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A COVID-19 Prediction Using a Blockchain Approach Integrated With UV-NET for Urban Management

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Abstract

Growing cities contributed to the increase in the COVID-19 virus. Consequently, many researchers are exploring the dynamics of the pandemic and to analyse the impacts of pandemic on such cities. The main aim of this research is to understand impacts of the pandemic in Vellore city, Tamil Nadu, India by building a viable solution which can be beneficial for the medical fraternity. A blockchain based approach integrating Artificial Intelligence (AI) is proposed for secure access and storage of Electronic Health Records (EHR) of COVID-19 patients in Vellore city. The blockchain follows the principle of absolute privacy and anonymity of medical records. The decentralized architecture is built to secure from different attacks as the hash of the records are stored in the blockchain. The proposed approach consists of a U-net and V-net model, one for segmenting lungs from the x-rays and second one for segmenting COVID-19 infection patches. The UV-net model is a Convolutional Neural Network (CNN) for fast and precise image segmentation. Experimental analysis is provided on nearly 33,920 chest X-ray images and text records gathered from a hospital in the Vellore city. The proposed model resulted in a precision, recall and F-score of 0.91, 0.87 and 0.89 respectively. The predicted results are manually analysed by the doctor in their login to finally cross verify and conclude the results which are stored in blockchain. This will aid doctors to centrally diagnose the patients and assist in proper treatment for faster recovery.

Keywords: Blockchain, COVID- 19, Deep Learning, UV-NET.

Introduction

Urban computing is a multi-disciplinary (transdisciplinary) area where the technology meets the needs of urban societies by means of imparting the digitalization. To be precise the urban computing involves about the data, environment and computational power. In particular, the data needs to be processed according to the environment, which will impart the advancements in urban areas (1). In the recent decades, the developments in urban computing has attained a lot of interest by different stakeholders. Such stakeholders can be researchers, urban developers, politicians and mainly industrial peoples (2). The Figure 1 shows the various stakeholders involved in the urban civilization. The developments in latest technology such as Internet of Things (IoT), Fog Computing, Block chain, Data analytics, Artificial Intelligence has paved a new way in the modernization of urban computing, in particular, which fulfils the needs of the development. The needs for such development can be smart health care, smart transportation, smart lighting, smart traffic control system, smart (green energy) buildings, smart industry, smart farming etc. In order to achieve the above (urban) scientific demands, the urban computing needs to be completely digitalized. Such digitalization mainly depends on the data, which needs to be customized. In particular, IoT and Block chain has created a new paradigm shift in gathering the data. In general, depending on the environment and needs, IoT can be mainly classified into Medical IoT (MIoT), Industrial IoT (IIoT), Cognitive IoT (CIoT). In urban computing MIoT, IIoT plays a vital role. First, we will discuss about the importance of the role played by IoT, Block chain in the modernization of urban computing (3). In particular, the (urban) civilization mainly depends on the data. Such data can be gathered by different sensors, actuators,

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relays that may be interconnected in a wired or wireless fashion (4). Once the initial framework has been established in terms of smart applications, which meets the needs of the urban computing, then the framework for sustainable urban computing can be established. To be precise, in sustainable urban computing the idea of smart application with the intelligence of human behaviors can be blended. Such a blending can produce phenomenal decision-making solutions for smart devices (5). Due to the increasing populations many areas in urban computing needs special attention such as critical decisions based on the real time data, safety measures, eco-friendly issues, societal impacts, power consumption. All the above-mentioned critical areas needs to be managed efficiently and intelligently (6). The above idea of nudging the intelligence of human beings with the smart applications paved a new way in research named intelligent urban computing (7). Intelligent urban computing mainly deals with the heterogeneous data received from diversity sources of data generating devices. Such data generating devices should be operated in an intelligent ambient environment, which pertains to the urban computing zone. For more details on the impact of IoT in urban computing, we referred to the publications (8-10).

