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Research article

Energy-efficient distributed federated learning offloading and scheduling healthcare system in blockchain based networks☆

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ABSTRACT

Many disease detection and prevention applications in digital healthcare systems are widely used but often focus only on prediction and classification, ignoring processing performance and data privacy issues. The study investigates the Energy-Efficient Distributed Federated Learning Offloading and Scheduling Healthcare Systems in Blockchain-Based Networks problem for healthcare applications. In order to solve the problem, the study presents the Energy-Efficient Distributed Federated Learning Offloading and Scheduling (EDFOS) system in blockchain based networks. EDFOS consisted of different schemes such as energy efficient offloading and scheduling and meet the quality of services (QoS) of applications during performing in the system. Simulation results show that EDFOS reduces power consumption by 39%, training and testing time by 29%, and resource leakage and deadlines by 36% compared to existing healthcare systems. The EDFOS platform is an effective solution for addressing the issues of power consumption and data privacy in healthcare applications.

1. Introduction

These days, the ratio of diseases among humans has been growing progressively. The number of patients in different countries and smart cities has been increasing daily. Artificial intelligence-based smart healthcare solutions are increasingly being used these

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days. The main focus is on improving the data that healthcare applications use to prevent, diagnose, and predict disease in different research institutions. Many studies that look at the reactive and proactive parts of the disease come up with different ways to treat it. These systems are episodic and discrete in prediction, preventing infections at different time intervals in the system [1]. Digital healthcare that uses AI is a new way of doing things in which many pieces of hardware and computer software work together to process data quickly and safely. To make healthcare automation systems, the usage of artificial intelligence has been growing progressively in practice. For instance, robotic-human, intelligent transport, distributed healthcare, education, supply chain management, and other Internet of Things (IoT) applications are designed based on energy-efficient healthcare system [2]. energy-efficient healthcare systems are beneficial when the data is processed more accurately and safely in a distributed network. Synthetic intelligence methods such as supervised, unsupervised, reinforcement, and deep learning paradigms widely exploit healthcare. The goal is to offer energy-efficient processing of healthcare data with optimal accuracy, precision, and recall of data in line with the network's quality of service (QoS) requirements [3]. Cloud computing is the key technology that makes it possible for healthcare applications to offer different services. The benefits are storage, computation, infrastructure, and products in the routine. Cloud providers, such as Amazon, Google, Azure, and others, provide numerous healthcare services to promote healthcare features at variously distributed hospitals [4]. Many existing disease detection and prevention systems designed for healthcare are incorporated with different service tools. For instance, consider service-oriented architecture (SoA) [5]. However, energy-efficient healthcare systems are complex and require data processing on different nodes. In distributed applications, each node needs a lot of resources and power to process data safely and efficiently. In the current era of research, many issues exist in the healthcare system in the current era of research [6].

These studies [7–12] imply different frameworks, architectures, and systems based on patients' healthcare applications in the network. A blockchain-based solution was presented to meet the network's security and validation requirements. Many healthcare datasets (e.g., chronic disease, heart disease, and blood pressure) are trained and tested in the healthcare system for the execution of the application. All the art literature focuses on disease detection, prevention, prediction, and treatment, along with training and testing them on the different fog and cloud nodes. Therefore, processing delay, privacy, and power consumption are widely ignored in these studies. Furthermore, these studies [13–15] suggested blockchain-driven smart healthcare systems for medical care applications. These studies suggested many scheduling and offloading schemes with different artificial intelligent (AI) schemes. Yet these studies did ensure the security and privacy of healthcare data. But blockchain-based healthcare as it is now still needs to be more energy efficient and uses a lot of power.

This paper presents energy-efficient distributed federated learning offloading and scheduling healthcare systems in blockchain-based networks. The study considered the different constraints, such as energy consumption (e.g., electricity price, execution per unit consumption in watts), training and testing, processing delays, and privacy and security for healthcare applications on the platform. The proposed system consists of three physical paradigms: mobile computing as the thin client, fog nodes as the thick client, and cloud computing as the thick client in the system. The objective is to minimize the energy consumption of mobile computing, fog computing, and cloud computing during execution. The work has made the following contributions.

- The study presents the blockchain-enabled healthcare system to the healthcare workloads on fog and cloud networks.
- The federated learning-enabled schemes that train and test the healthcare dataset at different nodes are presented in this study. For example, the chronic disease dataset will be set up and tested at fog and cloud nodes, then shared with mobile computing for the first processing.
- The study comes up with offloading and scheduling schemes that use the least amount of energy to handle blockchain security on all computing nodes and meet the quality of service needs of applications.
- The energy-efficient and lightweight hashing schemes of blockchain technology based on fog–cloud networks have been designed in this study.

The manuscript is organized in the following way. Section 2 discussed the existing studies and their constraints for healthcare systems in detail. Section 3 shows the proposed system and problem formulation. Section 4 shows the processes of the EDFOS framework. Section 5 shows the performance evaluation of the proposed scheme and existing studies. Section 6 is the conclusion and future work of the study.

2. Related work

Digital healthcare systems are increasing with the invention of wireless technologies and sensors that optimized the performance of healthcare applications in the blockchain network. Here, the manuscript discusses the existing efforts of research scholars to maximize the performance of healthcare applications in the network. In this study [1], the authors suggested an energy-efficient patient healthcare scheme for remote healthcare service security rules based on these certificate rules. To adopt the dynamic intrusion attacks, the study [2,3] suggested energy-efficient machine learning-based approaches with supervised labeling for mobile Android cloud healthcare applications. These studies aim to optimize the processing of applications in the blockchain-enabled network, where there are many authentication and authorization issues with patient data. These studies minimized the security and energy consumption risk in the edge with the processing node perspective during the execution of healthcare workloads. However, these studies considered static security and energy consumption in the centralized healthcare system. So, when there are more heterogeneous nodes in the healthcare domain, it uses many resources and poses more security risks.

