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Enhancing Secure Patient Monitoring with Asynchronous Federated Learning: An Extension to WideResNet and FWBO-Based Fog-Blockchain Architecture

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Abstract: Cardiovascular diseases continue to be among the leading causes of death globally. thus, effective and timely diag-

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nosis is highly necessary. This work proposes an intelligent detection framework, WideResNet FWBO, which will include classification with high accuracy using Wide Residual Networks together with the Fractional Wolf Bird Optimization technique. Empirical Mode Decomposition (EMD) will be utilized for pre-processing ECG signals, which will be further processed for feature extraction through MFCC, 1D-Local Ternary Patterns, and time-domain features. This shall be executed within a fog-assisted, blockchain-secured federated learning environment that will guarantee data privacy with low latency. The experiments conducted on ZENODO datasets recorded 94.2% for accuracy.The proposed model reduces computational overhead and latency, improving responsiveness in remote monitoring by 30%, while ensuring security and scalability in a healthcare analytics environment.

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Key Words Internet of Things, Fog computing, Blockchain, Federated Learning, Healthcare monitoring.

1. Introduction

The Internet of Things (IoT) envisions a future where digital and physical objects or things such as cars, TVs, and smartphones are associated through appropriate data and communication methodologies, which enables a variety of services and applications[1]. IoT is referred to as a group of smart devices and sensors connected to the internet for intelligent applications. Individual devices contain a specific IP address to facilitate communication within the network. By exploiting an application programming interface, these devices are linked to the Internet. Presently, several applications including vehicles, smart homes, healthcare, as well as educational applications, are integrated into IoT. Among the various applications, healthcare deliberates the extensive utilization of the IoT by facilitating immediate online connectivity with patients[2]. To enable faster data computation, fog computing is extensively employed in the IoT. In recent years, fog computing has been applied

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in the medical sector to process healthcare information[3]. IoT devices, particularly wearables such as smartwatches and smartphones are capable of monitoring the blood pressure, heart rate, and movements of users constantly and later those data are transmitted to the healthcare sector for assessment and analysis[4]. Fog computing, which integrates the components of edge computing and cloud computing, is rapidly gaining popularity for its efficacy in several aspects like minimizing the congestion as well as latency in the networks while also assisting autonomous systems. This evolving model paves the way for novel research areas concerning delivery services, sharing content, and data dissemination[5][6]. The quick adoption of IoT devices in healthcare gives rise to novel intricacy in maintaining patient safety, security, and data privacy[7]. Blockchain is referred to as a revolutionary scheme to protect information in a decentralized manner. Blockchain methodology is crucial for assessing and protecting identity management schemes. A consortium blockchain network often referred to as a permissioned or private blockchain network, is a branch of the blockchain network and is functioned and managed by several entities or organizations in which the authorized candidates alone are permitted to participate in verification and transactions[8]. In recent years, blockchain technology applications in cloud computing gained considerable focus because of their ability to improve privacy and security. In blockchain technology, the security attributes offered eradicate the necessity of third parties for processing transactions, and thus, aid decentralization through the exploitation of smart contracts framework[9]. The ML model named FL includes keeping data samples stored locally and evading the data transfer while fine-tuning the algorithm across multiple decentralized edge devices or servers[10]. The IoT networks based on healthcare are progressing from centralized to distributed schemes to communicate with one another offering high-quality healthcare to the patients. Based on the predictions, the present clinical-based healthcare monitoring schemes will be first developed into a hospital-at-home model in the year 2025 and eventually into a home-oriented model[11]. Advanced comput-

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ing paradigms, technologies, and architectural schemes are essential to comprehend such progression, particularly in the Healthcare Internet of Things (HIoT)[12]. IoT devices should be accurate and reliable for effectual healthcare since inexactness leads to improper treatment and false diagnostics. The sensitive data of patients gathered using IoT devices are suspectable to several cyber-attacks. Therefore, to guarantee security and safeguard patient privacy powerful safety measures are indispensable. Regulatory necessities like the General Data Protection Regulation (GDPR), and the Health Insurance Portability and Accountability Act (HIPAA), further accentuate the necessity for powerful solutions. Deep Learning (DL) aids in resolving important issues, like access to diverse data, data privacy, and security[13][14]. In order to fine-tune a single DL technique collaboratively and to gradually improve its potential, FL is used for the joint sharing of information across several individuals. This procedure is similar to the collaborative group report or presentation. FL provides an alternate approach for modeling issues by permitting several edge organizations or devices to fine-tune a global method with the help of multiple local data. FL chiefly or partially addresses the challenges related to data security as well as privacy[15]. The benefits of FL for IoT applications comprise high-quality learning, quicker network communication, enhanced data privacy [16] Blockchain assists in securing patient information but with centralized Machine Learning (ML) for detecting disease[17]. ML approaches trained on vast user information are commonly utilized in the present healthcare applications to create insight for enhancing public health products and services and in-home health monitoring[18] .

