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FUZZY FUSION: REVOLUTIONIZING SMART HEALTHCARE MONITORING WITH BLOCKCHAIN INTEGRATION

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Abstract
Blockchain and the Internet of Medical Things (IoMT) are widely used in numerous fields, including Healthcare, for applications like secure storage, transactions, in addition development automation. There are no security measures for IoMT devices, which can easily be hacked or affected. Providing remote patient diagnosis is another requirement of smart healthcare. Data protection, costs, memory, scalability, trust, and openness among diverse platforms are all major concerns for the smart healthcare framework. Moreover, blockchain is a revolutionary innovation by immutability structures that provide secure administration, authentication, and access control for IoMT devices. IoMT devices support immutability, as well as secure management provided by blockchain technology. Remote data processing and collection are key features of the IoMT service, a cloud-based internet application. To meet the needs of the healthcare area, an accessible, fault-tolerant, secure, perceptible, and private blockchain is required. In this research work, a blockchain-based autonomous model is being proposed by utilizing fused machine learning to enhance the quality of patient healthcare monitoring in a better and more efficient way. The proposed framework simulation results are enhanced than the previously published approaches in terms of 93% accuracy as well as a 7% miss rate.

Keywords: Blockchain; healthcare; IoMT; framework; measures.

Introduction
Hardware and software networking technologies have revolutionized healthcare data organizations in the previous century to better track diseases and their reasons, and medical treatment, and demonstrate worldwide anticipation tactics for chronic disease. Health records initially kept on the document have been replaced by computerized versions known as Electronic Health Records (EHRs) [1]. Accurate and timely patient care can only be provided if electronic health records (EHRs) are widely distributed and shared among many healthcare stakeholders. It's difficult and

time-consuming to distribute EHRs using the outdated client-server healthcare data management arrangement because every clinic keeps its patient medical records in a private database. The patient's treatment will be overdue if a patient is transmitted from one hospital to the other through various regions. As a result, a patient is commonly bound to replicate some laboratory and imaging tests.

Patients and healthcare providers can easily access the medical records of their near and dear ones from various hospitals thanks to the widespread use of remote cloud storage. The client server-centered system faces issues: scalability, real-time access, single point of insufficiency, confidentiality, and safety. These have all been addressed in the past with cloud-inspired health management systems [2-4]. There are two options here: Encryption or trust in the cloud service supplier with personal health information that should be kept private and secure. Using the first would require a massive portion of memory-intensive computing, unsuitable for a hospital setting [5]. Using the latter would be more problematic since patients are well conscious of the dangers of their data being misrepresented. There is still a single point of catastrophe in cloud-based schemes, besides client-server schemes' data security and patient privacy hazards. Medical records were breached through the Health Insurance Portability as well as Accountability Act (HIPAA) total records of 13,236,569 in 2018, associated with 5,138,179 records in 2017 [6].

Blockchain expertise [7], which utilizes a mutual, absolute, in addition, transparent ledger, may be able to alleviate the current client-server technology's troubles with real-time data admittance, insecurity, data destruction, an absence of traceability, and confidentiality. A block of timestamped connections is produced for each transaction in the blockchain. Immutability is ensured by using an encryption method to link each block to the preceding one. In 1991, scholars at Telcordia Techniques developed a methodology to generate an absolute record of cohesion using a timestamping mechanism. A document owner uses this method to timestamp their document by sending the hashed manuscript and the owner's uniqueness to a server. Hashing is performed by combining a digital signature with an existing timestamp and a hash of a previously hashed document on a server owned by the server. As a result, any attempt to alter the document's timestamp will be uncovered. Later, adding manifold documents to a single timestamped block was improved upon [8].

Data security, costs, memory, scalability, and trust, in addition to limpidity, among various stages, are all major concerns for the smart health framework. Data integrity in addition to privacy is critical because the user's identity can easily be compromised in an open internet environment. Forgery, timing, denial of service, as well as stolen smartcard outbreaks, are a few security issues that can be addressed using various techniques. It is possible to identify the individuals involved in a transaction without their knowledge using blockchain technology. Immutability, better data sharing, improved security, as well as limited overhead costs in distributed systems are some benefits of using blockchain in health informatics. In addition to the legal requirements, health informatics has specific security and privacy requirements.