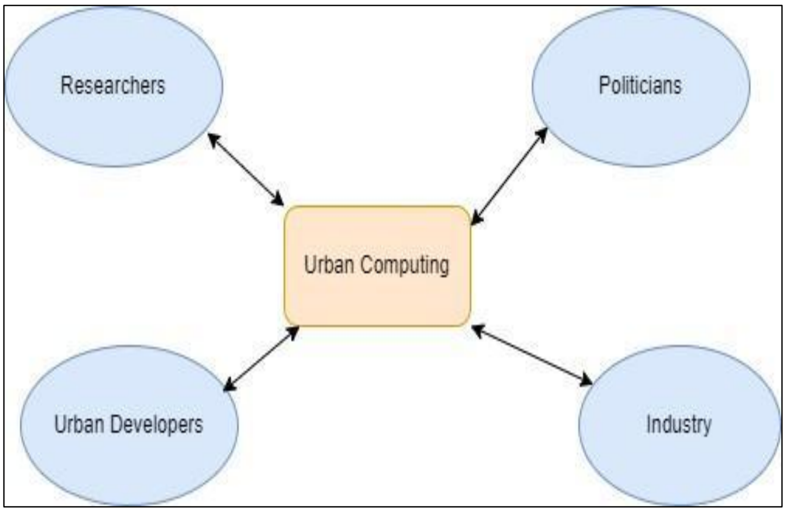

Figure 1: Stakeholders in Urban Civilization

The main idea behind intelligent urban computing is gathering and processing the data. When the storage of the data comes into picture security of the data plays a vital role. The attack on the data can be done at the following stages:

- Stage 1: At the sensor level
- Stage 2: At the data collection stage by the IoT boards
- Stage 3: At the transmission stage of the data to the cloud
- Stage 4: At the cloud storage
- Stage 5: At the analytics level

To protect the data at various stages different attempts have been carried out in these publications (11-14). Even though a lot of research has happened on protecting the data, still, the data is vulnerable to attacks. Under these circumstances, a strong cryptographic approach has to be embedded so that the data is not vulnerable. Blockchain is one such approach. Now, we will discuss about the functionality of blockchain. The main idea of blockchain is to store the hash value of the information, in such a way it is very hard to hack the data. The details are stored in a ledger fashion. The fundamental concept behind blockchain is to store sequence of blocks, where every block stores a bunch of transactions. The interesting fact is this chain is duplicated and scattered over the entire distributed network (15). Every blockchain starts with initial block called genesis block. This genesis block is used to store the entire details of the initial transactions in a hashed manner. For a new transaction, a subsequent block is added to the existing block chain with the previous hash value. This feature of storing the previous hash value provides an extra security to the existing infrastructure. Under this scenario, if any one block is tampered it will be reflected with the non-matching hash sequence by the subsequent block. This feature will help us to detect if there is any attempt to tamper the data by the intruder. This interesting feature of blockchain has thrown lot of applications where the (critical) data needs to be stored. As intelligent urban computing mainly deals with the data, a new research domain has been emerged on the application of blockchain with IoT (BIoT). In general, during this pandemic period medical data played a crucial role on determining the number of COVID cases. In particular, the medical data has thrown a light to the hackers to play with the medical data. In addition to that, tampering the medical data will lead to wrong claim of insurance, projecting false information about the number of COVID cases and other complications. Such a threat can be avoided to a maximum extent by storing the patient's medical data in blockchain.

In this section, we will discuss about the prediction of COVID case diseases using Deep learning models and the protection of COVID medical data using Blockchain in a detailed manner. VGG-16, ResNet50 and Xception deep learning models has been used to predict the COVID-19 disease (16) and attained recognition accuracies of 96.17%, 98.39% and 94.57%. They attained 98.79% accuracy by combining three models and proposed an ensemble-based learning model. Using a deep learning-based approach an automated analysis of CXR was attained. Identification of cases with respect to COVID-19, normal subjects and pneumonia and the proposed model achieved high specificity, accuracy and sensitivity. Using CXR achieved a high performance and made a useful tool to test COVID-19 (17-20). By combining machine learning models, DNNs and key point extraction methods the authors achieved a high classification performance. To poise between examination and manipulation stages and to speed up the convergence, the authors created three influential evolutionary operators. The optimal values of CNN's hyperparameters and to a substantial enhancement is attained by the proposed evolutionary algorithm (21). The efficient method which screens the COVID-19 affected patients is binary robust invariant scalable key-points (BRISK) algorithm and relates to VGG-19 model has attained 96.6% of highest testing accuracy (22). COVID-CXNet is the best method which adopts the medical decision support system. Improved the total accuracy of 87.88% with final scores of 0.8733 and 0.9767 respectively for COVID Pneumonia classes and community-acquired Pneumonia by using proposed COVID-CXNet algorithm (23). Using 959 X-ray images a survey was conducted. The results of diverse models were calculated using the confusion matrix. DenseNet has attained 97% of accuracy and MobileNetV2 has achieved best accuracy of 81% (24).

