ORIGINAL ARTICLE

Blockchain technology: A DNN token-based approach in healthcare and COVID-19 to generate extracted data

Basetty Mallikarjuna1 | Gulshan Shrivastava2 | Meenakshi Sharma1

1School of Computing Science and Engineering, Galgotias University, Greater Noida, India
2Department of Computer Science and Engineering, Sharda University, Greater Noida, India

Correspondence
Gulshan Shrivastava, Department of Computer Science and Engineering, Sharda University, Greater Noida, India.
Email: gulshanstv@gmail.com

Abstract
The healthcare technologies in COVID-19 pandemic had grown immensely in various domains. Blockchain technology is one such turnkey technology, which is transforming the data securely; to store electronic health records (EHRs), develop deep learning algorithms, access the data, process the data between physicians and patients to access the EHRs in the form of distributed ledgers. Blockchain technology is also made to supply the data in the cloud and contact the huge amount of healthcare data, which is difficult and complex to process. As the complexity in the analysis of data is increasing day by day, it has become essential to minimize the risk of data complexity. This paper supports deep neural network (DNN) analysis in healthcare and COVID-19 pandemic and gives the smart contract procedure, to identify the feature extracted data (FED) from the existing data. At the same time, the innovation will be useful to analyse future diseases. The proposed method also analyze the existing diseases which had been reported and it is extremely useful to guide physicians in providing appropriate treatment and save lives. To achieve this, the massive data is integrated using Python scripting language under various libraries to perform a wide range of medical and healthcare functions to infer knowledge that assists in the diagnosis of major diseases such as heart disease, blood cancer, gastric and COVID-19.

KEYWORDS
Blockchain, COVID-19 pandemic, deep neural network, electronic health records, feature extracted data

1 | INTRODUCTION

In modern times, every person need to maintain electronic health records (EHRs) for their entire lifetime by using blockchain and the present healthcare industry would move from digital patient record maintenance, EHRs to decentralized management system while using blockchain technology (Nakamoto, 2008). Though using EHRs physicians can be able to analyse and provide treatment, it is very useful to provide feature extraction of data, that will helpful for physicians and nurses to prescribe medicine and maintain digital records of patients for providing efficient treatment (Zhang et al., 2017). Health information on digital format using blockchain helps to manage health records securely and it is useful to prevent diseases for various locations. Since, specific location people suffering from the same disease, to verify and enforce the data with the smart contract, the illnesses, infections and prevention for providing precautions possible with feature extracted data (FED) becomes feasible.

This paper proposes the feature extraction approach to reduce the healthcare data by processing it accurately to the end-users based on blockchain technology. The objective is to reduce the data and process the different dimensional for manageable groups (Deng et al., 2020).
1.1 Motivation

At present, EHRs are maintained at the centralized database, without using blockchain technology and using centralization of data to increases the security issues, integrity problems and patients’ control, while taking medicine is not possible to predict by the data. The centralized database cannot use the token-based mechanism without using feature extraction of healthcare data. It has become more complex and without precautions. Autonomous consuming medicine by patients is the sole reason that a large amount of data without integrity are being unavailable. The token-based approach supported by the distributed system and deadlock-free approach used in the timestamp concept and the messages exchanged are accomplished to complete the task. Patients have used telemedicine to accesses healthcare application through their mobile phones, therefore the healthcare sector distributes the ledger technology (Nakamoto, 2008; Zhang et al., 2017). To improve the healthcare industry to provide better patient treatment in the form of decentralized application is possible to blockchain technology that provides the trust and single authority, integrity and provide accurate data for patients to control while taking medicine (Abu-Elezz et al., 2020).

Figure 1 provides the count of individual diseases occurring in the form of a pie chart (Mallikarjuna & Reddy, 2019). To count the rate of diseases occurring in the areas of NCR Delhi (Delhi, Ghaziabad, Gurugram, Sonipat, Noida and Faridabad) India. To get the pie chart this will depict every disease with its count, the major diseases are identified in heart disease 12%, blood cancer 12% and typhoid 9%.

In the following Figure 2 drawing the graph of total diseases occurring surroundings of Delhi (Jaipur, Agran, Aligarh and Patna). The count of diseases corresponding to the area identified that NCR Delhi is one of the major affected cities suffering from several diseases and as depicted on the graph as shown in Figure 2.

The various new mobile applications are invented in the COVID-19 pandemic, to find a person who is not wearing a mask by using data science technology (Khurshid, 2020). The Indian government decides to increase the COVID-19 test kits and India successfully implemented ArogyaSethu mobile application, it provides the healthcare status of every person in India (Marbouh et al., 2020). It connects the COVID-19 healthcare centers from different PHC with device locations and it connected the physicians and gives the GPS tracking of COVID-19 patients (Marbouh et al., 2020). The ArogyaSetu works on the Android operating system and consists of 120 million people information at the access of the Ministry of Health and Family Welfare Government of India, as per the reports on till June 23, 2020, as shown in Figure 3.

Most of the diseases occurring at Delhi and Patna are as per centralized data and token-based access digitized health records on maximizing the sharing data securely, blockchain technology are implemented digital tokenization. Blockchain technology is beneficial for cost reduction, patient control and effective medicine administration (Zhang et al., 2017). U.S. anti-determination released the reports of deaths happening from different disease mobile healthcare management (Mallikarjuna & Reddy, 2019) and reports provide those major deaths on heart disease and cancer happened in the United States as shown in Figure 4.