These studies [4–7] suggested a decentralized blockchain-based healthcare system based on the Internet of Things (IoT). The goal was to minimize the security risks of the centralized healthcare IoT system with a decentralized approach. These studies integrated public blockchain technologies for public healthcare data processing. The studies handle security data validity among heterogeneous groups with the minimum energy consumption of a centralized healthcare system. However, due to the limited blockchain, each blockchain-enabled fog and cloud network cannot process the vast datasets on the nodes. Therefore, controlling the big datasets here with the high-security ratio and minimum energy consumption of these blockchain-enabled healthcare systems is hard. However, these blockchain technologies still incurred higher training costs and processing delays during proof of validation among computing nodes.

The delay optimal and energy-efficient blockchain technologies enabled healthcare systems, as presented by [8,9] studies. These studies optimized one factor of the existing blockchain technologies regarding the delay. These blockchain technologies process healthcare data among fog and cloud nodes with the minimum delay possible using dynamic and machine learning scheduling algorithms. However, these studies trained and tested their models at the consensus blocks. Therefore, a final decision still incurred higher delays. These studies [10–14] suggested a federated learning-enabled healthcare system and lightweight offloading and scheduling algorithms. Based on smart-contract rules, the goal was to minimize the risks of delay, security, and energy use. Machine learning-based offloading and adaptive scheduling for healthcare data in fog–cloud networks.

The adaptive and artificial intelligence-based security and privacy and energy-efficient blockchain healthcare platform suggested in these studies [14–17] to predict security and energy risks in the network. The blockchain miners are created based on proof of stake, proof of work, and Byzantine failure methods in all miners to verify and predict the nodes in the network. The smart contracts already developed in existing blockchain frameworks such as Ethereum, Fabric, Corda, and IBM [18–20] are widely exploited in healthcare domains. The main goals of these frameworks are to improve decentralized security and ensure that all miners in the network check the hashing. However, these blockchain processes are integrated on the server side. In these studies, however, it is essential to look at the validity of data on the client side during offloading and local processing.

As far as we know, no one has examined how energy consumption affects mobile fog–cloud networks in blockchain networks for healthcare applications. All the studies that have been done so far have focused on delay, response time, cost, and security efficiency. However, the literature needs to consider how much power the mining process uses on all nodes. In this study, an EDFOS algorithm framework is used to ensure that nodes use the least amount of energy possible when using blockchain technology in the fog–cloud paradigm for healthcare.

3. Proposed system

The study presents Energy-Efficient Distributed Federated Learning Offloading and Scheduling Healthcare System Blockchain-Based Networks, as shown in Fig. 1. The proposed work has different layers, such as patient application, fog, and cloud. The components of the proposed work are described in the following way.

1. In the system, patients' healthcare applications are installed (Android packages (APK) on mobile devices. The Internet of Things (IoT) healthcare sensors collect data from different clinics in real-time, such as electroencephalograms (EEG), electrocardiograms (ECG), and random blood sampling. The study used patient data from various clinical sensors to process and keep an eye on IoT healthcare apps. The data-generating sensors are the glucometer, body temperature, pulse, oxygen, blood sample, air flow, galvanic skin, and GSR sweating. All the data was collected from different laboratories and tested in real-time on patients in the system. The EEG sensors monitor the mental and brain disorder activities (e.g., memory loss, language misunderstanding levels). They are placed in the patient's home or the hospital clinics to collect patients. The objective is to monitor healthcare remotely at different hospitals in real-time. The EEG laboratories or sensors send data to the user-deployed Android applications. The EEG data size is determined in megabytes (MB) and offloaded from mobile devices to the fog–cloud for further processing. Because the mobile devices did not have enough power, processing power, or storage to run applications on the distributed networks, they sent data to the fog node. IoT Arduino is connected to mobile devices via Bluetooth and wirelessly connected to get client connection for the data for the fog servers. Socket programming was used to make the Android apps, and the IoT apps ran in the X86 operating environment. The client socket has a blockchain node, e.g., bo, and implements a federated learning scheme where preprocessing data is offloaded to the fog node for further processing. The blockchain converted data into a cipher (e.g., SHA-256) and validated data at the immutable level while sending data from a mobile device to fog nodes via different base stations. The main goal of mobile offloading is to make sure that blockchain and federated learning use as little mobile energy as possible before being sent to fog nodes.
2. The Javascript Object Notation (JSON) encrypts data from mobile devices and sends it to fog nodes, which are set up in different hospitals and are spread out geographically. However, all hospitals are decentralized, and application data is randomly offloaded to any available fog nodes. All fog nodes are cooperative, and they train and test their models based on decentralized, federated learning. We are not using aggregated nodes because all hospitals are autonomous and validate their data based on blockchain technology without immutability and security issues in the network. The main goal is to minimize energy and process.
3. The cloud node offloaded data from fog nodes for storage to handle the energy complex in the system.

Table 1 describes the notation of paramedical model. These Sensors (Accelerometer), Glucometer Sensor, Body Temperature Sensor, Blood Pressure Sensor, Pulse and Oxygen in Blood Sensor, Airflow Sensor (Breathing), Galvanic Skin Response Sensor Electrocardiogram Sensors implemented in healthcare applications. The sensors generate data and connect to the mobile device via Bluetooth. The mobile device has an application interface that accepts the data for the functions needed for processing. Once the parts get the data from sensors, the mobile engine applies the blockchain process to the function data and offloads it to the fog node for processing. The fog engine accepts the requested hash and uses a blockchain miner to validate the hash for execution. If the fog node has limited resources, it will offload data functions for further processing to the cloud node for execution.