2. Related Work

This subsection shows how Blockchain, fog computing, and IoT improve healthcare. Edge data sources and strong servers are utilized in shared learning systems. It is Cloud, Edge, and Fog compatible. Device-level models are collected for the training of a global model.

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These are merged to produce a stronger, shared model. For additional local updates, the revised version is produced. To maintain the model up-to-date, global learning uses a range of approaches. To detect heart disease used a fuzzy GBDT approach. For both two-class and multiple-class tasks, their model worked very well.A fog-cloud healthcare system was envisioned.It detected cardiac complications through machine learning. Also, medical scans were integrated with each other using a deep learning model [19].There is no custom combination rules because the proposed combination structure is unsupervised. The system can be employed for various purposes in healthcare. FedAvg is a method of federated learning across private, secure edge devices. FedAvg posits that all participate at the same rate and removes slow-responding users [20]. The FedMA method discovers and merges nodes with comparable weights using a layer-by-layer learning process. Separately trained layers interact with the host machine [21]. FedProx distributes the training burden evenly across all the involved devices, thus overcoming issues of inconsistencies in federated systems. By adding a proximal term to regulate differences and combine part of the data from slow nodes, this method ensures precise and seamless joining [21].Performance is split into a common bottom layer and a special top layer through the FedPer method. As the personalized layers are maintained aside from the server, the shared server applies transfer learning mechanisms to consolidate the base layers [22]. A shared learning method named FedDist applies a Euclidean distance-based metric as the similarity measure to consolidate data. It combines the advantages of FedAvg and FedMA [23]. Separating local optimization from global aggregation helps to diminish the total training and communication costs generated by mobile devices. Experimental evaluations indicate that Edge Fed has better performance compared to existing approaches, reducing both computational cost and mobile device connection cost even with fluctuating bandwidth. Several studies have investigated using federated learning (FL) to ensure privacy in IoMT systems [24][25]. The authors [26] introduce a decentralized, efficient, and privacy-protected way

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of combined edge learning (DEEP-FEL) for the healthcare domain. In [27] proposed a unified deep learning model for biomedical monitoring. The authors kept people's cardiac activity data private yet utilized it to monitor stress levels. The FL-based method for stress detection in the framework has a success rate of 81.75%. In proposed deep transfer learning for infectious disease detection in edge networks. The main contribution is to propose a smart and secure remote patient monitoring system that integrates IoT, Fog computing, Federated learning (FL), and Blockchain technologies.

3.Methodology

A FL-based patient monitoring scheme [11] exploits decentralized ML to improve healthcare and maintain the privacy of the patient. The patient monitoring system is a three-layered architecture including the IoT devices layer, the fog computing layer, and the cloud computing layer.

IoT devices layer: This layer encompasses various wearable and biomedical sensor nodes. The main role of IoT medical devices is to gather important symptoms of the observed patient.

Fog computing layer: This layer assists in effectively processing the important signs that are obtained from the IoT layer. For instance, if the observed important signs surpass a particular threshold, an alert notification is triggered and transmitted to the patient as well as the supervising specialist in order to make a correct decision.

Cloud computing layer: This layer facilitates data analytics and helps to store the data permanently. The deep learning methods and intricate AI are executed in this layer to decide the treatment plan, disease prediction and detection, and classification of data. The ECG signals from patients are gathered by the IoT devices that encompass the remote monitoring system in the IoT layer and are transmitted to the Fog layer. The fog nodes in the fog layer function as local models that carry out the process of cardiovascular disease detection, these nodes are significant as they minimize the rate at which global aggregations are made and enhance the FL

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process. The cloud server aggregates the data from all the local models in the fog layer and generates a global model. FL assists in enhancing the privacy of the data by retaining the data at the local nodes and avoiding the need to store data in the cloud. However, the challenges associated with attacks and vulnerabilities still pose a threat to data privacy and security.

In the FedFWBO system, IoMT devices store medical records locally, and edge platforms train models using feature extraction and classification. Models trained locally are sent to a remote site to build a global model via Federated SGD and FedAvg. FWBO enhances FL using fractional calculus and hybrid swarm intelligence to weight client updates with a method that takes into consideration data quality and convergence, hence making the process of dealing with non-IID data considerably faster, personalized, and robust.

This approach is robust, communication-efficient, and suitable for heterogeneous federated learning tasks like ECG anomaly detection, since the proposed approach provides a proper balance between local refinement and global exploration. It enhances the prediction accuracy, reduces classification errors, and protects the IoMT data. For combined learning, several methods were evaluated independently and in conjunction with meta-heuristic techniques, such as the Unified Stochastic Angle Plunge, Combined Averaging, Unified Coordinated Averaging, and approaches leveraging Subterranean Insect Colony Optimization and Molecule Swarm Optimization [22, 23].