**Figure 1** Total count of individual diseases in NCR Delhi region in India (Khurshid, 2020)
Objectives

Blockchain technology in healthcare services could be used to maintain EHRs, data sharing between physicians, patients, laboratories and health insurance companies becomes smooth. The integrity of the data is most important in permissioned (private) and permission less (public) blockchain (Zhang et al., 2017; Sharma et al., 2019; Shrivastava et al., 2020). Ethereum technology uses the proof of stake (PoS) consensus protocol that useful for integrity, accuracy and cooperation between the stakeholders to distribute the decentralized data and security. PoS validates the size of the blocks and size of the chain, it executes the functions automatically it knowns as “smart contract” (SC). SC adds accuracy to the data and adaptability to the Ethereum chain, Blockchain technology has maintained EHRs with the use of SC which can be implemented by Ethereum, it is a decentralized platform that runs SC as shown in Figure 5 (Guo et al., 2017).

The blockchain paradigm and framework has been implemented with Ethereum virtual machine (EVM). It can extend to provide decentralized computer resources (Mallikarjuna, 2020a & 2020b). The transaction of EHRs by using cryptographic secured transactions by using a peer-to-peer protocol (Gupta et al., 2020). The overall smart contract structure is shown in Figure 5. Registrar contract (RC) associate each name with the Ethereum address and smart contract number and maps the identity discovery with the SC, the SC maintains a summary of patient-provider relationship contract (PPR), it manages the overall EHRs associated with PPR address and status of each record (Mayer et al., 2020). The PPR identify the records and provide access permissions that identify the records. PPR is associated with several pointers, each pointer can be used to provide the information from database. In addition to that PPR also have a special feature that can access the network hostname, port number and
network topology. It stores the data, provides privacy, quality of accessing and accurate data (AlShamsi et al., 2021). Blockchain-based healthcare data-sharing is a challenging task to protect healthcare information and install blockchain software, another challenging task is the transparency of feature extraction of data by using collection cryptographic algorithms, the crucial issue to store EHRs by using blockchain technology is the maintained cloud-based assistance. Cloud based assistance (Sharma et al., 2019) provides EHRs better control and services to the end-users (physicians and patients) the feature extraction of data guarantees to provide accurate data prediction (Aleesa et al., 2020). The streamlined deployment by using blockchain technology in healthcare industry is to provide complete freedom to access EHRs. To provide a containerized solution

FIGURE 4  Death in United States (Guo et al., 2017)

FIGURE 5  Smart contract implementation in Ethereum (Hakak et al., 2020)
that guarantees portability to provide accurate data, integrity and patient control over the data while administering the medicine (Mayer et al., 2020). The primary objectives of this paper are as follows:

- To feature extraction that reduces the number of resources in the healthcare industry and maintain the integrity of data. In feature extraction, the variables act as features that reduced the amount of data to be processed in healthcare while accurately giving the original dataset.
- The transmission of data by using feature extraction without losing the important or relevant data.
- The feature extraction reduced the amount of redundant data in healthcare.
- The redundant data is useful for the machine learning approach to build the variables to work like features (Gao et al., 2017).

1.3 Contributions

This paper helps to generate extracted data that provides accurate predicted data and the proposed architecture using blockchain. This is done by providing efficient integrity of exchange data of permissioned and permission less for accessing the EHRs. The proposed architecture accesses the EHRs to generate FED by using a token-based approach from cloud assistance, it interacts with the blockchain nodes, to facilitating large file sharing, generate isolated data and access the indexed based approach from deep neural network (DNN) trained prediction computation model high-level token-based approach and it accesses the EHRs unique approach that generates the FED. To get a better and quick response to generate the FED from the following sample tokens as shown in Table 1. The tokenization is merged with the FED that identifies the key features to drive the new data of token class $T_{Class}$.

To keep the EHRs of the diseases that have been reported frequently $freq(i,c)$, what is the count of the disease and in which particular area that disease has been reported more frequently; How it has opted for this project so that it can help in maintaining the record of such diseases which in extracted data can help to minimize the count of such diseases (Khezr et al., 2019). As the number of such reported diseases would have already been with the hospitals, they can prepare themselves at the best level for reducing the impact of such diseases. Each $T_{Class}$ extracts the words used in EHRs treatment as a feature that help to identify the diseases and classify the frequency of use.

1.4 Justification of the proposed methodology

This paper is useful to the healthcare departments that can utilize the FED, that data can be useful to consider to improve the medical facilities in the hospitals and specific areas. The extracted data is useful to the hospital and its staff can be maintained medicines and provide the precautions according to the diseases which are reported in those areas. In future all the analysis help in maintaining the good medical care that is being provided to patients moreover it helps the overall world healthcare organizations such as WHO to invent and declared abundant research is possible by using machine learning algorithms in the healthcare industry (Aleesa et al., 2020). Deep learning algorithms and methods are almost a requirement in the healthcare industry, the Figure 6 shows the research papers are available on machine learning methods in the healthcare industry (Mayer et al., 2020).

The proposed methodology is implemented by using Python object-oriented scripting language. The dataset which is used for Greater Noida (NCR Delhi) https://www.kaggle.com/dheerajmpai/ of COVID-19 dataset https://www.kaggle.com/sudalairajkumar/novel-corona-virus-2019-dataset, the opensource COVID-19 datasets maintained by the Kaggle database from India https://www.kaggle.com/sudalairajkumar/covid19-india. It is essential for healthcare analysis to provide better medical treatment as per the FED.

### TABLE 1 General categorization of tokens (Jalan et al., 2018)

| Category          | Definition of category                                      | $T_{Class}$ |
|-------------------|------------------------------------------------------------|-------------|
| Basic Personal Details | Age, Gender, Profession, Ethnicity, etc.                   | $T_{Class(1)}$ |
| Diseases          | Allergies, Addiction, Deficiency diseases, Degenerative diseases, Coughing, Wounds, Cholera, Dysentery, Common-gastro, etc. | $T_{Class(2)}$ |
| Treatment         | Insight therapy, Behaviour therapy, Biomedical Therapy, Surgery, Hormone therapy, Immunotherapy etc. | $T_{Class(3)}$ |
| Goal-based        | Exercises, Weight management, Exercise regimen, etc.       | $T_{Class(4)}$ |
| Pregnancy         | AIDS test, Thyroid test, RBC test, Iron-Calcium medicine, Delivery time treatment, Abortion treatment etc. | $T_{Class(5)}$ |
| Family Support    | ill child, caregiver issue, spouse, caretakers etc.         | $T_{Class(6)}$ |
| Socialization     | Hobbies related to healthcare, activities related to healthcare, etc. | $T_{Class(7)}$ |
1.5 | Structure of the paper

The main aspect of this paper is to identify the major diseases in a particular area and to generate FED at a specific region and generate EHR to transmit. In this paper Section 2, provides related work, Section 3 gives the proposed methodology, Section 4 states the simulated results and discussions and Section 5 draw the conclusion and future enhancements of the proposed model.