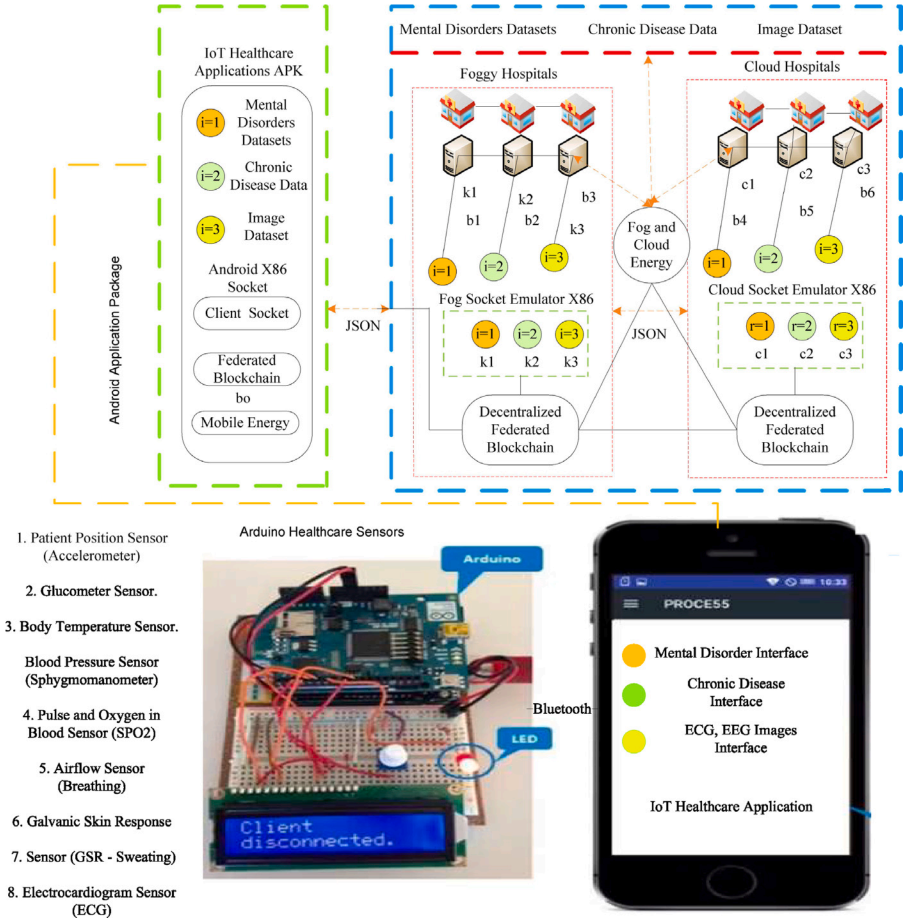

Fig. 1. Energy-efficient distributed federated learning offloading and scheduling healthcare system in blockchain-based socket networks.

Table 1
Mathematical notation.

Notation	Description
I	The healthcare medical applications
i	The specific medical application
w_i	Each medical workload
w_i'	Partial execution of workload on fog
w_i''	Partial execution of workload on cloud
wd_i	Deadline of application workload i
D	Number of trained dataset
d	Particular dataset trained at any node
t_d	Training and testing time of the dataset
K	Number of different computing nodes
$b \in B$	Blockchain process in the system
$ck_p w$	Communication time and energy of nodes
k	Particular computing node
ζ_k	Speed of node k
ϵ_k	Resource capability of node k
$w_i \leftarrow b, k$	Blockchain hashing on k
pw_k	Power consumption of particular node
p_{cost}	Electricity cost
$p_{threshold}$	Power consumption threshold
$T_e^{w_i,k} \times w_i \leftarrow b, k \times pw_k$	Execution time and energy consumption

3.1. Blockchain based Mobile-Fog–Cloud networks

The study considers the three computing nodes for socket-based client–server healthcare applications. All computing nodes have the same runtime socket environment based on a Java virtual machine. For simplicity, all nodes have the same runtime environment, and we add the blockchain miners with the rules and regulations and the following features. For instance, each node can encrypt/decrypt data based on Sha-256 with asymmetric regulations (e.g., the public and private keys) and share data with the other miners for execution. All fog nodes are miners and meet the proof of validation, credibility, private keys, and other requirements during processing of healthcare applications.

3.2. Mathematical model

The study implements different healthcare workloads, e.g., $I = \{w_i = 1, \dots, iI\}$. Each workload has different attributes such as deadline wd_i, hashing $\langle Enc, Dec, Validation \rangle$. The computing nodes are represented by K and each node has particular speed and resources, ϵ_k, ζ_k. Each node has particular power consumption, e.g., pw_k during processing workload on different nodes. The study makes the assignment of the workloads computing nodes.

$$x_{i,k,b} = \begin{cases} \frac{w_i}{\zeta_{k1}}, & x_{i,k,b} = 1 \\ \frac{w_i'}{\zeta_{k2}}, & x_{i,k,b} = 2 \\ \frac{w_i''}{\zeta_{k3}}, & x_{i,k,b} = 3 \end{cases} \tag{1}$$

3.3. Energy-efficient and processing delay formulation

The study determines the energy-efficient based on three rules such as healthcare processing energy, electricity cost, and heat-threshold for the each healthcare workload in the proposed platform. Eq. (1) determines the basic assignment of workload at different nodes.

$$y_{kK} = \begin{cases} \frac{w_i}{bw_{k1}}, & y_{k1\sim k2} = 1 \quad Mobile - Fog, \\ \frac{w_i' \sim ''}{bw_{k2\sim k3}}, & x_{i,k,b} = 2 \quad Fog - -Cloud, \end{cases} \tag{2}$$

Eq. (2) determines the offloading between mobile to fog and fog to cloud node during execution of application in nodes. The execution of workload determined in the following way.

$$T_e^{w_i,k} = \times w_i \leftarrow b, k \times pw_k \frac{w_i}{\zeta_{k\in K}}. \tag{3}$$

Eq. (3) determines the execution time and required power consumption for execution any workload on any mobile fog–cloud node.

$$ck_{pw} = \times w_i \leftarrow b, k \times pw_k \frac{w_i}{bw_{k\in K}} \times P_{cost} + P_{threshold}. \tag{4}$$

Eq. (4) determines the communication time and required power consumption for communication between any mobile fog–cloud node. The blockchain mechanism to save the patient record with the healthcare workloads determined in the following way.