In the proposed WideResNet_FWBO model, ECG signals are trained locally on each device, thus enabling privacy-preserving cardiovascular disease detection. First, ECG data acquisition is performed. Then, the raw ECG data is preprocessed using EMD [19]. After that, MFCC, 1D-LTP [20], along with time-domain [21, 22], are extracted. These features are then concatenated and input into WideResNet enhanced by the new optimization algorithm called Fractional Wolf Bird Optimization, which combines fractional calculus [24] and WBO [25].

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3.1 ECG Signal Acquisition

The input ECG signal taken from the ZENODO [26] database is contemplated for cardiovascular disease detection and is expressed as

$$G = \{G_1, G_2, \ldots, G_\lambda, \ldots, G_0\} \tag{1}$$

Where G_λ signifies that the λ-th ECG signal is taken as ECG signal is taken as input, the overall ECG signals in the database are implied as O, and G stands for the input database.

3.2 Signal pre-processing

The input ECG signal G_λ is directed to the signal pre-processing module as input. Signal pre-processing is the method that enhances the database quality by eliminating artifacts and noise and smoothens the signal. Here, EMD is applied to perform the signal pre-processing procedure.With the support of the EMD [19], the signals are decomposed into various Intrinsic Mode Functions (IMFs). The signal itself determines the basic operation of EMD. The EMD is highly flexible and has the ability to characterize the signal precisely. IMFs should fulfil two conditions. First is that the maximal value of signal amplitude and number of zero crossing in the overall signal time domain must be equal or the maximal difference is 1. Secondly, the average value of the envelope generated by the minimal and maximal signal amplitude must be zero. The steps of EMD are detailed beneath.

(i) Determine the minimal and maximal signal value G_λ (x). (ii) Exploits the cubic spline interpolation operation in order to fit the upper envelope for the maximal value, similarly, concerning the minimal value, the cubic spline interpolation operation is employed to fit the lower envelope. (iii)The mean function $z(x)$ among the mentioned envelopes is computed based on the following expression

$$z(x) = \frac{e_{\max}(x) + e_{\min}(x)}{2} \tag{2}$$

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(iv) In order to attain the modal function $a(x)$, the mean function $a(x)$ is subtracted from the signal and is formulated as

$$a(x) = G_{\lambda}(x) - z(x) \tag{3}$$

(v) Check if $a(x)$ meets the criteria of the intrinsic mode operation. If $a(x)$ satisfies the criteria, it is an IMF element, and the actual signal tends to be $G_{\gamma_{j+1}}$, and is designated as

$$G_{\lambda_{j+1}}(x) = G_{\lambda_j}(x) - a(x) \tag{4}$$

If the condition is not satisfied return back to step (iii).

(vi) The residual component $\gamma(x)$ is reserved, and the decomposition terminates only if the resulting signal is smaller than the binary extremum points. The actual signal is decomposed to j intrinsic mode functions (IMFs), and the residual factor is symbolized as $\gamma(x)$, which is given by

$$G_{\lambda}(x) = \sum_{n=1}^{J} a_n(x) + \gamma(x) \tag{5}$$

The pre-processed signal thus attained using EMD is signified as Z_1.

3.3 Feature extraction

The outcome Z_1 attained from the signal pre-processing process is fed to the feature extraction procedure. Feature extraction is the method of transforming raw data into valuable inputs that accentuate anomalies, trends, and patterns linked to cardiovascular disorder and assist in early detection. In this method, features including MFCC, 1-D LTP, and time domain features are excerpted from the pre-processed signal .

MFCC [20] is demarcated as a set of features for a speaker/speech recognition scheme and currently becomes a significant attribute in classifying heart sounds. Mel frequencies depend on the nonlinear features of sensitivity of the human ear to various

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frequencies. The mapping of the MEL frequency is related to linear frequency, which is represented as

$$\mathrm{Mel}(\nu) = 2595\ \log_{10}\left(1 + \frac{\nu}{700}\right) \tag{6}$$

Equation (6) shows how the Mel frequency relates to the linear frequency ν. In the above expression, the Mel frequency is denoted as Mel(ν), where ν signifies the linear frequency in Hertz. LTP is an improved version of commonly exploited temporal features and is broadly employed in the computer vision field. 1D-LTPs [20] are the enhanced feature descriptors used in applications related to signal processing . Firstly, the pre-processed signal Z1 is categorized into windows with dimensions Q+1 for mining 1D-LTP features. The lower and upper bounds are represented as $\theta - \mu$ and $\theta + \mu$, where θ specifies the central sample of every window. All windows with dimensions Q+1 are partitioned into right and left frames of the same dimensions about the central sample P(C) and is characterized as

$$H\left(p_e, \theta, \mu\right) = \begin{cases} +1, & p_e - (\theta + \mu) \geq 0 \\ 0, & (\theta + \mu) < p_e < (\theta - \mu) \\ -1, & p_e - (\theta - \mu) \leq 0 \end{cases} \tag{7}$$

here, H(.) implies the outcome of the three-valued vector with values +1,0,and -1.H(.) is partitioned into lower as well as upper