2 | RELATED WORK

Blockchain technology provides significant opportunities to maintain and digitized health records, patients and doctors required feature extraction data for FED to make improvements to the healthcare systems to generate and control medical reports for patients. In blockchain technology, each healthcare record block connected to the next healthcare record block in a peer-to-peer network. The healthcare records are in a decentralized manner, the patients have the right to privacy while data sharing (Khurshid, 2020). The header of each healthcare record contains the hashes of previous healthcare record. The major hash algorithm used SHA256, the hash of current block of healthcare record connected to the previous hash of the healthcare record. The genesis block of every healthcare record starts with the information of the patient, the name of the person, age, location and the deceases he faced recommended as tokens that provide sensitive data (Mayer et al., 2020).

2.1 | Research challenges

In information technology, one of the most considered research has healthcare sector, that ensures to provide quality of (Kalla et al., 2020). In 1980, IT sector changed the healthcare industry and brought many benefits to provide pervasive computing (Salah et al., 2019). Big data is the processing of a huge amount of data, in healthcare that data stored are in a centralized manner, integrity of data, control over the data, accuracy of the data and data mining provides the knowledgeable information existing data. Security, integrity and accurate data can be built with blockchain technology with a token-based approach (Jalan et al., 2018). (Khezr et al., 2019) proposed, the provider adds a new patient record it stores EHRs as shown in Figure 7, the maintenance of EHRs can be classified as two sets of information such as provider information and patient information, when a new record is identified, the provider can add EHR manager, the patient data are stored in local database server with network connectivity (Khezr et al., 2019), EHR manager is a user interface API, it interacts with the SQLite database. The prototype is designed for when a user to SELECT data query automatically EHR manager enables with the condition of patient address for viewing (Mayer et al., 2020). The application has built with a Python front end application (Zheng et al., 2018).
Ethereum platform can create an infrastructure to implement smart contracts, it contains metadata about the record ownership and viewing. Backend library creates multiple utilities and supports the communication between blockchain and end-users, it provides function-call API and communication between the blockchain Ethereum-client (Khurshid, 2020). When a new record is added RC created the new registration as per Figure 5 and it maps the PPR contract with the Ethereum links and SC address and stores in the blockchain. Ethereum-client provides peer-to-peer network connectivity it encoded with the python software, it is mapping with SC address via RC address and update the SC and PPR status, it interacts with the EHR manager and provides notifications to the clients. Administer and patient’s information's maintained on its local database which is implemented off-chain block data as per requests sent the resultant query (Marbouh et al., 2020).

2.2 A DNN token-based approach in healthcare

Kalla et al. (2020) said that patient role in healthcare is the major aspect, this model improves. Using artificial intelligence, solutions can be provided efficiently to patient healthcare while reducing costs. Many researchers observed that artificial intelligence (Kalla et al., 2020; Salah et al., 2019), machine learning, deep learning and semantic computing solutions are most efficient while transmitting the data, analysing, accuracy and reliability to develop healthcare applications (Jalan et al., 2018). Deep learning solutions are very smart to develop and design healthcare applications; while quick transmission and classification of data between patient and physician (Khezr et al., 2019). In DNN arrange the data in matrix format the features data arranged into the columns, let ‘i’ be the feature vector $f_i = \begin{bmatrix} f_{i0} \\ f_{i1} \\ \vdots \\ f_{in} \end{bmatrix}$.

the input matrix $i = \begin{bmatrix} i_{11} & i_{12} & \cdots & i_{1p} \\ i_{21} & i_{22} & \cdots & i_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ i_{n1} & i_{n2} & \cdots & i_{np} \end{bmatrix}$

weighted matrix $W_d = \begin{bmatrix} w_{d11} & w_{d12} & \cdots & w_{d1q} \\ w_{d21} & w_{d22} & \cdots & w_{d2q} \\ \vdots & \vdots & \ddots & \vdots \\ w_{dn1} & w_{dn2} & \cdots & w_{dnq} \end{bmatrix}$.

the bias matrix generated in each layer $b = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1q} \\ b_{21} & b_{22} & \cdots & b_{2q} \\ \vdots & \vdots & \ddots & \vdots \\ b_{n1} & b_{n2} & \cdots & b_{nq} \end{bmatrix}$.
The output computation of each layer $w_T^2 \times b + b = z$.

DNN surely supports the healthcare analysis to generate the extracted data (Marbouh et al., 2020). Featured extracted data comes from the trained data that gives the self-monitoring and taking precautions for feature plan, people are suffering from major diseases like heart diseases, blood cancer (He et al., 2020) to classify the data and predict the healthcare data (Abu-Elezz et al., 2020). The blockchain is associated with “medicalchain.com” and provide a decentralized secured platform that provides an exchange of bitcoins and usage of medical data (Xu et al., 2020). The following ‘MedTokens’ (medical tokens) drastically transform productivity within every sector of healthcare (Mamoshina et al., 2016). The MedToekns are most useful for private blockchain and it is easy to use and buy a hosting service, most of the physicians and pharmaceutical companies receive the tokens and doctors give the telemedicine with the use of medical tokens (Aliper et al., 2016).