$$\begin{aligned} &b = hash \leftarrow w_i \leftarrow enc\langle SHA - 256 \leftarrow w_i + public - key \rangle \\ &+dec\langle SHA - 256 \leftarrow w_i + Private - key \rangle + Validation. \end{aligned} \tag{5}$$

Eq. (5) determines encryption and decryption inside particular block b in the system.

$$Validation = hash \leftarrow w_{i,k1} \leftrightarrow hash \leftarrow w_{i,kK}. \tag{6}$$

Eq. (6) determines the validation of hash between nodes.

$$d_t = training + test \leftarrow d, k \quad ,\forall d = 1, \dots, D. \tag{7}$$

Eq. (7) determines the training and testing time of the dataset at the particular node.

$$m_i^e = T_e^{w_i,k=1} + ck_{pw} \times x_{i,k=1} \times y_{kK} + d_t. \tag{8}$$

Eq. (8) calculates the execution time and communication time along with the execution and communication energy for each workload in the system.

$$f_i^e = T_e^{w_i',k=2} + ck_{pw} \times x_{i,k=2} \times y_{kK}. \tag{9}$$

Eq. (9) calculates the execution time and communication time along with the execution and communication energy of the nodes.

$$c_i^e = T_e^{w_i'',k=3} + ck_{pw} \times x_{i,k=3} \times y_{kK}. \tag{10}$$

Eq. (10) determined energy and communication time and energy of the nodes. The objective of the study determines in the following ways.

$$T \sim E = \sum_{i=1}^{I} \sum_{k=1}^{K} \sum_{b=1}^{B} m_i^e + f_i^e + c_i^e. \tag{11}$$

Eq. (11) determines the objective function of the study. The study optimizes the objective function in the following way.

$$\min T \sim E, \quad \forall i = 1, \dots, I, k = 1, \dots, K. \tag{12}$$

The objective function is to be minimized the response time of the applications and energy consumption of the nodes in the system.

$$m_i^e + f_i^e + c_i^e x_{i,k} w_i \leq \epsilon_k, \quad \forall i = 1, \dots, I, k = 1, \dots, K. \tag{13}$$

Eq. (13) determines that, all workloads must be executed under the limit of resources.

$$m_i^e + f_i^e + c_i^e x_{i,k} w_i \leq wd_i, \quad \forall i = 1, \dots, I, k = 1, \dots, K. \tag{14}$$

Eq. (14) determines that, all workloads must be executed under the deadlines.

4. Energy-efficient federated enabled learning scheme training and testing and validation on different node

The study devises the Energy-Efficient Distributed Federated Learning Offloading and Scheduling (EDFOS) scheme, which ensures the testing and training of the healthcare datasets on the different nodes. The EDFOS algorithm framework has finished calibrating the devices and sensors, and offloading (fog, cloud) has begun. EDFOS, processed the patients' healthcare applications, which were installed (Android packages (APK) on mobile devices. The Internet of Things (IoT) healthcare sensors collect data from different clinics in real-time, such as electroencephalograms (EEG), electrocardiograms (ECG), and random blood sampling. The study used patient data from various clinical sensors to process and keep an eye on IoT healthcare apps. The sensors that make data are the glucometer, the body temperature, the pulse, the oxygen level, the blood sample, the airflow, the galvanic skin, and the GSR sweating. All the data was collected from different laboratories and tested in real-time on patients in the system. The EEG sensors monitor the mental and brain disorder activities (e.g., memory loss, language misunderstanding levels). They are placed either in the patient's home or the hospital clinics for the data collection of patients. The objective is to monitor healthcare remotely at different hospitals in real-time. The EEG laboratories or sensors send data to the user-deployed Android applications. The EEG data size is determined in megabytes (MB) and offloaded from mobile devices to the fog–cloud for further processing. Because the mobile devices did not have enough power, processing power, or storage to run applications on the distributed networks, they sent data to the fog node. IoT Arduino is connected to mobile devices via Bluetooth and wirelessly connected to get client connection for the data for the fog servers. Socket programming was used to make the Android apps, and the IoT apps ran in the X86 operating environment. The client socket has a blockchain node, e.g., bo, and implements a federated learning scheme where preprocessing data is offloaded to the fog node for further processing. The blockchain converted data into a cipher (e.g., SHA-256) and validated data at the immutable level while sending data from a mobile device to fog nodes via different base stations. The main goal of mobile offloading is to make sure that blockchain and federated learning use as little mobile energy as possible before being sent to fog nodes. Whereas offloading and scheduling of the applications are to be done on the different nodes based on the socket programming model and socket architecture as shown in Fig. 2. To load balance, the study devised the three mobile fog–cloud-enabled sockets based on the blockchain fog–cloud paradigms as shown in Fig. 2. Three different datasets Mental disorders, chronic diseases, and imaging datasets are trained and tested at different nodes based on their power consumption based on Algorithm 2. The main goal is to reduce the centralized node's training and testing time and node energy. The study devises the decentralized nodes to enable training and testing to minimize the resources, time, and power consumption of the nodes in the system. The healthcare application is executed on different nodes such as mobile device, fog node, and cloud computing. The mobile device only processes the requests of the particular applications, hashes them locally, and offloads and schedules them to the fog node for execution, as shown in Fig. 2.

4.0.1. *Real-case-scenario*

The initial workload is $i = 1, k = 1, 2, d = 1, b = 1, p_w$ converted into a cipher hash at the mobile device $k1$, and offloaded to the $k2$ for execution and validation in the network. It means we utilize the mobile energy very short as compared to the fog node in the shared socket programming-based environment in the system. The other workloads, such as $i = 2, k = 2, d = 2, b = 2, p_w$ and $i = 3, k = 3, d = 3, b = 3, p_w$ executed workloads on different decentralized servers to minimize the power consumption in the network. In these models, the study implemented the public blockchain based on attributes b with the hashing based on SHA-256 (e.g., the public key with the parent node and the private key with the receiving node). The study validated every data transaction in the node before it was processed and told all nodes about validation and verification in the network. The study devises Algorithm 1 to execute the healthcare applications and train and test their models on the different computing with the different steps. Algorithm 1 determines the hashing, blockchain validation, offloading and scheduling in the following ways.