Deep learning has been confirmed to be an operational tool in the previous few decades owing to its ability to knob massive quantities of information efficiently. In pattern recognition, the apprehension to utilize hidden layers has exceeded outdated methods. CNN is considered of Deep Neural Network (DNN) that is very prevalent. CNN is a sort of DNN that is commonly utilized to examine visual imagery. It applies a convolution method on two roles that produces a third function to direct how the form is reformed over the form of the other. At last, the CNN summarizes the images into an arrangement that is comfortable with the process, whereas defensive features are energetic for making a good prediction.

Related Work

According to [9], a framework for recognizing activities of daily living (ADL) based on sensor data, such as cell phone data, has been proposed. The ADL Recorder App collects raw data from a client's smartphone, which has a slew of embedded sensors. With the help of multiple sensors, the ADL Recognition System is capable to quite profiling an individual's ADL in addition to determining their daily routines. Audio processing, indoor Wi-Fi placing, contiguity sensor localization, as well as time-series sensor data fusion are the pillars of this research. Many outlines have been used to maximize battery life and network traffic in terms of meeting long-term requirement.

The authors of [10] have developed Blockchain-enabled cloud storage as well as sharing systems for medical data. This system does not confirm the user's integrity if someone is listed as a patient or doctor as well as can stock fake archives constantly. To ensure the safety of each record, it creates a hash value. By the way, the structure produces hash values in addition stores them; it makes no distinction between different types of data, such as images, text, or numbers.

Using blockchain technology, the authors of [11] have created a database that allows users to exchange medical records securely. If the patient visits another doctor at another hospital, data latency is possible because of system failures, such as when the patient switches doctors. The users who mine data into ledgers aren't rewarded either.

Using Proof of Work (PoW) protocols, a Blockchain-based conservation framework for medical data storage has been proposed in a research study [12]. Encryption and hashing were used in the model to protect data that do not permit data allocation and necessitate a massive amount of computational power and time for mining to be completed.

The authors of a research study [13] planned a context for the storage as well as distribution of medical records that comprised of two blockchain frameworks, namely private also consortium systems. It's better for storing and sharing information, according to the research. The use of two separate blockchain frameworks makes this prohibitively exclusive and impossible from a technical standpoint. In addition, the proposed solution does not include any mechanism for verifying the accuracy of the data. A comprehensive review in [14] also shows how blockchain can benefit the healthcare industry.

Most of the researchers have worked on multiple ML methods [15,16, 25-27, 28, 30], like transfer learning [17-18], deep ensemble learning [19-20], computational intelligence methods [21], and hierarchical fuzzy inference systems [22-23], fusion-based approach [29] those have been utilized in research to mature monitoring and management frameworks.

Machine learning [34-36] can assist in healthcare prediction by analyzing large amounts of data to help physicians diagnose diseases and predict patient outcomes. It has the potential to improve patient care and reduce healthcare costs by identifying high-risk patients earlier and recommending personalized treatment plans.

Proposed Methodology

Blockchain technology is a way of storing data that makes it more difficult to alter, hack, or cheat. When a transaction takes place on the blockchain, a log of that transaction is introduced to the ledgers of every participant in the network. Every device on the blockchain network has a duplicate copy of the block-digital chain's ledger, which is called a "blockchain". In this research work, blockchain technology is entangled with CNN while improving the quality of patient healthcare monitoring in a better and enhanced way.