In this paper, we identify the major diseases in the area and providing precautions with better medical facilities by using extracted data. The doctors and drugs can be available according to diseases reported in the area, each patient EHR can analyse to know why a particular area is affected by a particular disease. By analysing the count of diseases, we can analyse which disease occurs more in number and accordingly the vaccines and other measures can be taken. The analysis also helps in splitting up the data according to a particular location to know which location is severely affected by what diseases and what measures can be taken to prevent the diseases or reduce its number. It helps the area’s hospital to maintain the medical facility to those diseases by which their area is affected to reduce the death zone.

3 | PROPOSED METHODOLOGY

The sensors collect the data, it classifies the tokens that provide for patients in an absolute log of their medical history and it also generates the FED. The patients access the data through blockchain technology. The patient information received from the sensors is accessed through API and process the Ethereum SC, the Figure 5 and Figure 7 architectures observed in cloud-based assistance as shown in Figure 8 (Mallikarjuna & Shahajad, 2019), the data is collected from sensors and it can be evaluated using the machine learning algorithms, it can be generated feature extracted from the given dataset. The sensors acquired the data as per the patient application, it produces the data and reliable information to the SC, the RC use the cryptographic public key to discover the patient record in PPR, the local database server provides authentication, encryption and process with the data via blockchain. Confidentiality and data sharing has been performed at the provider side. The decryption, key receiving, key storage, key releasing has been done and the provider side. The provider database performs server query and provides the resultant query to the network. It checks and verifies the blockchain contracts and it allowed to access the query, if the address is invalid the local database provides the resultant query is invalid. The central records EHR manager stored in cloud data server, it maintains the cloud DB software (Ethereum maintained the SQLite database software), the cloud database software is flexible to the web interface service and built upon python framework, the cloud database service compatible with the mobile devices and end-users and records with high quality as shown in Figure 8 (Zheng et al., 2018). The patient information received from the sensors and passed to the cloud storage. The EHRs are made with cloud-based assistance with blockchain technology.

Ethereum client continuously monitoring all entities on the provider side, it recognizes all activities of user data (RC, SC and PPR) collection and data retrieving and provide the information to the database as it can transmit the data to the wearable devices. Backend library interacts with all components of the provider by parsing the Ethereum protocol and provide sufficient data transmission to the cloud EHR manager (Kalla et al., 2020). Cloud based assistance provides accessibility, ownership, security, privacy and process with the decentralization of data distributed to be handled by the consensus by the trusted entities (Kalyampudi et al., 2021).

The SC enabled private blockchain used a token-based approach; it functions on the provider side the backend libraries interact with the blockchain technology and make it able to run the SC, it involved compression, encryption, decryption and key management system (key releasing,
key receiving and key storage). This cloud-based assistance provides data transparency and trusts the relationship between the entities. The provider stored data process without third party interaction.

Deep learning techniques are required to categorize the data with high correctness and quality of data to process through wearable devices (Wen et al., 2017). To maintain EHRs and provide feature extraction of data can be possible to implement by using deep learning, it provides hierarchical learning to generate FED, the data is filtered from several layers such as hidden layers, each successive layer output is the input of the predecessor layer. The result of DNN model can be more accurate and provide exact FED, fundamentally learning can be started from the collected data, the data can be categorized as tokens, the set of tokens can be treated as predecessor layer. The result of DNN model can be more accurate and provide exact FED, the data is filtered from several layers such as hidden layers, each successive layer output is the input of the predecessor layer.

\[
FED = \frac{\text{freq}(i, c)}{\text{freq}(i, \neg c)}
\]

Equation (3).

The Ethereum platform can be observed in DNN, it performs self-training blockchain data with supervised training dataset, one layer to connect layer to process information and provide accurate data. The extracted data and stored with the help of cloud-based assistance each subsequent layer receives the data from its neighbouring neurons.

**Algorithm 1**

**DNN Self Training data under the evaluation of blockchain**

**Input:** Token Dataset \( T_D = \{i, c\}_{-1}^n, \forall D \) in the state space.

**Output:** Classifier \( C_T \), Blockchain dataset \( B \).

**Step 1:** Initializing the token set \( C_D = \emptyset \forall D \in \{t_1, t_2, t_3, \ldots, t_k\} \).

**Step 2:** while (1) do

**Step 3:** \( C_T \leftarrow \text{Train}(B) \)

**Step 4:** Hidden layer training set \( H_D = \emptyset \forall D \in \{t_1, t_2, t_3, \ldots, t_k\} \).

**Step 5:** \( P(i, c) \leftarrow \emptyset \forall D \in \{t_1, t_2, t_3, \ldots, t_k\} \) probability of classifying instance for the class \( C \).

**Step 6:** for each \( C_T \in B \) do

**Step 7:** \( A_c \leftarrow \text{accurate}(P(i, c)) \)

**Step 8:** if \( P(i, c) > C_T \) then

**Step 9:** \( C_D = \emptyset \forall D \in \{t_1, t_2, t_3, \ldots, t_k\} \)

**Step 10:** else

**Step 11:** \( H_D = \emptyset \forall D \in \{t_1, t_2, t_3, \ldots, t_k\} \)

**Step 12:** for \( C_D = \emptyset \forall D \in \{t_1, t_2, t_3, \ldots, t_k\} \)

**Step 13:** \( C_D = \emptyset \forall D \in \{t_1, t_2, t_3, \ldots, t_k\} \)

**Step 14:** Return \( B, C_D \).

In DNN each layer can be assigned frequency of instances of class and data could be traversed multiple times to train data and refine. The multiple layers can serve the refined results to the next layer. The computation of FED as follows.

\[
FED = \log_2 \left( \frac{\text{freq}(i, c) \times \text{freq}(\neg c)}{\text{freq}(i, \neg c) \times \text{freq}(c)} \right)
\]

Equation (3).