- From steps 1 to 10, the algorithm takes the input from the mobile socket as the application package (apk) file and applies the hash to the application's data on the mobile device. Algorithm 2 calls for the training and testing of decentralized, federated learning datasets for the processing of healthcare application workloads in the appropriate way.

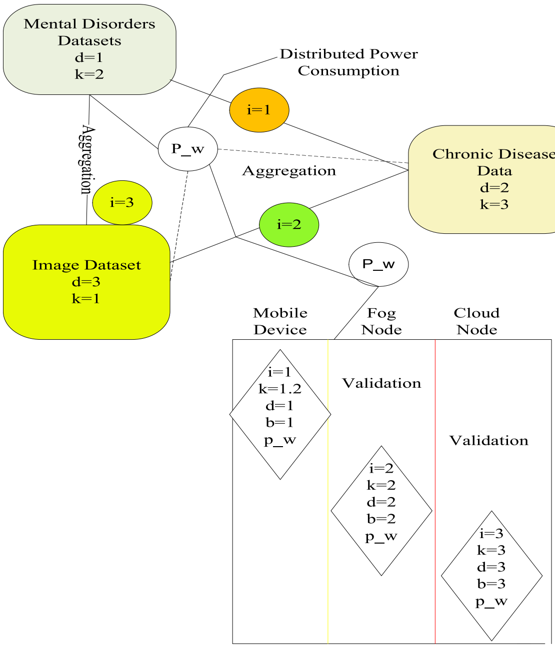

Fig. 2. Energy-efficient blockchain hashing and validation in healthcare network.

- From steps 11 to 17, the algorithm takes the offloaded hash of workloads from the mobile socket and applies blockchain validation to match the received hash from the sender. Algorithm 2 calls for the training and testing of decentralized, federated learning datasets for the processing of healthcare application workloads in the appropriate way. The mobile socket exploited the Java virtual machine and socket classes and applied the blockchain, and processed the workload under the limitation of resources and workload deadline before offloading to the fog node for processing. If the fog node has not have sufficient resources, the fog node will offload workloads to the cloud node for processing.
- From steps 19 to 28, the algorithm takes the offloaded hash of workloads from the fog node socket and applies blockchain validation to match the received hash from the sender. Algorithm 2 calls for the training and testing of decentralized, federated learning datasets for the processing of healthcare application workloads in the appropriate way.
- Overall objective of Algorithm 1 to optimize the objective functions and executed applications on different nodes with the decentralized trained and test models on all nodes.

4.1. Energy-efficient pre-processing decentralized federated learning scheme

The primary goal of data preprocessing is to provide the mechanism in which data ambiguity, noise, and errors are removed and converted into a meaningful format. This considers the data of the different sensors, which may suffer from noise, inference, and other errors during offloading from devices to the fog nodes before processing in the system. Algorithm 2 scheme has the following steps.

The Algorithm 2 has many steps to complete the process at work. Step 1 prepares the dataset and matches the input data to the set. In step 2, exactly match the data with the dataset values. Step-3: Split the dataset based on the training and testing scheme. Step-4: make the data standardization based on Euclidean distance. Step-5: makes the normalization of all data.

4.2. Energy-efficient blockchain mining and validation

Fig. 3 shows the real-case scenario and mechanism in the study. Let us suppose the application has a function, e.g., brain analyzing, which has only one definition on the local mobile device (e.g., w_i, b, k); for the processing. Furthermore, the fog engine exploits the test and trained models, which are trained and tested at different nodes and help execute the workload with lower power consumption in the network. Fig. 3 shows that mobile device energy can be saved by offloading data to the fog node and the fog node offloading further to the cloud for processing to save the energy in the system.

5. Experimental performance and result analysis

In this part, the study will show the implementation part of Generative Federated Learning and Blockchain Enabled System for Patients Healthcare Application as shown in Table 2, datasets Tables 3 and 4.

Algorithm 1: Energy-Efficient Distributed Federated Learning Offloading and Scheduling (EDFOS)

Input : I, D, B, K
begin
  for (I, D, B, K) **do**
    Determined initial assignment based equation (1);
    $x_{i,k,b}$=1;
    if $(\frac{w_i}{\zeta_{k1}} \leq \epsilon_k 1 \& \leq wd_i\ )$ **then**
      Find blockchain $b, w_i, k1$ on equation (5) and trained (7) ;
      Find time and power consumption based on equation (8);
      Offload data for processing on equation (2);
      Optimize $T \sim E = \sum_{i=1}^{I} \sum_{k=1}^{K} \sum_{b=1}^{B} m_i^e$ equation (12);
    Offloading done;
    if $(Hash \leftarrow w_i \leftarrow k1 {=}{=} Hash \leftarrow w_i \leftarrow k2)$ **then**
      Determined validation time and energy based on equation (6);
      if $(\frac{w_i'}{\zeta_{k2}} \leq \epsilon_k 2 \& \leq wd_i)$ **then**
        Determined blockchain $b, w_i, k1$ based on equation (5) and trained (7) based on Algorithm 2 ;
        Determined time and power consumption based on equation (9);
        Offload data for processing based on equation (2);
        Optimize $T \sim E = \sum_{i=1}^{I} \sum_{k=1}^{K} \sum_{b=1}^{B} f_i^e$ equation (12);
      Offloading done;
    if $(Hash \leftarrow w_i \leftarrow k1 {=}{=} Hash \leftarrow w_i \leftarrow k2)$ **then**
      Determined validation time and energy based on equation (6);
      if $(\frac{w_i''}{\zeta_{k2}} \leq \epsilon_k 1 \& \leq wd_i)$ **then**
        Energy and Time equation (7) and Algorithm 2,$b, w_i, k1$ based on equation (5) ;
        Determined time and power consumption based on equation (10);
        Offload data for processing based on equation (2);
        Optimize $T \sim E = \sum_{i=1}^{I} \sum_{k=1}^{K} \sum_{b=1}^{B} c_i^e$ equation (12);
      Offloading done;
    End validation;
  Executed All workloads;
End Main;

