in Edge nodes, which is a crucial factor. Additionally, updating the systems with new data increases the overall cost, making it essential to consider this in evaluations. We propose to conduct experiments comparing various ML and DL techniques as shown in Figure 1 in the eHealth domain using three health-related datasets. The selection of these techniques is based on state-of-the-art research. The objectives are to compare the performance of these methods on the same three datasets and enhance accuracy while determining computational cost compared to baseline results. For ML, we will use SVM, KNN, RF, and LR; for DL, we will use CNN, ANN, AE, and CNNF.

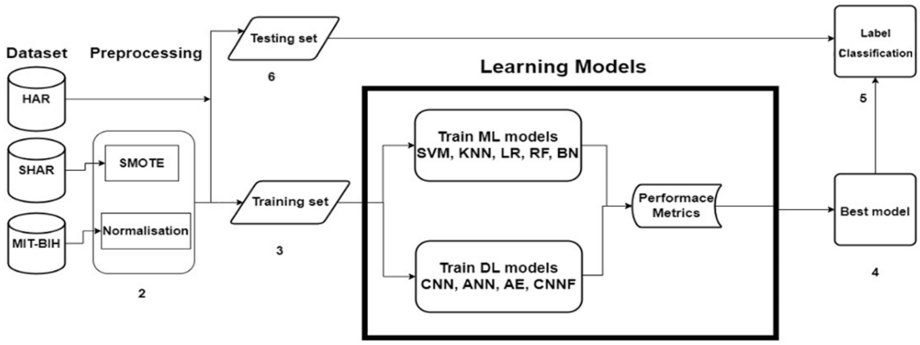

Fig. 1. The proposed approach

4.1 Datasets

In this experiment, we utilized three datasets, which are outlined below. The HAR dataset is a balanced collection that examines human movements and activities, consisting of 102,099 records and identifying six activities (standing, walking up, walking down, sitting, walking, and lying). The MIT-BIH Arrhythmia dataset consists of ECG recordings from 47 individuals, recorded at a 360 Hz sampling rate [39]. The UniMiB SHAR dataset is a compilation of data that encompasses 11,771 activities and falls performed by 30 individuals aged between 18 and 60. These instances are decomposed into 17 separate classes, further grouped into two more significant classifications: one that encompasses nine types of everyday activities and a second that contains eight types of falls [40]. Table 2 represents the description of each dataset.

Table 2. Dataset description

Dataset	Size	Type of Information	Number of Data	Number of Activities
MIT-BIH-ARRHYTHMIA	104Mo	signal data	100,012	5
SHAR	119Mo	sequential data	11,771	17
HAR	288Mo	sequential data	102,099	6

4.2 Preprocessing

First, we performed preprocessing, which involved cleaning, formatting, and transforming the data to make it more suitable for ML and DL models. The MIT-BIH Arrhythmia and UniMiB SHAR databases are unbalanced, requiring balancing techniques such as Synthetic Minority Oversampling (SMOTE) and resampling. For the MIT-BIH dataset, we used the resampling method. At the same time, for SHAR, we employed the SMOTE technique to balance the class distribution by randomly increasing the number of minority class examples.

4.3 Machine learning and DL models

To determine the best set of hyperparameters for the SVM, KNN, RF, and LR models, we used the Grid search cross-validation technique, which combines Grid search and cross-validation with 5-fold techniques. The method performs a grid search over specified hyperparameter values and uses cross-validation to assess the effectiveness of each model. For each algorithm, we compiled a list of hyperparameters that improve performance. For the DL models, we used CNN, ANN, AE, and CNN with Fourier (CNNF), which performed better in the signal processing case, which is the focus of our work for the three databases. Table 3 displays the hyperparameters of our models.

Table 3. DL model parameters

Model	Attributes' Values
CNN	Neuron =107862, Dropout=0.5, Optimizer= Adam, Activation Function=Relu, Loss Function= Categorical_crossentropy, Epochs=100, and Batch size=36.
ANN	Neuron =9734, Dropout=0.5, Optimizer= Adam, Activation Function= SoftMax, Loss Function= Categorical_crossentropy, Epochs=100, and Batch size= 36.
CNNF	Neuron=63972, Dropout=0.5, Optimizer= Adam, Activation Function= Relu, Loss Function= SoftMax, Epochs=100, and Batch size=36.
AE	Neuron=9734, Dropout=0.5, Optimizer= Adam, Activation Function= Relu, Loss Function= SoftMax, Epochs=100, and Batch size=36.

4.4 Experiment results

To determine the relative effectiveness of ML and DL models, we employed several metrics, defined as follows.

Accuracy (Acc): Refers to the metric used to determine the accuracy of a prediction by calculating the ratio of correct predictions to the total number of predictions made.