DNN consist of a multi-layered strategy to provide effective and desired output to complete the classification of tasks at each layer. If any layer identifying the abnormalities in medical data, medical images, medical reports and it applies the probability to generate the FED as per the Equation (3).
The vast quantity of unstructured medical data and medical records are classified as tokens with input to Algorithm 1 and Algorithm 2. This generates FED; the medical images can be defined as rows and columns of pixels to classify as tokens to generate FED. The FED provides the probability of diseases that can occur in association with ageing. The DNNs trains the tokens from one layer to another layer and provides resultant FED by using multi-modal data ranging from photographs and videos. This is most useful for a paediatrician that classifies the medical reports such as liver functional test, lipid profile, kidney function test, thyroid profile, creative protein, complete blood count (CBC), urine routine report, x-ray medical radiation technology (MRT), CT scan etc. The FED is most useful for the paediatrics; the ageing reports are most useful to generate activity and performance of the human being even captures the age and capture the many biologically features related to collect the particular disease, such as the DNNs that can be used to extract the healthcare data to target the specific disease, it retrains the dataset of specific disease with the use of the token. The tokens are the identical information of the genesis block. There are many types of tokens generated by the category in biological data. Herewith the proposed DNN trained predicted data computational model is shown in Figure 9.

Blockchain based EHRs gives input to the DNN, which generates the predicted computational model. The model generates the FED as per the chronological age of individuals. Individual data evaluated through the DNNs to detect the future occurrence of diseases, that outliers and data quality control (Mamoshina et al., 2016). The evaluation of data under the control of blockchain based DNNs is multi-modal. This architecture allows not only for accurate data but also provides the integrity of data and patients control over the data while taking medicine to extract the data analysis (Vandenberghe et al., 2017). Results of such analysis to fix the goal state; the input results across all predictors will lead to reaching the goal state (Kadurin et al., 2017). The healthcare industries need to measure the FED that routinely identifies the diseases in the clinic, separate tests are administered for each disease. Patient needs to share his medical history with the physician with his first meeting of appointment, the

\[
FED = \log_2 \left( \frac{p(i, c)}{p(i, \neg c)} \right). \tag{3}
\]
doctor gains some kind awareness on the treatment required for the patient, then blockchain technology provides crucial to share the decentralized and peer-to-peer access; the sharing of EHRs should happen individual and maintain confidentiality between patient and physician. Sharing the EHRs from cloud storage is essential to improve the quality of healthcare system and make it smarter. Sharing the EHRs between the patient and provider through the blockchain and the primary data generated between the physicians and doctors that can be formed as EHRs are essential as well. The EHRs provide the complete medical history of patient. The EHRs provides the complete history of patient, which is stored in the database and provide as a cloud-based service. The patient-relevant data is stored in a cloud database in the form of medical images and process the data by using blockchain (Ordóñez & Roggen, 2016). In DNN systematically applies the filters $filter\; size = f_l^{(1)}$ to input and creates the output features maps, the high feature parameters called as padding, to improve the accuracy output provides the $padding = p_l^{(2)}$ and stride, it depends on the filter size $Stride = s_l^{(3)}$, the filter size impact the input and output of each layer.

$$input_{i_k} = \frac{i_k^{-1}}{l_{k_1}} + \frac{i_k^{-1}}{l_{k_2}} + \frac{i_k^{-1}}{l_{k_3}}$$

Apply the filter size in each layer $F_k = f_k^{(1)} \times f_k^{(2)} \times f_k^{(3)}$.

Weights of each layer $F_w = f_w^{(1)} + f_w^{(2)} + f_w^{(3)}$.

Output of each layer $Z_k = z_k + z_k + z_k$.

Bias of each layer $b_k = b_{k_1} + b_{k_2} + b_{k_3}$.

The FED output computed as the number input features with padding size compared with the stride size $FED = \frac{b_l + 2p_l^{(2)}}{s_l^{(3)}}$.

The blockchain based EHRs are given input to the DNN, which generates the customized access control and ownership of the receiver (Gordon & Catalini, 2018). DNN receives EHRs as input of the ownership of blockchain and process the training data and produce the predicted computational output in the form of FED. The FED is enhanced to store in EHRs, which is the overall proposed general architecture is shown in Figure 10. It provides precise data and integrity to balance privacy and accessibility.

The EHRs records stored in the cloud are processed through the blockchain in a distributed manner. It provides authentication, confidentiality, data sharing and accountability to the end-users. The proposed architecture consists of an ad hoc nature of accessing the EHRs for physicians and patients. It has flexible access through mobile phone and validated through the blockchain. Hence it must process the distributed ledger.

### 4 RESULTS AND DISCUSSIONS

To develop the proposed model, which it has prepared a questionnaire with the help of which the data is collected from different users in the NCR Delhi (India) region, then we converted the Comma Separated Value (CSV) file as shown in Figure 1 and Figure 2 drawn as per the collected dataset. The processing of results on the database collected through Questionnaire then analyse this dataset to get the results as follows:

- Collect data through Google forms.
- Installation python and its libraries.
- Working on data via proposed algorithms and database queries.
- Feature extracted data evaluated through Python and MATA LB R2016b.

The DNN network trained with heart diseases applied algorithm 1 and algorithm 2 self-training data using token-based learning rate. The six tokens used for heart diseases, the four classes are used, class 0 for normal person, class 2 for first stroke, class 3 for second stroke, class 4 for end life, the total 24 number of instances have occurred. The outer layer generated the training data to reach the goal state, whereas the goal state is fixed as the FED to set as 1. The input layer starting with 12% of people affected with heart diseases, the performance to generate FED is shown in Figure 11.
In python programming libraries (pandas as pd, matplotlib, the system package URL https://bootstrap.pypa.io/pip.py) python. Installation of Pip: STEP 1: For installation of pip we need to type pip in command prompt and get the following result which shows pip is installed.