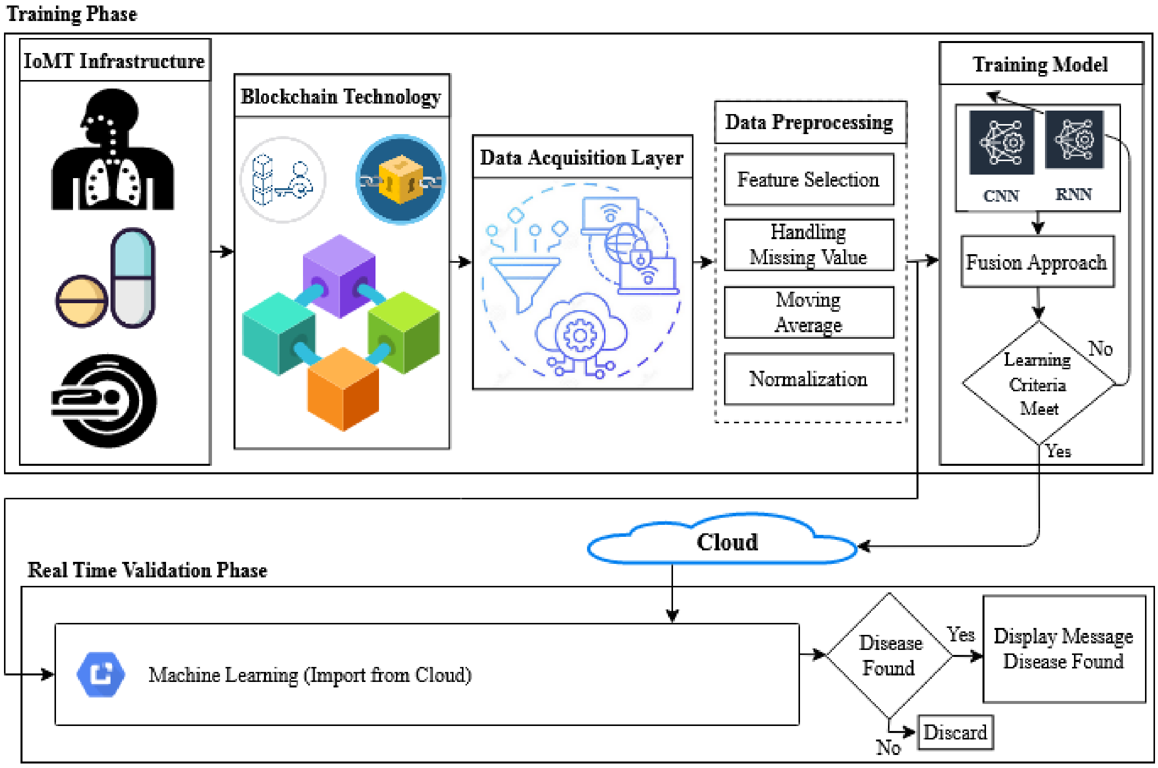

Figure 1: Proposed framework for patient healthcare

Fig. 1 describes that the proposed framework is encompassed of two stages; training and validation. The training phase is divided into six steps: IoMT infrastructure, blockchain technology, data acquisition layer, data preprocessing, training model, and the fusion approach. The first step is the IoMT infrastructure, which assembles the patient input parameters and passes through the blockchain technology. This vital layer is utilized to lessen the security restrictions by utilizing a private blockchain. The data is scrambled for security challenges, and private blockchain can diminish the security hazards by restricting the right of entry to the public who are authorized to contribute. The encoded data is sent to the data acquisition layer.

The data attained from the blockchain layer is situated in the data acquisition layer's raw procedure. The raw data is diverted to the preprocessing layer, which uses feature selection, missing value handling, moving averages, as well as normalization to reduce the noise. The preprocessed data is formerly sent to the training layer that is responsible for predicting the patterns based on CNN, and RNN algorithms to predict the output.

The Loss function in the mathematical model can be

$$\mathrm{L} = -\sum_{i=1}^{c}(\mathrm{Y}_i \log(y_i)) \quad (1)$$

We used SoftMax transformation in Eq. (2)

$$\mathrm{y}_i = \frac{e^{Z_i}}{\sum_{j=1}^{n} e^{Z_K}} \quad (2)$$

$$Z_l = \sum_{j=1}^{noot}(W_{jl} * \mathrm{X}_j\ )$$

Z_l gained by unified weights with the X_j

$$\frac{\partial L}{\partial W_{j,l}} = \sum_{j=1}^{noot\,'}\sum_{l=1}^{c}\left(\frac{\partial L}{\partial Z_l}\frac{\partial Z_l}{\partial W_{j,l}}\right) \quad (3)$$

$$\frac{\partial y_i}{\partial Z_l} = softmax\ derivative$$

In Eq. (1), Loss having y_i as its limitation that is ultimately associated to Z_i in subsequent expression

$$y_i = \frac{e^{Z_i}}{\sum_{k=1}^{c} e^{Z_K}}$$

$$Z_l = \sum_{j=1}^{noot}\left(W_{jl} * X_j\right) \quad (3a)$$

$$Z_i = Z_l$$

Two circumstances are imperative, where ‘l’ is the single neuron in SoftMax output neurons, as well as ‘1’ neuron, has the heights values, in addition, the rest close to zero.

case1: $(i = l)$

Compelling the derivative of Eq. (2) over quotient rules

$$\frac{\partial y_i}{\partial Z_{(i=l)}} = \frac{e^{Z_i}\sum_{k=1}^{c} e^{Z_K} - e^{Z_i} e^{Z_l}}{\sum_{k=1}^{c} e^{Z_K} * \sum_{k=1}^{c} e^{Z_K}} \quad (4)$$