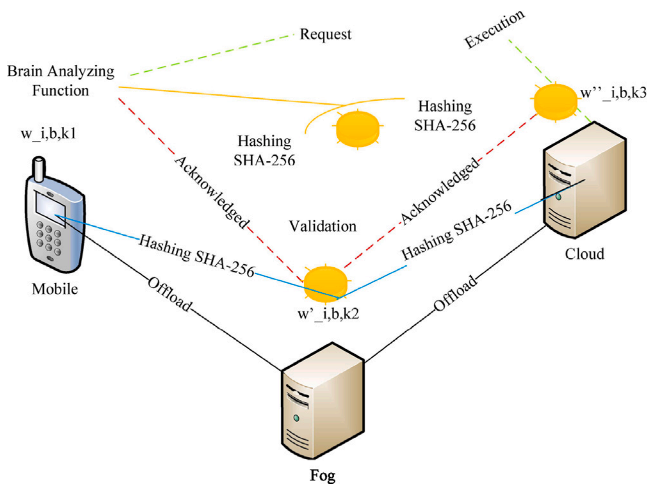

Fig. 3. Energy-efficient blockchain hashing and validation in distributed fog–cloud network.

Algorithm 2: Energy-Efficient Pre-Processing Decentralized Federated Learning Scheme

Input : $d = 1, \dots, D, k = 1, \dots, K$
begin
  foreach $(d, k = 1 \in D, K)$ **do**
    Step-1: Prepare all healthcare datasets;
    $d = 1, \in D$;
    Step-2: Extract and match data with the dataset on the node;
    $k \leftarrow d$;
    Step-3: Categorize and split the data;
    Call Training and Testing Scheme;
    $pw_k,\ ck_p w, wd_i$;
    Based on Euclidean distance align between dataset and data;
    $d\left(pw_k, ck_p w, wd_i\right) = \sqrt{\sum_{d=1}^{D}\left(d_1 - wd_i\right)^2}$;
    Step-4: Data selection node;
    $d = \frac{d-mean(d\leftarrow k1)}{d}$ mean and Standard deviation on mobile device;
    $d'' = \frac{d-mean(d\leftarrow k2)}{d}$ mean and Standard deviation on fog node;
    $d'' = \frac{d-mean(d\leftarrow k3)}{d}$ mean and Standard deviation on cloud;
    Step-5: Normalization;
    $d^{d\sim d'\sim d''} = \frac{d-mean(d)}{max(d)-min(d)}$;
  End processing;
End Main;

Table 2
Experimental parameters in simulation.

Metric	Values
Language	JAVA
Model	Socket Programming
$k1$	64 GB ROM,8 GB RAM,100 joule (j)
$k2$	1500 GB ROM,16 GB RAM,1000 joule (j)
$k3$	5000 GB ROM,40 GB RAM,10000 joule (j)
w_1	2 GB Data
w_2	7 GB Data
w_3	10 GB Data
bw	$12MBPS \sim 15MBPS$
Arduino	Measuring Heart-RapplicationSpO2 with MAX30102
Arduino	Heart-Rating Monitoring Wearable-WiFi ECG)

5.1. Data collection for experiment

In the labs, where additional blood and EEG signal data were gathered, we gathered real-time human data for the experiment, such as pictures of Alzheimer's disease. A description and other files were added to the system with the human data sample, as shown in Tables 3 and 4. During offloading and scheduling, each data result image will be encrypted and decrypted on all nodes with the immutable feature. The datasets for spontaneous brain activity and chronic diseases included the date, where the samples were taken, the gender, encryption, blockchain technology that uses energy-efficient protocols, and the amount of power used in kilowatts. In the simulation, we are analyzing the power consumption prices of the healthcare platform during patient applications, as shown in Table 5. Three datasets are implemented in the simulation: Alzheimer, chronic disease, and random brain activities. Each dataset was collected at different laboratories, and the values changed for the experiment.

5.2. Result discussion

The study implements the existing blockchain frameworks such as Ethereum proof of work (PoW) [12], Ethereum proof of stake (PoS) [13], and centralized training and testing blockchain model [15] as the baseline approaches in work. The main idea behind these studies is that healthcare applications on the distributed heterogeneous computing nodes in the healthcare system use the same amount of resources and energy and take the same amount of time to process. In the part where we talk about the results, we will talk about how well each blockchain approach works for different healthcare workloads using separate training and testing methods in a simulation environment based on the client–server architecture of the healthcare system. We implement the proof-of-concept and prototype Android application blockchain healthcare system, where code is available here on the given link: https://github.com/ABDULLAH-RAZA/Blockchain-Socket.

Table 3
Chronic disease dataset and Alzheimer image dataset: 1000 features.

Disease	Pain	Breathing	Sweating	Anger	Over-react	EEG	MRI
Brain	0.1777	0.145	0.21234	0.6789	0.98123	Image×24/24	Image
Blood	0.1823	0.1685	0.1567	0.8732	0.89265	Image×16/16	Image
Nerve	0.1923	0.9854	0.9823	0.8762	0.39265	Image×18/18	Image
Depression	0.5823	0.8675	0.9567	0.2732	0.79926	Image×22/20	Image
Hopelessness	0.1673	0.5885	0.3567	0.2732	0.49265	Image×24/24	Image
Trouble	0.1873	0.9885	0.2567	0.3732	0.85265	Image×15/15	Image
Breathing-level	0.1173	0.1885	0.9567	0.3732	0.19265	Image×12/12	Image
Breathing-rate	0.1273	0.4885	0.9567	0.6732	0.19265	Image×12/256	Image
Breathing-ratio	0.1273	0.6885	0.2567	0.8732	0.19265	Image×12/256	Image
Brain	0.1777	0.145	0.21234	0.6789	0.98123	Image×24/24	Image
Blood-Hemoglobin	0.1823	0.1685	0.1567	0.8732	128	Image×16/16	Image
Sugar-Level	180	140	132	133	129	Image×18/18	Image
Depression	0.5823	0.8675	0.9567	0.2732	0.79926	Image×22/20	Image
Temperature (F)	99	100	100	101	102	Image×24/24	Image
ECG	0.1873	0.9885	0.2567	0.3732	0.85265	Image×15/15	Image
Blood	0.1173	0.1885	0.9567	0.3732	0.19265	Image×12/12	Image
Oxygen	0.1273	0.4885	0.9567	0.6732	0.19265	Image×12/256	Image
Skin	0.1273	0.6885	0.2567	0.8732	0.19265	Image×12/256	Image