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patterns with the help of the succeeding equations.

$$LTP_{upper} = \sum_{\phi=1}^{8} K_{upper}\Big(H(\phi)\Big) \cdot 2^{\phi} \tag{8}$$

$$K_{upper} = \begin{cases} 1, & \text{if } H(\phi) = 1 \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

$$LTP_{lower} = \sum_{\phi=1}^{8} K_{lower}\Big(H(\phi)\Big) \cdot 2^{\phi} \tag{10}$$

$$K_{lower} = \begin{cases} 1, & \text{if } H(\phi) = -1 \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

Where the resulting LTP feature vectors, $\mathrm{LTP}_{\mathrm{lower}}$ and $\mathrm{LTP}_{\mathrm{upper}}$, are extracted from the ECG signal. The 1D LTP attribute is expressed as .Generally, the statistical metrics offer effective and modest attribute sets to accomplish ECG signal processing. The existence of abnormal sounds in the ECG signal results in divergence in the probability density function of the ECG signal. Therefore, kurtosis, skewness, variance, and mean [22] are exploited as time domain attributes. The data concentration of a distribution function is referred to as the mean. The estimation of the mean function is articulated as

$$S_1 = \sum_{g=0}^{\beta-1} g\, X(g) \tag{12}$$

here, the likelihood of an event g is symbolized as $X(g)$, β stands for the overall amplitude levels, g signifies individual amplitude levels in the signal, and the mean attribute is termed as S_1.

FedHealthFog is a federated learning framework for IoT healthcare in resource-constrained environments. It strategically deploys fog nodes for efficient local processing and picks nodes on which to perform the global model aggregation using a heuristic method to reduce network bottlenecks and minimize reliance on centralized servers. Enabling location-aware model training, the proposed framework provides minimal energy consumption, communi-

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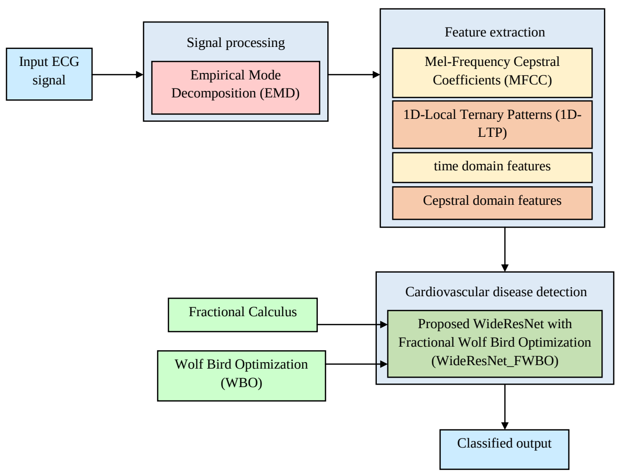

Figure 1: Block diagram of the proposed system.

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cation delay, and improved stability. Each local gateway caches patient data and maintains a blockchain for secure, continuous health record updates to support real-time monitoring even during slow or disrupted cloud connections that ensure rapid and reliable responses in critical situations as shown in Figure 1.

Cardiovascular disease detection is the method of finding and determining the circumstance that affects the heart as well as blood vessels. To accomplish this process, WideResNet with FWBO is exploited here. The FWBO is established by assimilating fractional calculus [24] and WBO [25]. Here, cardiovascular disease detection is established by applying the WideResNet with the feature vector. The WideResNet detects whether the signal is diseased or normal. The feature vector is input to WideResNet [23], a deep learning model that widens layers instead of deepening them. This design enhances feature extraction, captures complex patterns, and mitigates vanishing gradients via residual connections. Compared to conventional networks, WideResNet offers lower computational cost, faster training, robustness to over fitting, and higher accuracy. It has been applied in domains such as facial recognition, NLP, object recognition, and medical imaging. The residual block with identity mapping function is represented as,

$$U_{A+1} = U_A + \alpha\left(U_A, V_A\right) \tag{13}$$

Here, the entity parameters are specified as V_A , the residual function is emphasized as α, and the input as well as output of the unit in the network is indicated as U_{A+1} and U_A. The residual network encompasses two kinds of blocks such as basic and bottleneck residual block.