Taking common $\frac{\boldsymbol{e^{Z_i}}}{\sum_{k=1}^{c} \boldsymbol{e^{Z_K}}}$ from Eq. (4), we get following

$$\frac{\partial y_i}{\partial Z_l} = \frac{e^{Z_i}}{\sum_{k=1}^{c} e^{Z_K}}\left[\frac{\sum_{k=1}^{c} e^{Z_K} - e^{Z_l}}{\sum_{k=1}^{c} e^{Z_K}}\right]$$

By dividing, we get

$$\frac{\partial y_i}{\partial Z_l} = \frac{e^{Z_i}}{\sum_{k=1}^{c} e^{Z_K}}\left[1 - \frac{e^{Z_i}}{\sum_{k=1}^{c} e^{Z_K}}\right] \qquad \{\because i = l\} \quad (5)$$

As we know

$$Y_i = \frac{e^{Z_i}}{\sum_{j=1}^{n} e^{Z_K}}$$

So, Eq. (5) can be further written as.

$$\frac{\partial y_i}{\partial Z_l} = y_i\ \left(1 - y_i\ \right) = y_i\ \left(1 - y_i\ \right) for(i = l) \quad (6)$$

case2 $(i \neq l)$:

By the derivation of Eq. (5) with quotient rules concerning Z_l

$$\frac{\partial y_i}{\partial Z_l} = \frac{\frac{\partial}{\partial Z_l} e^{Z_i} * \sum_{k=1}^{c} e^{Z_K} - e^{Z_i}\frac{\partial}{\partial Z_l}\left[\sum_{k=1}^{c} e^{Z_K}\right]}{\sum_{k=1}^{c} e^{Z_K} * \sum_{k=1}^{c} e^{Z_K}}$$

$$\frac{\partial y_i}{\partial Z_l} = 0 - \frac{e^{Z_i} * e^{Z_l}}{\sum_{k=1}^{c} e^{Z_K} * \sum_{k=1}^{c} e^{Z_K}} = -\frac{e^{Z_i}}{\sum_{k=1}^{c} e^{Z_K}} * \frac{e^{Z_l}}{\sum_{k=1}^{c} e^{Z_K}}$$

As we know that

$$y_i = \frac{e^{Z_i}}{\sum_{k=1}^{c} e^{Z_K}}$$

and

$$y_l = \frac{e^{Z_l}}{\sum_{k=1}^{c} e^{Z_K}}$$

So, we can drive this equation as:

$$\frac{\partial y_i}{\partial Z_l} = -y_i\ y_l\ \ for(i \neq l) \quad (7)$$

Subsequently Eq. (6) and Eq. (7)

$$\frac{\partial y_i}{\partial Z_l} = \begin{bmatrix} y_i\ \left(1 - y_i\ \right) for(i = l) \\ -y_i\ y_l \qquad for(i \neq l) \end{bmatrix} \quad (8)$$

$$L = -\sum_{i=1}^{c}\left(Y_i * \log(y_i)\right)$$

Subsequently, taking the derivative concerning Z_l , it can be written as

$$\frac{\partial L}{\partial Z_l} = -\sum_{k=1}^{c}\left(Y_K * \frac{\partial}{\partial Z_l} log(y_k)\right)$$

$$\frac{\partial L}{\partial Z_l} = -\sum_{k=1}^{c} \frac{Y_K}{y_k}\frac{\partial y_k}{\partial Z_l} \quad (9)$$

$\frac{\partial y_k}{\partial Z_l}$ Has been intended for the SoftMax gradient, and equation 9 is divided in two parts.

$$\frac{\partial L}{\partial Z_l} = -\frac{Y_k}{y_k} * y_k \left(1 - y_l\ \right) - \frac{\partial y_k}{\partial Z_l}$$

Where,

$$\frac{\partial y_k}{\partial Z_l} = \begin{bmatrix} \sum_{k \neq l}^{c} (-\frac{Y_k}{y_k} * y_k\, y_l\ ) \; for(\, k \neq l) \\ \frac{Y_k}{y_k} * y_k \left(1 - y_l\ \right) \qquad for(k = l) \end{bmatrix}$$

$$\frac{\partial L}{\partial Z_l} = -Y_k \left(1 - y_l\ \right) + \sum_{k \neq l}^{c} Y_k\, y_l$$