STEP 2: Next, we need to upgrade of pip. To update pip we type the command pip3 install

Upgrade pip. Now another library must be installed as matplolib. The Figure 11–15 plotting graphs are built on libraries using object-oriented API for real time data visualization.

The eight tokens are used for blood cancer, the four classes used to implement the neurons, class 0 for the initial state, class 1 for starting state, class 2 for intermediate state and class 3 for end-stage. A total 32 number of instances has occurred. The output layer generated the training data to reach the goal state; the goal state is fixed as per the FED to set as 1.2. The input layer starts with 12% of people affected with blood cancer. The performance to generate FED is shown in Figure 12.

The four tokens are used for gastrointestinal diseases, the four classes used to implement the neurons, class 0 for children’s, class 1 for teenagers, class 2 adults, class 3 elderly. A total 16 number of instances have occurred, the output layer generated the training data, the children and teenagers are goal state is 1. The output layer generated the training data to reach the goal state. The goal state is fixed as per the FED to set as 1.2. The input layer starting with 10% of people affected with gastrointestinal diseases. The performance to generate FED is shown in Figure 13.

The four tokens are used for typhoid diseases: the four classes used to generate the neurons, class 0 for weak 1, class 2 for weak 2, class 3 for weak 3, class 4 for weak 4. A total 16 number of instances have occurred. The output layer generated the training data. The goal state is fixed as per the FED to set as 0.978. The input layer starting with 10% of people affected with typhoid diseases. The performance of typhoid disease extracted data is shown in Figure 14.

**FIGURE 11** Training dataset of heart diseases

**FIGURE 12** Training dataset for Blood cancer
**FIGURE 13**  Training dataset for Gastrointestinal

**FIGURE 14**  Training dataset for Typhoid

**FIGURE 15**  Training dataset for COVID-19
The three tokens are used for COVID-19 diseases: the three classes used to generate the neurons, class 0 for weak 1, class 1 for weak 2, class 2 for weak 3, class 3 for weak 4. A total four number of instances have occurred, those are the number of positive cases, number of negative cases, number of deaths and number of people in quarantine. The output layer generated the training data. The same goal state is fixed as per the FED to set as 0.978. The input layer starting with 13% of people affected with the COVID-19 at the NCR Delhi region in India. The performance to COVID-19 disease extracted data is shown in Figure 15.

For collecting the samples of various tested data, the test data given are computed as various trained and network. The outputs of the network were calculated to the adjusted weights. The obtained results are tabulated as follows (Table 2).

### Table 2 Experimental results of deep neural network (DNN) classification

| Training samples | Test samples | DNN classification |
|------------------|--------------|--------------------|
|                  |              | Input layer | Forward layer 1 | Forward layer 2 | Output layer |
| 100              | 300          | 75         | 77               | 86               | 88           |
| 120              | 220          | 79         | 81               | 94               | 92           |
| 140              | 320          | 85         | 87               | 96               | 98           |
| 160              | 250          | 74         | 76               | 85               | 87           |
| 180              | 350          | 85         | 87               | 96               | 98           |
| 200              | 246          | 82         | 90               | 93               | 95           |
| 220              | 150          | 76         | 78               | 87               | 89           |
| 240              | 123          | 73         | 75               | 84               | 86           |
| 260              | 125          | 74         | 76               | 85               | 87           |
| 280              | 130          | 72         | 74               | 83               | 85           |
| 300              | 156          | 76         | 78               | 97               | 98           |
| 320              | 186          | 78         | 80               | 89               | 91           |
| 340              | 156          | 76         | 78               | 87               | 89           |
| 360              | 200          | 72         | 74               | 83               | 85           |

The three tokens are used for COVID-19 diseases: the three classes used to generate the neurons, class 0 for weak 1, class 1 for weak 2, class 2 for weak 3, class 3 for weak 4. A total four number of instances have occurred, those are the number of positive cases, number of negative cases, number of deaths and number of people in quarantine. The output layer generated the training data. The same goal state is fixed as per the FED to set as 0.978. The input layer starting with 13% of people affected with the COVID-19 at the NCR Delhi region in India. The performance to COVID-19 disease extracted data is shown in Figure 15.

For collecting the samples of various tested data, the test data given are computed as various trained and network. The outputs of the network were calculated to the adjusted weights. The obtained results are tabulated as follows (Table 2).

## 5 Conclusion and Future Enhancements

Blockchain technology creates distributed ledger and peer-to-peer network to transmit the digital data publicly and private to all end-users. The DNN with FED problem is most suitable for the classification of data in business, science, engineering, transportation and healthcare. This paper classifies the healthcare dataset in NCR Delhi (India) and generated the extracted data as per the given dataset with the observation of blockchain technology. It is significant attention to the healthcare industry, nearly all kind of dimensions. The proposed methodology can transform the process of maintaining patients records from the traditional method into blockchain. It is easy to access the web-based service, the outcomes of this approach are most suitable for mobile devices to access the EHRs by the end-users. The proposed model provides the integrity and accuracy of the data transmission. In future, the proposed model can be enhanced to incorporate the improvements in blockchain as smart contract and its binding policy. Blockchain is an essential requirement in the healthcare industry, as per the EHRs to provide the medicines for those diseases in that area and provide precautions for the betterment of treatment planning.

### Data Availability Statement

No required

### ORCID

Basetty Mallikarjuna [https://orcid.org/0000-0003-4354-4684](https://orcid.org/0000-0003-4354-4684)

Gulshan Shrivastava [https://orcid.org/0000-0003-3671-4921](https://orcid.org/0000-0003-3671-4921)

### References

Abu-elezz I. ... Abd-alrazaq A. (2020). The benefits and threats of blockchain technology in healthcare: A scoping review. *International Journal of Medical Informatics*, 142, 1–9. [http://doi.org/10.1016/j.ijmedinf.2020.104246](http://doi.org/10.1016/j.ijmedinf.2020.104246).
Aleesa, A. M., Zaidan, B. B., Zaidan, A. A., & Sahar, N. M. (2020). Review of intrusion detection systems based on deep learning techniques: Coherent taxonomy, challenges, motivations, recommendations, substantial analysis and future directions. *Neural Computing and Applications, 32*(14), 9827–9858.