The Basic Residual block contains a shortcut connection that incorporates the input with the outcome. The basic residual block comprises two or multiple convolutional layers subsequent to ReLU activation and batch normalization. The bottleneck residual block includes three convolutional layers. The initial layer is responsible for minimizing the dimension, the next layer aids in processing the feature mapping function, and the actual dimensionality is restored

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using the third layer. The outcome obtained using WideResNet is stipulated as U_1 .

The FWBO technique is introduced by merging the fractional calculus and WBO techniques, which promote the detection of cardiovascular disease. Fractional calculus [24] is a branch of mathematical assessment that extends the integral and derivatives concept to non-integer orders. Fractional concepts can model these intricacies better than simple categorical approaches. The WBO [25] is a relatively novel approach motivated by the wolf's foraging strategies as well as the hunting behaviours of ravens. This approach has the potential to adjust their strategies according to the problem domain and allowing adjusting to several kinds of optimization intricacy. WBO can balance exploitation and exploration, resulting in faster convergence regarding high-quality solutions than the classical optimization approaches. Thus, the unification of fractional calculus and WBO boosts the efficacy of cardiovascular disease detection by determining the optimal hyper parameters of the WideResNet. The established FWBO Pseudocode is as shown in algorithm 1.

4. Performance Evaluation

We assessed our proposed blockchain-based health record network facilitated by the Hyper ledger tool set in respect to interoperability, latency, and throughput. We implemented a Restful API in charge of enabling SGIs for patients, doctors, and nurses through functions such as GetVitalSignReadings, AddHealthcareSensor, and DetectStatus. The transaction, assets, and access rules (.bna files) are handled by the Hyper ledger Composer framework while Hyper ledger Caliper benchmarks execution and consensus performance. In testing, we used Postman to simulate 300–1000 device registrations and data retrievals, yielding average registration times of 2400 to 3450 ms and data retrieval times of 2570 to 2795 ms. As shown in figure 2 .This showcases low-latency scaling under heavy

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Algorithm 1 FWBO Model Pseudocode

The primary location of the solution candidate as ravens and wolves in the search region are determined.

Access the fitness value for the primary solution candidate as appetite level .

While iteration count < maximal sum of iterations

determine the total ravens count .

Optimal raven having high appetite level is determined.

determine the total wolves count .

Totality of random walks are conducted by the optimal raven .

Updated position of the optimal raven and novel appetite level are determined.

Complete distance among the optimal raven and wolves are computed.

The updated location of the wolves is determined

else

The updated location of the wolves is determined .

end

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loads with stability. To determine the efficiency of consensus, experiments were performed where five REST servers and five IoT gateways served equal shares of devices. Results highlighted that increasing the number of devices from 300 to 1000 increased the consensus time by only 13.5 ms for a mean consensus time of 130 ms, much more efficient compared to Ethereum, which has a range of 10 to 19 s, and Bitcoin, which takes as long as 10 min to 1 h. This evidences that the proposed consensus mechanism is highly scalable and efficient as shown in figure 3. The proposed IoT-based healthcare system with a distributed data flow model. The client module in charge of collecting sensor data from IoT devices receives patient information and communicates with actuators. Following that, the data will be analyzed by the data processing module through AI techniques, such as machine learning, after pre-processing and filtering. The module may thus provide emergency actions through actuators and send results to an aggregator module that collaborates with the blockchain module at the IoT gateway and cloud for secure, immutable data integration. Off-chain data is handled through the storage module.For better communication, the client module is deployed at IoT gateways, while other modules utilize Fog computing for real-time monitoring and cloud resources for blockchain, storage, and processing. To quantify the performance, an iFogSim-based Fog–Cloud infrastructure layout used for experimentation.This includes 64 ECG machines that were connected over four Fog local servers (FLSs). These FLSs connect to a Fog regional server (FRS) that interfaces with the cloud data center. Experiments have shown that Fog-based deployment results in much better latency and energy efficiency than cloud-only settings.

Table 1 lists the simulation parameters obtained using real-world values from [29][30] and [31] so that the Fog devices will have minimal idle energy consumption. With iFogSim time-based energy model, the Fog-based RPMS consumes around 36% lesser energy compared to the cloud-based RPMS, as shown in Figure 4. Since the blockchain module is executed on Fog nodes, transaction retrieval delay is much faster (6.16 ms for a 600 KB and 6.9 ms for

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a 3000 KB transaction) compared to 16.54 ms and 19.34 ms for the cloud system, thus reducing the retrieval delay by about 55.1%.The application module architecture used in the simulations was evaluated for runtime, resource usage, and communication latency. In summary, the Fog-based RPMS cuts down sensing-processing-actuation delays, improves emergency alert response by 30%, and reduces overall energy consumption by about 37% compared to the cloud-based setup because analytics are executed closer to sensors. This paper proposes a new WideResNet_FWBO for the detection of cardiovascular diseases. ECG signals are pre-processed using Empirical Mode Decomposition (EMD) [19]. Features such as MFCC, 1D-LTP [20], and time-domain metrics such as kurtosis, skewness, variance, mean [21,22] are extracted and then concatenated as input to WideResNet. The detection capability is improved by the proposed Fractional Wolf Bird Optimization (FWBO), which combines fractional calculus [24] with WBO [25].