By simplifying:

$\left(y_k\ + \sum_{k \neq l} Y_k\ \right)$ = 1, then

$$\frac{\partial L}{\partial Z_l} = \left(y_l\ - Y_k\ \right)$$

$$\frac{\partial L}{\partial Z_l} = \left(y_l\ - Y_l\ \right) \quad \{\because k = l\}$$

$$\frac{\partial L}{\partial W_{j,l}} = \sum_{j=1}^{noot} \sum_{l=1}^{c} (\frac{\partial L}{\partial Z_l}\frac{\partial Z_l}{\partial W_{j,l}}) \quad (10)$$

Where,

$$\frac{\partial Z_l}{\partial W_{j,l}} = x_j$$

$$\frac{\partial L}{\partial W_{j,l}} = \sum_{j=1}^{noot} \sum_{l=1}^{c} (y_l\ - Y_l\ ) x_j \quad (11)$$

Eq. 10 signifies the derivative of Loss regarding weights for the fully connected layer.

The result of the training layer is then fed to the fusion approach. In the fusion based approach, the fused machine learning empowered by fuzzy logic is accountable for combining the CNN, and RNN calculations utilizing a fuzzy logic design approach. In this layer, the decision-level approach is entangled to accomplish higher accuracy

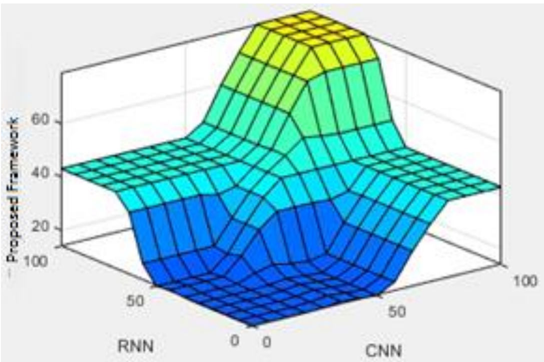

Figure 2: Rule surface of Proposed framework for patient healthcare

Figure 2 shows that if the value of RNN lies within 0-60 and CNN lies between 0-60, then the proposed framework for patient healthcare is bad (blue). If the value of RNN lies amid 60-70 and CNN lies amid 60-70, then the proposed framework for patient healthcare is satisfactory (green). If the value of RNN lies amid 70-100 and CNN lies amid 70-100, then the proposed framework for patient healthcare is good (yellow).

After the fusion approach, the outcome is checked to determine whether the learning criteria are met or not. In the case of no, the CNN, and RNN algorithms will be retrained but in the case of yes, the data is stored on the cloud. The trained patterns are formerly introduced from the cloud for forecasting in the validation phase, as well as; it is rechecked that if a disease found, a message will be shown that the disease is predicted, and if not, the process is discarded.

Results and Simulation

This study presents an intelligent framework that leverages blockchain and ML to enhance the quality and efficiency of patient healthcare monitoring. The proposed approach was tested on a dataset containing 35,250 instances, demonstrating its potential to improve patient care. Furthermore, the dataset is divided into 70% (24675 samples) and 30% (10575 samples) for the mentioned training in addition to validation purposes. Several performance parameters are as follows:

$$Sensitivity = \frac{\sum True\ Positive}{\sum Condition\ Positive} \quad (12)$$

$$Specificity = \frac{\sum True\ Negative}{\sum Condition\ Negative} \quad (13)$$

$$Accuracy = \frac{\sum True\ Positive + \sum True\ Positive}{\sum Total\ Population} \quad (14)$$

$$Miss - Rate = \frac{\sum False\ Negative}{\sum Condition\ Positive} \quad (15)$$

$$Fallout = \frac{\sum False\ Positive}{\sum Condition\ Negative} \quad (16)$$

$$Likelihood\ Positive\ Ratio = \frac{\sum True\ Positive\ Ratio}{\sum False\ Positive\ Ratio} \quad (17)$$

$$Likelihood\ Negative\ Ratio = \frac{\sum True\ Positive\ Ratio}{\sum False\ Positive\ Ratio} \quad (18)$$

$$Positive\ Predictive\ Value = \frac{\sum True\ Positive}{\sum\ Predicted\ Condition\ Positive} \quad (19)$$

$$Negative\ Predictive\ Value = \frac{\sum True\ Negative}{\sum\ Predicted\ Condition\ Negative} \quad (20)$$