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

Precision (P): represents the percentage of positive predictions that were correct.

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

Recall (R): the percentage of true positive cases correctly predicted.

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

AUC: defines the probability that the classifier ranks a randomly selected fake user higher than a randomly chosen legitimate user.

Loss: is a main aspect of neural networks to evaluate how well your algorithm models your data set.

The performance results of the SVM, KNN, RF, and LR models, as well as the CNN, ANN, and CNNF models on the HAR, SHAR, and MIT-BIH datasets, are presented in Table 4. On the HAR database, the SVM and LR models achieved the best performance with 96% accuracy, precision, and recall, though they differ in AUC (96% for SVM and 97% for LR). The execution time of the SVM model was 3.20s, while the LR model was slower at 16.56s. The KNN and Random Forest (RF) models had an accuracy and recall of 92%. The precision was 93%, while the AUC was 97% for KNN and 95% for RF. The performance of our KNN model was higher than the results of 90.26% reported in [18]. Among the DL models, the CNNF model achieved 94.44% accuracy, 94.49% precision, 94.27% recall, and 90% AUC in 8.19s. Still, AE reaches the low result of 87.92% for accuracy, 88.32% for precision, 87.51% for recall, and 98.83% at the AUC level in 0.93s.

For MIT-BIH, the best performing ML applied is KNN with 96.9% for all metrics except the AUC, which reaches 98.64% within **0.10s**, which is the least time compared to the other models. Our SVM model showed an accuracy of 90.29%, higher than the results reported in [10]. For DL models, CNNF reached an excellent accuracy of 98.72%, a precision of 98.73%, a recall of 98.70%, and 99% for AUC. Our CNN model achieved an accuracy of 97.98%, more than the outcomes from the CNN proposed in [12]. Our ANN model took less than **0.39** seconds, but it still needs to be faster than the results obtained from the ANN model in [10].

Our results improved the accuracy compared to [20]. The experiments on the SHAR dataset indicate that the KNN performed the best, with an accuracy of 88.61%, precision of 88.73%, recall of 88.61%, and AUC of 88.82%. SVM had an accuracy of 86.8%, which was higher than the result reported with the same dataset in [20].

Among DL models, CNN performed well with an accuracy of 96.90%, a precision of 97.10%, a recall of 96.77%, and an AUC of 99.15%.

In general, the performance of this database could be better [41]. However, the AE model did not produce satisfactory results even after using the SMOTE balancing method (30.46%) in accuracy. The database has 17 classes and 453 features, which requires more efficient preprocessing and feature extraction. Also, examine the correlation between features to make a dimensional reduction. Some papers achieve excellent and high performance, but their results may only apply to some classes [42] because this database consists of two parts (ADL and fall) which indicates that they only worked on one aspect, which shows it's not the same dataset. Additionally, they may only consider a fixed data length, transforming it into a product matrix based on the temporal window size and the sliding step [43].

Table 4. Performance of models on HAR, SHAR, and MIT-BIH dataset

Dataset	Techniques		Accuracy	Precision	Recall	AUC	Mean Execution Time
HAR	ML	**SVM**	**96%**	**96%**	**96%**	**96%**	**3.20s**
		KNN	92%	93%	92%	97%	0.20s
		RF	92%	93%	92%	95%	4.61s
		LR	**96%**	**96%**	**96%**	**97%**	**16.56s**
	DL	CNN	91.52%	92.12%	91.21%	99.46%	8.10s
		ANN	93.93%	94.18%	93.89%	99.37%	1.94s
		AE	87.92%	88.32%	87.51%	98.33%	0.93
		CNNF	**94.44%**	**94.49%**	**94.27%**	**90%**	**8.19s**
SHAR	ML	SVM	86.8%	87.62%	86.8%	93.54%	4.70
		KNN	**88.61%**	**88.73%**	**88.61%**	**88.82%**	**0.03**
		RF	87.03%	87.4%	87.04%	89.74%	8.13
		LR	56.52%	56.61%	54.52%	52.13%	18.39
	DL	**CNN**	**96.90%**	**97.10%**	**96.77%**	**99.15%**	**19.50**
		ANN	93.98%	93.33%	92.98%	98.91%	3.67
		AE	30.46%	31.20%	30.44%	84.26%	0.78
		CNNF	92.28%	92.45%	92.19%	98.64%	20.95
MIT-BIH	ML	SVM	90.08%	90.29%	90.08%	92.55%	199.90
		KNN	**96.9%**	**96.9%**	**96.9%**	**98%**	**0.10**
		RF	92.44%	95.51%	95.44%	94.44%	98.15
		LR	84.96%	85.05%	84.96%	89.95%	32.56
	DL	CNN	97.98%	99.01%	99.03%	99%	1.88
		ANN	96.40%	96.73%	96.05%	99%	0.39
		AE	95.80%	96.16%	95.47%	99.59%	0.88
		CNNF	**98.72%**	**98.73%**	**98.70%**	**99%**	**1.95**

This experiment demonstrates that among the Machine Learning models, KNN is the strongest in terms of high performance and speed. However, LR requires more time to process the data than the other three models. In the case of DL models, CNNF offers good results, though it takes longer compared to the ANN model, which is fast and provides acceptable performance.