Table 4
Mental disorders dataset: 1000 features.

Disease	Pain	Breathing	Sweating	Anger	Over-react
Nervous	0.1777	0.145	0.21234	0.6789	0.98123
Neuron	0.1823	0.1685	0.1567	0.8732	0.89265
Nerve	0.1923	0.9854	0.9823	0.8762	0.39265
Depression	0.5823	0.8675	0.9567	0.2732	0.79926
Hopelessness	0.1673	0.5885	0.3567	0.2732	0.49265
Trouble	0.1873	0.9885	0.2567	0.3732	0.85265
Breathing-level	0.1173	0.1885	0.9567	0.3732	0.19265
Breathing-rate	0.1273	0.4885	0.9567	0.6732	0.19265
Breathing-ratio	0.1273	0.6885	0.2567	0.8732	0.19265

Table 5
Node power-consumption, cost and threshold specifications.

K	P_{Cost}(KWH)PKR	Hours	$P_{Threshold}$	Region
$k1$	15	9 am to 1 pm	98%	Karachi
$k1$	13	2 pm to 5 pm	98%	Karachi
$k1$	12	6 pm to 10 pm	98%	Karachi
$k1$	11	1 pm to 1 am	98%	Karachi
$k1$	10	2 am to 6 am	98%	Karachi
$k1$	9	7 am to 8 am	98%	Karachi
$k2$	15.5	9 am to 1 pm	98%	Lahore
$k2$	14	2 pm to 5 pm	98%	Lahore
$k2$	12.3	6 pm to 10 pm	98%	Lahore
$k2$	11.4	1 pm to 1 am	98%	Lahore
$k2$	10.4	2 am to 6 am	98%	Lahore
$k2$	9.4	7 am to 8 am	98%	Lahore
$k3$	25.7	9 am to 1 pm	98%	Global
$k3$	24	2 pm to 5 pm	98%	Global
$k3$	22.8	6 pm to 10 pm	98%	Global
$k3$	21.5	1 pm to 1 am	98%	Global
$k3$	20.9	2 am to 6 am	98%	Global
$k3$	16.1	7 am to 8 am	98%	Global

5.2.1. Mobile blockchain energy consumption

In this section, the study looked at how well the client socket worked when all healthcare applications were running, and the healthcare datasets were trained and tested while the applications were running in the system. Fig. 4 analyzes that the proposed algorithm EDFOS outperformed all workloads on request regarding hashing, validation, training, testing, resource leakage, and application deadlines. The main reason is that Ethereum PoW uses a lot more resources than Ethereum PoS when blockchain mechanisms are used on different types of healthcare data. Whereas centralized blockchain still consumes much more resources and has resource leakage and deadline issues on mobile devices when executing all workloads at the initial application level in the healthcare system. Therefore, a decentralized socket based on federated learning can save power consumption and minimize processing and resource consumption in the healthcare for all healthcare applications, as shown in Fig. 4.

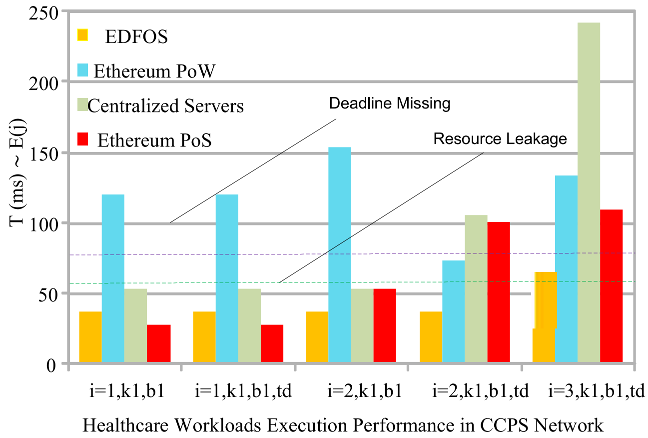

Fig. 4. Different workloads (e.g., Chronic, Brain and Alzheimer diseases) enabled energy-efficient blockchain on mobile in healthcare network.

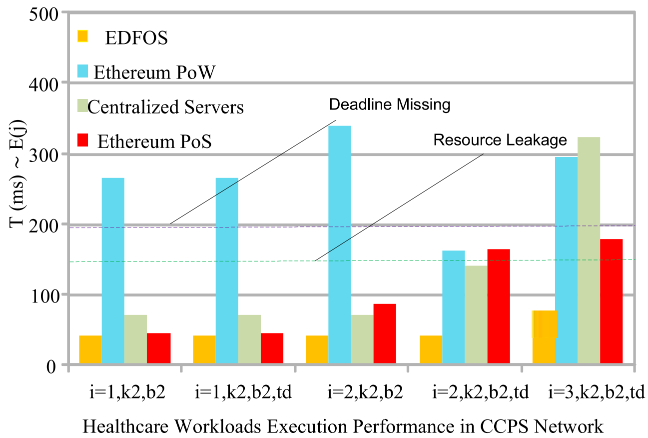

Fig. 5. Different workloads (e.g., Chronic, Brain and Alzheimer diseases) energy-efficient blockchain on fog in healthcare network.