Table 1: Proposed framework for patient healthcare in training (CNN)

Proposed Model Training			
	Total samples (24675)	Result (output)	
Input	Expected output	Predicted Positive (PP)	PN
		True Positive (T.P.)	False Positive (F.P.)
	14570 Positive	13327	1243
		False Negative (F.N.)	True Negative (TN)
	10105 Negative	446	9659

It is demonstrated in Tab. 1 that the proposed framework in taining uses a total of 24675 samples are utilized, which are divided into 14570,10105 positive and negative samples, correspondingly. Thirteen thousand three hundred twenty-seven true positives are positively predicted, and no disease is recognized, but 1243 records are incorrectly foreseen as negatives, representing disease. Likewise, 10105 samples are gotten, by negative presenting disease as well as positive presenting no disease, by 9659 samples appropriately recognized as negative presenting disease and 446 samples imprecisely predicted as positive, representing no disease even though the presence of the disease.

Table 2: Proposed framework for patient healthcare in validation (CNN)

Proposed Model Validation			
Input	Total samples (10575)	Result (output)	
	Expected output	PP	PN
		T.P.	F.P.
	5845 Positive	5213	632
		F.N.	TN
	4730 Negative	379	4351

It is shown in t Tab. 2 that the proposed prediction framework in validation uses a total of 10575 samples are utilized, which are divided into 5845,4730 positive as well as negative samples, correspondingly. 5213 true positives are positively foreseen, as well as no disease is recognized, but 632 records are incorrectly predicted as negatives, specifying disease. Likewise, 4730 samples are gotten, by negative presenting disease and positive presenting no disease, by 4351 samples correctly recognized as negative presenting disease in addition 379 samples were imprecisely foreseen as positive, specifying no disease regardless of the presence of the disease.

Table 3. Proposed framework for patient healthcare in training (RNN)

Proposed Model Training			
Input	Total samples (24675)	Result (output)	
	Expected output	PP	PN
		T.P.	False Positive (F.P.)
	12707 Positive	12310	397
		F.N.	TN
	11968 Negative	1456	10512

Table 3 shows the proposed smart healthcare framework training while predicting the disease. During training, individually, a sum of 24675 samples is utilized, which are isolated into 12707,11968 positive as well as negative samples. 12707 true positives are effectively anticipated, and no disease is recognized; however, 397 records are mistakenly anticipated as negatives, demonstrating disease. Essentially, 11968 samples are acquired, with a negative appearance of disease and a positive appearance of no disease, with 10512 samples accurately recognized as awkward appearance of disease as well as 1456 samples mistakenly anticipated as sure, demonstrating no disease despite the presence of the disease.

Table 4. Proposed framework for patient healthcare in validation (RNN)

Proposed Model Validation			
Input	Total samples (10575)	Result (output)	
	Expected output	PP	PN
		T.P.	F.P.
	5213 Positive	4823	390
		F.N.	TN
	5362 Negative	703	4659

Table 4 shows the proposed smart healthcare framework validation while predicting the disease. During validation, a sum of 10575 samples is utilized, separated into 5213,5362 positive as well as negative samples. 4823 true positives are effectively anticipated, and no disease is distinguished; however, 390 records are mistakenly anticipated as negatives, demonstrating disease. Essentially, 5362 samples are obtained, with the negative appearance of disease in addition positive appearance of no disease, with 4659 samples accurately distinguished as awkward appearance of disease and 703 samples incorrectly anticipated as sure, showing no disease despite the presence of the disease.

Table 5: Performance of proposed patient healthcare monitoring framework in training and validation with CNN, RNN

		Accuracy	Sensitivity TPR	SpecificityTNR	Miss-Rate (%) FNR	Fall-out FPR	LR+	LR-	PPV (Precision)	NPV
CNN	Training	0.93	0.96	0.88	0.07	0.114	8.42	0.080	0.91	0.95
	Validation	0.90	0.93	0.87	0.1	0.126	7.38	0.115	0.89	0.91
RNN	Training	0.92	0.89	0.96	0.08	0.036	24.72	0.083	0.96	0.87
	Validation	0.89	0.87	0.92	0.11	0.077	11.30	0.120	0.92	0.86

Table 5 (CNN) depicts that throughout training, the recommended framework accuracy, TPR, TNR, FNR, and precision are 0.93, 0.96, 0.88, 0.07, and 0.91, respectfully, but throughout validation, the suggested model is 0.90, 0.93, 0.87, 0.1, and 0.89. Furthermore, the proposed framework yields 0.114, 8.42, 0.080, and 0.95 during training and 0.126, 7.38, 0.115, and 0.91 during validation in aspects of collapse down likelihood positive ratio, likelihood negative ratio, and NPV, correspondingly.