5. Results and discussion

The WideResNet_FWBO devised for cardiovascular disease detection with fog, block chain, and FL is estimated for its efficiency in this section. Furthermore, the description of the experimental setup, dataset, and image outcomes are also demonstrated beneath.

The ECG signals are taken from the ZENODO dataset [28] . ZENODO dataset is established using a real-time dataset gathered from the PhysioNet/CinC Challenge in 2016. This dataset encompasses five databases (A through E) containing a total of 3,126 heart sound recordings, lasting from 5 seconds to just over 120 seconds. The entire dataset can be downloaded in the zip archive format (169 MB). Various metrics, such as TPR, TNR, and accuracy are utilized to estimate the effectiveness of the proposed model.

a) Accuracy

Accuracy is defined as the totality of correct detections relative to the overall number of detections, and is characterized as

$$Accuracy = \frac{M_{TP} + M_{TN}}{M_{TP} + F_{FP} + M_{TN} + F_{FN}} \tag{14}$$

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b) TPR

TPR is often referred to as sensitivity, which is the likelihood of the cardiovascular disease being detected precisely with the support of WideResNet_FWBO and is represented as

$$TPR = \frac{M_{TP}}{M_{TP} + F_{FN}} \tag{15}$$

c) TNR

The ratio of true negatives recognized correctly by the WideResNet_FWBO from the normal instances is described as TNR and is formulated as

$$TNR = \frac{M_{TN}}{M_{TN} + F_{FP}} \tag{16}$$

The performance metrics shown in Table 2 depict the comparative effectiveness of the examined deep learning models in terms of Accuracy, True Positive Rate (TPR), and True Negative Rate (TNR) The models examined, WideResNet-FWBO provides the highest accuracy combined with very strong sensitivity and specificity, demonstrating excellent performance in detecting abnormalities and also recognizing normal cases reliably. By contrast, WideResNet, MobileNetV2, and EfficientNet-B0 provide relatively lower but consistent performance, indicating a trade-off between model complexity and predictive power.

Performance evaluation using iFogSim reveals that the integration of fog computing in a remote patient monitoring system significantly improves the service latency and energy efficiency of the system compared to a cloud-only environment. The hierarchical simulation involves ECG machines, Fog Local Servers (FLSs), a Fog Regional Server (FRS), and a cloud data centre. It is observed that the fog-based RPMS consumes 36% less energy while reducing blockchain transaction retrieval delay by 55.1%, achieving 7.16 ms vs. 16.54 ms for 500 KB transactions. This is explained by performing blockchain operations closer to the data sources through fog nodes. The results from the simulation experiments carried out in

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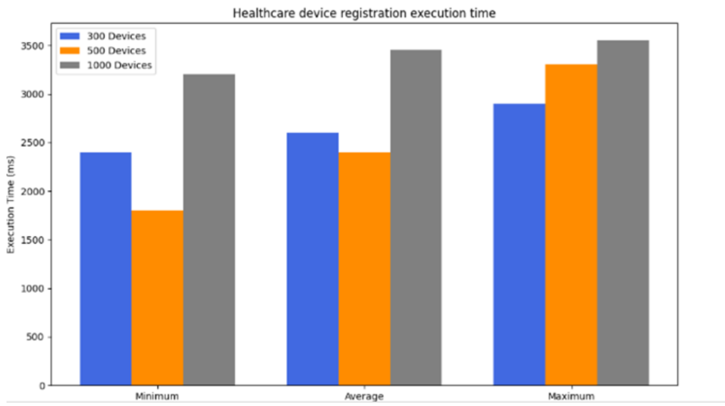

Figure 2: Healthcare device registration Execution Time

the previously mentioned computing setup reveal that our proposed Fog computing-based RPMS surpasses the Cloud computing-based RPMS in terms of minimizing sense-process-actuation delay (calculated using the iFogSim AppLoop model on ECG sensors client module data analytic module client module emergency alert system data flow) and energy consumption. Figure 5 illustrates that the enhancement of Fog computing can increase the responsiveness of RPMS by 30% in sending alert messages during emergency situations when compared to its cloud counterpart.The remote cloud server data transfer delay subsequently reduces due to the execution of the data analytics module in proximity to the sources which will primarily enhance the performance. Subsequently the computing devices within fog environment utilize less energy than cloud server. This distinctiveness furnishes to decrease idle energy consumption of the computing devices. The fog computing based RPMS is anticipated to give services consuming 37% less energy than its cloud based counterpart when time based energy consumption model is implemented using ifogsim simulator.