Aliper, A., Pitis, S., Artemov, A., Uilloa, A., Mamoshina, P., & Zhavoronkov, A. (2016). Deep learning applications for predicting pharmacological properties of drugs and drug repurposing using transcriptomic data. *Molecular Pharmaceutics, 13*(7), 2524–2530.

AliShamsi, M., Salloum, S. A., Alshurideh, M., & Abdallah, S. (2021). Artificial intelligence and blockchain for transparency in governance. In *Artificial intelligence for sustainable development: Theory, practice and future applications* (pp. 219–230). Springer.

Deng, L., Wang, G., Li, G., Li, S., Liang, L., Zhu, M., Wu, Y., Yang, Z., Zou, Z., Pei, J., Wu, Z., Hu, X., Ding, Y., He, W., Xie, Y., & Shi, L. (2020). TianJic: A unified and scalable chip bridging spike-based and continuous neural computation. *IEEE Journal of Solid-State Circuits, 55*(8), 2228–2246.

Gao, M., Igata, H., Takeuchi, A., Sato, K., & Ikegaya, Y. (2017). Machine learning-based prediction of adverse drug effects: An example of seizure-inducing compounds. *Journal of Pharmacological Sciences, 133*(2), 70–78.

Gordon, W. J., & Catalini, C. (2018). Blockchain technology for healthcare: Facilitating the transition to patient-driven interoperability. *Computational and Structural Biotechnology Journal, 16*, 224–230.

Guo, H., Na, X., Hou, L., & Li, J. (2017). Classifying Chinese questions related to health care posted by consumers via the internet. *Journal of Medical Internet Research, 19*(6), e220.

Gupta, S., Malhotra, V., & Singh, S. N. (2020). Securing IoT-driven remote healthcare data through blockchain. In *Advances in data and information sciences* (pp. 47–56). Springer.

Hakak, S., Khan, W. Z., Gilkar, G. A., Imran, M., & Guizani, N. (2020). Securing smart cities through blockchain technology: Architecture, requirements and challenges. *IEEE Network, 34*(1), 8–14.

He, C., Ma, M., & Wang, P. (2020). Extract interpretability-accuracy balanced rules from artificial neural networks: A review. *Neurocomputing, 387*, 346–358.

Jalan, R., Gupta, M., & Varma, V. (2018). Medical forum question classification using deep learning. In *European conference on information retrieval* (pp. 45–58). Springer.

Kadurin, A., Aliper, A., Kazennov, A., Mamoshina, P., Vanhaelen, Q., Khrawrov, K., & Zhavoronkov, A. (2017). The cornucopia of meaningful leads: Applying deep adversarial autoencoders for new molecule development in oncology. *Oncotarget, 8*(7), 10883–10890.

Kalla, A., Hewa, T., Mishra, R. A., Ylianttila, M., & Liyanage, M. (2020). The role of blockchain to fight against COVID-19. *IEEE Engineering Management Review, 48*(3), 85–96.

Kalyampudi, P. L., Krishna, P. V., Kuppani, S., & Saritha, V. (2021). A work load prediction strategy for power optimization on cloud based data Centre using deep machine learning. *Evolutionary Intelligence, 14*, 519–527.

Khezi, S., Moniruzzaman, M., Yassine, A., & Benlaml, R. (2019). Blockchain technology in healthcare: A comprehensive review and directions for future research. *Applied Sciences, 9*(9), 1736.

Khrushid, A. (2020). Applying blockchain technology to address the crisis of trust during the COVID-19 pandemic. *JMIR Medical Informatics, 8*(9), e20477.

Mallikarjuna, B. (2020a). Feedback-based fuzzy resource management in IoT-based-cloud. *International Journal of Fog Computing (IJFC), 3*(1), 1–21.

Mallikarjuna, B. (2020b). Feedback-based resource utilization for smart home automation in fog assistance IoT-based cloud. *International Journal of Fog Computing (IJFC), 3*(1), 41–63.

Mallikarjuna, B., & Reddy, D. A. K. (2019). Healthcare application development in mobile and cloud environments. In *Internet of things and personalized healthcare systems* (pp. 93–103). Springer.

Mallikarjuna, B., & Shahajad, M. (2019). Master slave scheduling architecture for data processing on internet of things. *International Journal of Innovative Technology and Exploring Engineering, 8*(6), 556–559.

Mamoshina, P., Vieira, A., Putin, E., & Zhavoronkov, A. (2016). Applications of deep learning in biomedicine. *Molecular Pharmaceutics, 13*(5), 1445–1454.

Marbouh, D., Abbasi, T., Maasmi, F., Omar, I. A., Debe, M. S., Salah, K., , Ellahham, S. (2020). Blockchain for COVID-19: Review, opportunities and a trusted tracking system. *Arabian Journal for Science and Engineering, 45*(12), 9895–9911. http://dx.doi.org/10.1007/s13369-020-04950-4.

Mayer, A. H., da Costa, C. A., & Right, R. D. R. (2020). Electronic health records in a blockchain: A systematic review. *Health Informatics Journal, 26*(2), 1273–1288.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. *Decentralized Business Review, 1–9*. https://bitcoin.org/bitcoin.pdf.

Ordóñez, F. J., & Roggen, D. (2016). Deep convolutional and lstm recurrent neural networks for multimodal wearable activity recognition. *Sensors, 16*(1), 115.

Salah, K., Rehman, M. H. U., Nizamuddin, N., & Al-Fuqaha, A. (2019). Blockchain for AI: Review and open research challenges. *IEEE Access, 7*, 10127–10149.