Table 5 (RNN) further shows that throughout training, the proposed framework accuracy, TPR, TNR, FNR, and precision are 0.92, 0.89, 0.96, 0.08, and 0.96, consecutively, but during validation, the suggested model is 0.89, 0.87, 0.92, 0.11, and 0.92. Furthermore, the proposed framework yields 0.036, 24.72, 0.083, and 0.87 throughout training and 0.077, 11.30, 0.120, and 0.86 during validation in terms of dropout likelihood positive ratio, likelihood negative ratio, and NPV, correspondingly.

Table 6. Fusion results of the proposed framework for patient healthcare using machine learning techniques (CNN and RNN)

	CNN	RNN	The proposed smart healthcare framework using ML methods	The human expert decision of smart healthcare framework	Probability of correctness	Probability of errors
1	12.4 (L)	24.1 (L)	13.9 (L)	Low	1	0
2	21.6 (L)	17.7 (L)	13.9 (L)	Low	1	0
3	54.6 (L)	10.5 (L)	13.9 (L)	Low	1	0
4	50 (N)	55 (N)	43 (N)	Low	1	0
5	51.8 (N)	51.4 (N)	43 (N)	Normal	1	0
6	51.8 (N)	70.5 (N)	43 (N)	Normal	1	0
7	55.5 (N)	86.8 (H)	44.1 (N)	Normal	1	0
8	55.5 (N)	71.8 (H)	44.1 (N)	Normal	1	0
9	21.6 (L)	17.7 (L)	13.9 (L)	Low	1	0
10	51.8 (N)	51.4 (N)	43 (N)	Normal	1	0
11	87 (H)	83.6 (H)	79.2 (H)	High	1	0
12	89.5 (H)	83.6 (H)	79.2 (H)	High	1	0
13	51.8 (N)	70.5 (N)	43 (N)	Normal	1	0
14	55.5 (N)	86.8 (H)	44.1 (N)	Normal	1	0
15	87 (H)	90.6 (H)	79.2 (H)	High	1	0
16	51.8 (N)	51.4 (N)	79.2 (H)	Normal	0	1

Table 7. Performance evaluation of proposed patient healthcare monitoring framework during validation and training

CNN	Accuracy	0.90
	Miss rate	0.1
RNN	Accuracy	0.89
	Miss rate	0.11
Fusion based Approach	Accuracy	0.93
	Miss rate	0.07

Table 8: Comparison of the proposed framework for patient healthcare with other machine learning algorithms

Method	**Accuracy**	**Miss-Rate**
Support Vector Machine [24]	86%	14%
ML [31]	88.4%	11.6%
DFC-Net [32]	84.58%	15.42%
MC-CNN-NP [33]	86.24%	13.76%
Proposed Framework	93%	7%

Table 6 displays the results of 16 tests, indicating that only one test conflicted with the proposed smart healthcare framework and human-based decision, resulting in an accuracy of 0.93 and a miss rate of 0.07. Table 7 compares the performance of the proposed framework using CNN and RNN models, with accuracies of 0.90 and 0.89 and miss rates of 0.1 and 0.11, respectively. The fusion-based approach achieved an accuracy of 0.93 and a miss rate of 0.07, demonstrating higher performance compared to alternative algorithms in Table 8.

Conclusions

This proposed research is introducing a blockchain-based model as a potential solution to tackle security concerns related to the sharing of intelligent data in the healthcare industry. With the advent of the Internet of Medical Things (IoMT), handheld devices are being used to provide patients with timely and effective healthcare services. As sensitive medical data is being transferred, it is crucial to ensure quick and secure healthcare services without any interruption. To this end, the proposed blockchain model employs a fusedmachine-learning approach to enhance the quality of patient healthcare monitoring, while protecting the security of patient data transactions. The proposed framework is reliable and provides end-users with easy access to health information, while also providing better results compared to previous approaches, with a remarkable accuracy rate of 93% and a low miss rate of only 7%.

Data Availability

Data will be provided on demand.

Conflicts of Interest

The authors declare they have no conflicts of interest to report regarding the present study.

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