Table 3 shows the Performance Comparison of Deep Learning Models.To assess the real-time practicality of the proposed WideResNet_FWBO model for ECG signal detection in edge or

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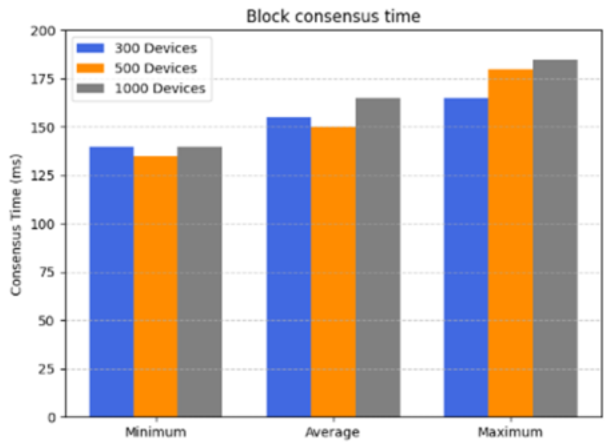

Figure 3: Block consensus time

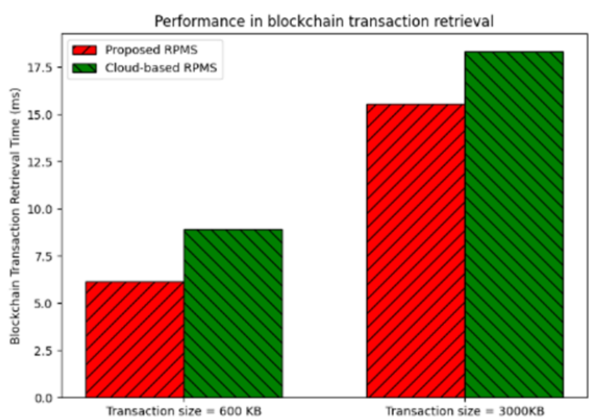

Figure 4: Performance in reducing energy consumption

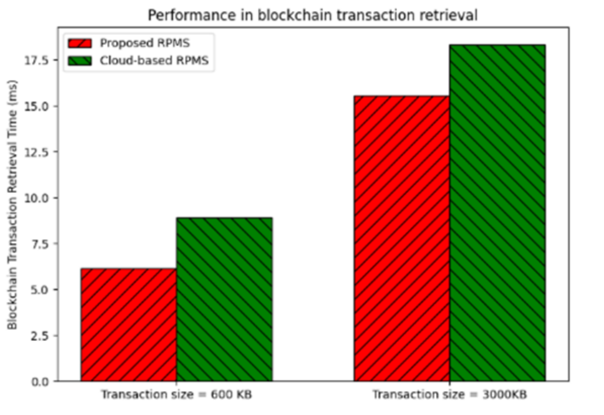

Figure 5: Performance in blockchain transaction retrieval

Table 1: Parameters of simulated environment

Name	Processing speed	Downlink bandwidth	Uplink bandwidth	Memory capacity	Busy power	Idle power
EM	1000	10	5	8	1.1	0.2
FLS	7000	8	3	12	1.3	0.4
FRS	15000	6	2	16	1.6	0.8
CLOUD	40000	3	4	24	3.2	1.4

Sensing frequency of ECG sensors: 8 signals per second
Simulation time: 600 seconds

Table 2: Performance Metrics of Deep Learning Models

Model	**Accuracy (%)**	**TPR**	**TNR**
WideResNet_FWBO	94.2	0.75	0.91
WideResNet	92.8	0.71	0.88
MobileNetV2	90.1	0.68	0.85
EfficientNet-B0	91.4	0.70	0.86

fog-based remote patient monitoring systems, we performed a detailed hardware-level performance evaluation. This section covers the operational metrics, a comparison with baseline models, and

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energy-latency trade-offs on a typical edge AI device. The following performance metrics were used to evaluate deployment efficiency. Inference Latency (ms) is the time needed to process a 10-second ECG segment on edge or fog nodes. CPU Utilization (%) is the average processing load during model inference. Memory Consumption (MB) is assessed by peak RAM usage during execution. Energy Consumption (mWh) is the total energy used per inference session, measured using power monitoring tools such as JetsonStats and Power TOP.To confirm the efficiency of WideResNet_FWBO, we compared it with baseline models like Standard WideResNet, MobileNetV2, and EfficientNet-B0. All models were modified to use quantized or TensorRT-accelerated inference pipelines to ensure fairness across edge and fog deployment platforms. We tested the models on NVIDIA Jetson TX2 hardware configurations.