Sharma, K., Rafiqui, F., … Yadav, S. K. (2019). A two-tier security solution for storing data across public cloud. *Recent Patents on Computer Science, 12*(3), 191–201. http://doi.org/10.2174/221327591166181010112601.

Shrivastava, G., Le, D. N., & Sharma, K. (2020). Cryptocurrencies and Blockchain Technology Applications. USA: John Wiley & Sons.

Vandenbergh, M. E., Scott, M. L., Scorer, P. W., Söderberg, M., Balcerzak, D., & Barker, C. (2017). Relevance of deep learning to facilitate the diagnosis of HER2 status in breast cancer. *Scientific Reports, 7*(1), 1–11.

Wen, M., Zhang, Z., Niu, S., Sha, H., Yang, R., Yun, Y., & Lu, H. (2017). Deep-learning-based drug-target interaction prediction. *Journal of Proteome Research, 16*(4), 1401–1409.

Xu, X., Cao, D., Zhou, Y., & Gao, J. (2020). Application of neural network algorithm in fault diagnosis of mechanical intelligence. *Mechanical Systems and Signal Processing, 141*, 106625.

Zhang, P., Walker, M. A., White, J., Schmidt, D. C., & Lenz, G. (2017). Metrics for assessing blockchain-based healthcare decentralized apps. In *2017 IEEE 19th international conference on e-health networking, applications and services (Healthcom)* (pp. 1–4). IEEE.

Zheng, X., Mukamala, R. R., Vatrapu, R., & Ordieres-Meré, J. (2018). Blockchain-based personal health data sharing system using cloud storage. In *2018 IEEE 20th international conference on e-health networking, applications and services (Healthcom)* (pp. 1–6). IEEE.
AUTHOR BIOGRAPHIES

Basetty Mallikarjuna is currently working as an Assistant Professor (Grade III) in the School of Computing Science and Engineering, Galgotias University, Gautam Buddh Nagar, Greater Noida. Previously, he worked as an Assistant Professor in the GITAM University Hyderabad Campus, and in the Nedurumalli Balakrishna Reddy Institute of Science and Technology (NBKRIST) Vidyanagar, Vakadu. He has more than 11 years of teaching experience. He obtained his Ph.D in Computer Science from the School of Computing Science and Engineering, Bharathiar University Coimbatore and M.Tech. from the School of Computer Science and Engineering from the VIT University and B.Tech. in Computer Science and Engineering from the Sri Annamacharya Institute of Technology and Sciences (affiliated at Jawaharlal Nehru Technological University, Hyderabad), New Boyanapalli, Rajampet. His area of interest includes Cloud computing, Internet of Things, Fog computing and Blockchain.

Gulshan Shrivastava is working as an Assistant Professor in the Department of Computer Science & Engineering at Sharda University, Greater Noida, U.P. Prior to his current role, he was associated with Galgotias University and Dronacharya Group of Institutions, Greater Noida, U.P., India. He was also visited at Datec Ltd., Papua New Guinea (PNG) as a technical trainer and researcher. He received Ph.D. (Computer Science & Engineering) from the National Institute of Technology Patna (Institute of National Importance), India, and M.Tech. (Information Security) from GGSIPU Delhi, India, and MBA (IT & Finance) from IKGPTU, India and B.E. (Computer Science & Engineering) from the MDU Rohtak, Haryana, India. He also earned numerous international certifications from Coursera, NPTEL, Sun Microsystems etc. He has 5 patents (1 Granted, 4 Published) and published 55 articles, books and editorials in International Journals and Conferences of high repute including IEEE, Elsevier, Wiley, ACM, Springer etc. He is Associate Editor of IJ-ICT (Scopus Indexed) and served as Associate Editor of JGIM (SCIE Indexed) & IJDCF (Scopus Indexed), IGI Global and Section Editor of Scalable Computing (SCPE) (Scopus Indexed). He is also serving many repute journals as guest editor, editorial board member, international advisory board member, reviewer board member. Moreover, Dr. Shrivastava is Convenor in ICICC 2022, ICICC 2021, ICICC 2020 and ICICC-2019, Organizing Chair in 5th IEEE ICCCIS-2021, ICCIDA-2018, Publication Chair in MARC-2018. He also served as Organizing Chair of Special Session and Technical program committee member of international conferences worldwide. He is the life member of ISTE, senior member of IEEE and professional member of ACM, SIGCOMM, and many professional bodies. He has an ardent inclination towards the field of Data Analytics & Security. His research interest includes Information Security, Digital Forensic, Data Analytics, Machine Learning, Malware Detection and Analysis.

Meenakshi Sharma is Dean of the University Center of Research & Development (UCRD) and Professor in the School of Computer Science & Engineering, Galgotias University, Greater Noida, India. She has over more than 16 years of experience in teaching and research. She is a highly qualified professional with Ph.D in Computer Science and M.Tech. in Computer Science & Engineering (both from Kurukshetra University). She has published over 60 research papers in high repute journals including IEEE Transaction, Elsevier, Wiley etc. in the area of Machine Learning, Deep learning, and AI, in collaboration with international researchers. She has four granted international patents and published seven national patents. She was awarded as Best Research and Teacher Award in 2017 and 2018. Dr. Sharma has capably guided three PhD candidates and 40+ students in postgraduate/undergraduate programs, with five currently under guidance. She is a valuable member of various engineering societies, including Senior Member in IEEE, ISTE, ACM, InSc, ISDS Society, Japan, IEAE, and many others. Her research interests are Machine learning, Image processing, Big Data analytics, Data Compression, and Data Warehousing.

How to cite this article: Mallikarjuna, B., Shrivastava, G., & Sharma, M. (2022). Blockchain technology: A DNN token-based approach in healthcare and COVID-19 to generate extracted data. Expert Systems, 39(3), e12778. https://doi.org/10.1111/exsy.12778