5.2.2. Fog blockchain energy consumption

In this subsection, the study analyzed the performance of the fog socket when it executed all healthcare applications and trained and tested the healthcare datasets during execution in the system. Fig. 5 analyzes that the proposed healthcare algorithm EDFOS outperformed all workloads in terms of hashing, validation, training, testing, resource leakage, and deadlines for applications. The main reason is that Ethereum PoW consumes much more resources when performing blockchain mechanisms on homogeneous or heterogeneous healthcare data than Ethereum PoS. Whereas centralized blockchain still consumes much more resources and has resource leakage and deadline issues on mobile devices when executing all workloads at the initial application level in the healthcare system. Therefore, a decentralized socket based on federated learning can save power consumption and minimize processing and resource consumption in the chronic critical processing healthcare system (CCPS) for all healthcare applications, as shown in Fig. 5.

5.2.3. Cloud blockchain energy consumption

In this subsection, the study analyzed the performance of the cloud socket when it executed all healthcare applications and trained and tested the healthcare datasets during execution in the system. Fig. 6 analyzes that the proposed healthcare algorithm EDFOS outperformed all request workloads regarding hashing, validation, training, testing, resource leakage, and application deadlines. The main reason is that Ethereum PoW uses a lot more resources than Ethereum PoS when blockchain mechanisms are used on different types of healthcare data. Whereas centralized blockchain still consumes much more resources and has resource leakage and deadline issues on mobile devices when executing all workloads at the initial application level in healthcare system. Therefore, a decentralized socket based on federated learning can save power and minimize processing and resource consumption in healthcare applications, as shown in Fig. 6.

5.3. Electricity-cost during processing of different workloads (e.g., Chronic, Brain and Alzheimer diseases)

We implemented Alzheimer dataset that have different classes and data description which is publically available on the following link. https://github.com/grantgasser/Alzheimers-Prediction. The dataset of healthcare datasets such as Alzheimer consisted of

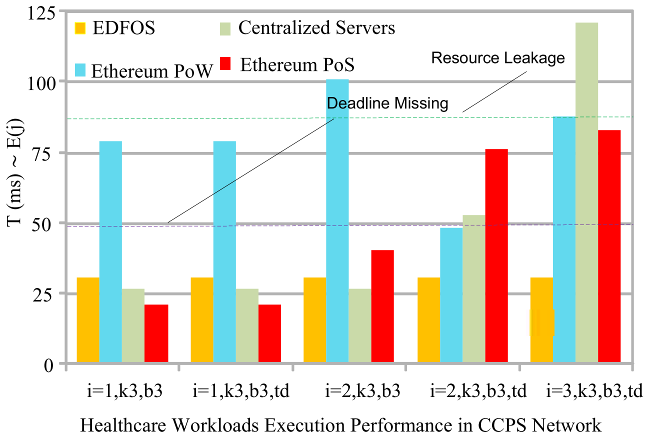

Fig. 6. Different workloads (e.g., Chronic, Brain and Alzheimer Diseases) energy-efficient blockchain on mobile in healthcare Network.

Table 6
EDFOS with the power consumption for different workloads (e.g., Chronic, Brain and Alzheimer diseases).

GAI-Algorithm K	W	P_{Cost}(KWH)PKR	$P_{Threshold}$
EDFOS	$w = 1, 2, 3$	500∼1000	96%
[12] I-Servers	$w = 1, 2, 3$	1500∼10000	100%
[13] GAI-Ethereum PoW	$w = 1, 2, 3$	900∼2000	105%
[15] GAI-Ethereum PoS	$w = 1, 2, 3$	1500∼5000	110%

different features such as brain, chronic disease which is available in following link:https://github.com/grantgasser/Alzheimers-Prediction.

Table 6 shows the performances of all schemes for the healthcare workloads based on different constraints in the experiment. EDFOS algorithm schedules the application's tasks and workloads based on available resources for each resource type. While EDFOS ran the healthcare workloads with proof of work validation on the different nodes and checked the data as it moved through the network during transactions. The EDFOS put in place a proof-of-stake system used for different workloads involving datasets for healthcare applications. All the simulations showed that the proposed work minimized the time, energy, and cost of healthcare applications as compared to existing schemes.

6. Conclusion and future work

In this paper, the study presents the Federated Learning and Blockchain Enabled System for Patients Healthcare Application based on the socket programming model in the distributed mobile fog–cloud network. The idea is to minimize the power consumption of all computing nodes, minimize training and testing time based on the decentralized, federated learning-based model, minimize processing time, and meet the resource leakage and deadline constraints of applications in the system. The simulation results showed that EDFOS minimized the 39% power consumption, training and time by 29%, and hashing and validation resource leakage and deadline by 36% by all existing patient healthcare systems for the patients healthcare applications. EDFOS reduced the 50% power consumption, training and time by 40%, and hashing and validation resource leakage and deadline by 50% by all patient healthcare system for the different datasets of the healthcare applications during offloading and scheduling on the heterogeneous cloud in the network. The study implemented different datasets, such as Alzheimer's, brain activity, and chronic disease, with the different features and implemented them with the user applications. The power consumption is a critical element. Therefore, this study optimized the power consumption for remote healthcare applications.

In the future work, the study will considers the dynamic intrusion attacks on the socket based mobile fog–cloud network and will suggest the deep reinforcement federated learning enabled detection framework for the distributed healthcare applications in patient healthcare system. The future constraints such as fault tolerant, tardiness, and storage costs will be considered in the hypothesis of the work.

Ethical approval

The manuscript does not report on or involve the use of any animal or tissue and "Not applicable" for this manuscript.

Declaration of competing interest

The authors whose names are listed immediately below certify that they have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

Data availability

Its public datasets used (e.g., chronic, Alzehiemer, brain activities). The primary chronic and brain activity datasets downloaded from https://www.kaggle.com/datasets/tourist55/alzheimers-dataset-4-class-of-images.

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