Figure 2 depicts the ROC Curve (Receiver Operating Characteristic Curve), a metric used to evaluate models using the AUC (Area Under the Curve). The SVM model for the HAR databases exhibits curves closer to 1 for most classes, indicating that the model is effective and provides improved classification with an AUC of 96%. For the

SHAR and MIT-BIH databases, the KNN model attains an accuracy of 96.9% with an AUC of 98% and an accuracy of 88.61% with an AUC of 88.82%, respectively.

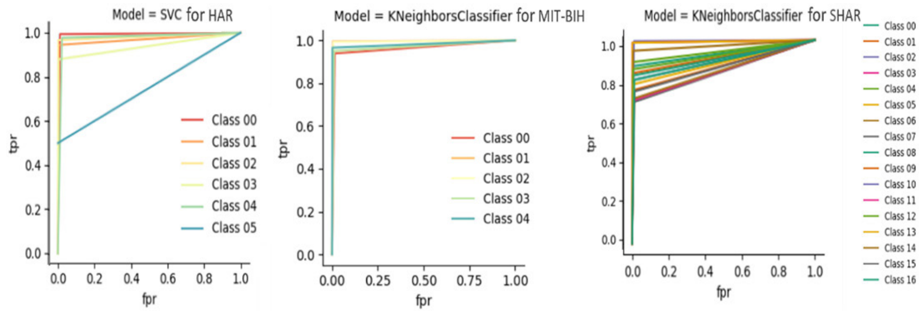

Fig. 2. ROC-curve

To ensure our models are not overfitting, we evaluated their performance using the loss and accuracy curves. As shown in Figure 3, the training and validation data accuracy curve converge towards 1, indicating that accuracy increases with each epoch. The training loss and validation loss curves also decrease with each epoch and have a small gap. The final accuracy of the CNNF model for the HAR dataset is 94.44%, with a loss of 0.23, and it took 8.19 seconds to run. For the MIT-BIH dataset, the CNNF model achieved 98.83% accuracy and 0.03 for a loss in 1.95 seconds. The CNN model for the SHAR dataset had an accuracy of 96.90% and a loss of 0.15 in an unspecified time.

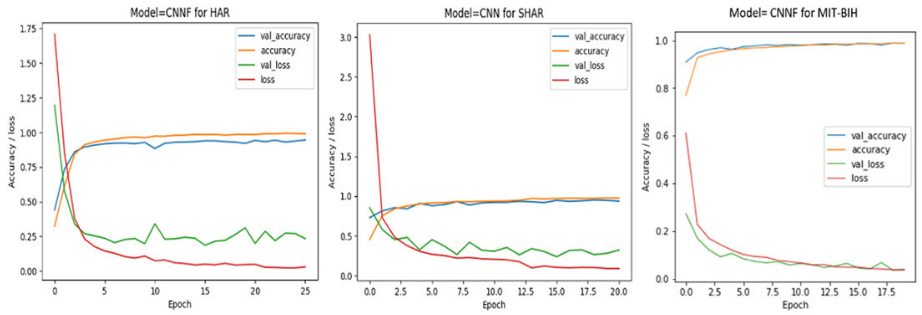

Fig. 3. Loss and accuracy of CNNF and CNN models

5 Conclusion and future works

This paper compares edge and fog computing-based architectures incorporating machine learning and deep learning algorithms to minimize latency, enhance data security, and optimize bandwidth utilization at the sensor or local level. Data processing encompasses multiple layers, including IoT devices, fog or edge layers, and cloud layers, and employs machine learning techniques to enhance performance. Our experimentation is based on three datasets: HAR, SHAR, and MIT-BIH, and compares the results of different techniques. KNN has the best processing time and performance for the SHAR and MIT-BIH datasets, with an accuracy of 88.61% and 96.9%, respectively. For the HAR dataset, SVM outperforms other techniques with an accuracy of 96%. Among the DL techniques, CNNF achieves the best results for the HAR and MIT-BIH datasets, with an accuracy of 94.44% and 98.72%, respectively. The CNN model has 96.90% accuracy for the SHAR dataset. In future work, we will focus on eHealth data analysis and propose a comprehensive architecture that guarantees data security, optimizes task dispatch between the edge and cloud, and selects the appropriate ML or DL technique to provide a prompt and satisfactory response time.

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