Table 3: Performance Comparison of Deep Learning Models

Model	**Latency (ms)**	**CPU Usage (%)**	**Memory (MB)**	**Energy (mWh)**
WideResNet_FWBO	92	60	135	210
WideResNet	150	80	180	320
MobileNetV2	70	48	100	180
EfficientNet-B0	85	50	120	200

The latency and energy use of four neural network architectures running on the NVIDIA Jetson TX2 platform for 10-second ECG segment detection. WideResNet_FWBO, the hardware-optimized model, reaches almost real-time performance while greatly cutting down energy use. Compared to the baseline WideResNet, it reduces latency by 38.6% (from 150 ms to 92 ms) and energy consumption by 34.4% (from 320 mWh to 210 mWh) without sacrificing classification performance. While MobileNetV2 has the lowest latency and energy use, its diagnostic accuracy is lower. These results support WideResNet_FWBO as a strong choice for low-latency, energy-efficient cardiac monitoring at the edge.The hardware-aware inference performance of the suggested FWBO optimizer on the NVIDIA Jetson TX2 platform alongside the state-of-the-art techniques AdamW, Optuna, and SGD-Momentum as

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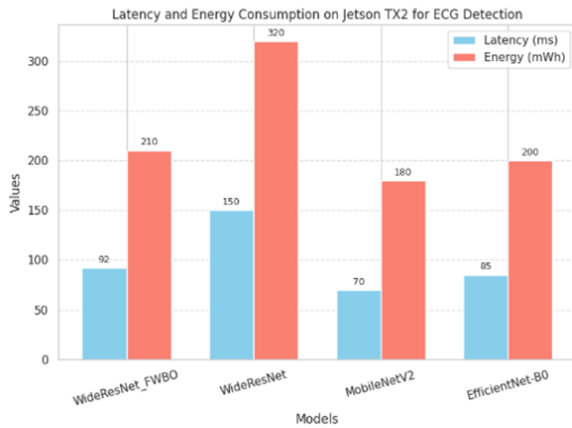

Figure 6: Hardware Performance Comparison of FWBO with Other Optimizers

shown in figure 6. AdamW decouples weight decay from gradient updates, ensuring faster convergence and better generalization for CNNs and transformers.Optuna automates hyper parameter tuning using Bayesian/TPE methods to optimize client-level federated training.The Momentum variant of SGD accelerates convergence because of smoothing updates, but it might struggle on heterogeneous data. FWBO introduces adaptive inertia and fractional calculus into Butterfly Optimization to balance global-local search. It enables robust energy-efficient federated learning over edge devices. FWBO outperforms the other metrics by having the lowest latency (38.2 ms), the lowest power consumption (4.2 W), the highest throughput (26.2 FPS), and the lowest memory usage (512 MB). These results show that FWBO is efficient and works well for real-time federated healthcare systems that don't have a lot of resources .In order to thoroughly verify the suggested WideResNet_FWBO model's performance in clinical ECG classification, we compared it to three popular architectures: WideResNet, MobileNetV2, and EfficientNet-B0.The WideResNet_FWBO model outperformed WideResNet, MobileNetV2, and EfficientNet-B0 in

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clinical ECG classification with an accuracy of 94.2%, F1-score of 0.91, AUC-ROC of 0.75, and the lowest ECE of 0.031. It maintained its strong robustness under Gaussian noise at AUC 0.748, while other models showed performance degradation, making FWBO usable in real-time noisy clinical environments.Healthcare blockchain using Hyperledger Composer, RESTful APIs, and smart contracts enabled the sharing of data securely with access tokens. Performance tests for 300–1000 devices resulted in the time taken for registration as 2400–3450 ms and vital sign retrieval as 2525–2775 ms, with very minimal scaling effects. The consensus mechanism reached an average block validation time of 140 ms, much faster compared to Ethereum or Bitcoin, which proved its efficiency for large-scale IoT healthcare systems.

6.Conclusion

In this work, we designed a three-layer RPM system by incorporating blockchain technology to guarantee advanced data security and Fog computing to maintain low-latency service delivery for IoT-based healthcare environments. The main functional components of the proposed architecture were described and evaluated, ensuring effective interoperability among patients, medical professionals, and IoT gateways. Moreover, a consensus protocol especially designed for RPM environments was introduced and analyzed with the aim of optimizing transaction validation and block generation. The implementation and testing of the blockchain module, based on the Hyperledger Fabric framework, showed very low execution and consensus delays, which validated the suitability of the solution in real-time healthcare scenarios. Moreover, the adoption of Fog computing enhanced the overall responsiveness of the system by about 30%, witnessing the effectiveness in mitigating communication latency and enhancing the performance of remote patient monitoring operations.

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