The final scores of accuracies of 0.98 (98%), F1-score of 0.96337, loss of value is 0.06 and loss of 0.32.b has been attained by using the proposed method Genetic Deep Learning Convolutional Neural Network (GDCNN) (25). To assess the efficiency of the projected exemplary, it is associated with other prevailing models like SqueezeNet, VGG16, resenet18, resenet50. An F-score of 0.982, accuracy of 0.970, a recall of 0.986 is achieved by this model and improved the performance results with the clinical data and CXR (26). There is a significant enhancement of the projected progression algorithm which is helpful to achieve the ideal standards of CNN's hyper parameters with an enhanced accuracy (27). In the research field of Artificial Intelligence (AI) based techniques with the conceptual structures have been studied. COVID-19 diagnostic systems like RNN, GAN, ELM and LSTM techniques have been incorporated for the better results (28). There are 1000 chest CT images has been evaluated in order to examine the proposed deep learning model U-Net architecture (29). Experimental result shows better result in identifying the accuracy of COVID-19 infested areas by using different classifiers of 4-fold cross validation (30).

The current health care system lacks in reliable data surveillance system to provide the information they need about potential outbreaks to the relevant healthcare organizations. In the study, Nguyen *et al.*, has used block chain-based techniques to identify automatically COVID patients in public and their outbreak risk (31). Further, there are insufficient human-depending medicine tools to work with difficult configurations and big sizes of Coronavirus data. The block chain helps to fight against COVID 19 by providing security solutions (32). Any entities cannot modify the COVID data saved in blockchain which is stored as transaction. A block is formed from multiple transaction and multiple blocks form block chain. Moreover, block chain manages every server of health data independently, namely COVID related data gathering in the cloud (33). It also traces the data usage in network. Leveraging block chain techniques to overcome the crisis of trust caused by the outbreak of corona virus (34). The distributed governance structure and privacy-preserving features of the block chain technology can be used to create systems that can help resolve the conflict between protecting privacy and meeting public health needs in the fight against COVID-19, as demonstrated by this examination of current and potential uses of block chain technology for medical care (35). Several use cases for block chain applications, including tracking of contacts, disaster assistance, sharing of patient data, administration of supply chain, learning in online, and management of immigration, are also explained by "Souri A" in the study (36). Supply chain tracking system using clever agreements and independent storage database by application of block chain technology (37). A sequence diagram-detailing stakeholder interactions are presented by the author with a framework supported by algorithm. The donation records integrity from their sources to their final recipients without being altered or changed, are done using a block chain-based technology called Hyper chain (38). It provides path for more COVID patients to get the donated goods as it connects millions of nodes.

To find solutions for battling COVID-19, crowdsourcing tools built on the block chain (39) can be highly helpful. Crowdsourcing does indeed allow for the utilization of the populace to gather data necessary for the identification of COVID-19 patients. Block chain-based architecture to enhance the health care management to avoid security shortcomings (40). AI and block chain-based method to forecast COVID infection was proposed (41). Online immunity document generation using block chain-based technology was introduced (42). The secrecy and anonymity of the test-doer's problems also discussed. Block chain was used to review the Caribbean health care system (43). To tackle the COVID-19 crisis, the research suggested employing block chain to get healthcare support as well as joint systematic examination. Urban distribution network powered by block chain design was suggested for examining horizontal collaboration for strata of urban dispersal and constituent parts (44). A smart contract, one of the cutting-edge block chain applications, is created to plan the routes for distribution for an urban- distribution system. Unchallengeable and tamper-proof block chain might be used to package and upload the charging histories of electric vehicle owners. This approach is intended to be more useful for managing urban traffic thanks to the intricate block chain hierarchy (45). Gland volume errors (GVEs) and target registration errors (TREs) were estimated by using CNN- engendered dissections. Among various dissimilar networks there was no arithmetical variance originate in either GVsEs or TREs ($p = 0.44$ and $p = 0.32$) (46). Under deep supervision of UNet++ an average IoU gain of 3.8 and 3.3 points on U-net and V-net has been achieved (47). To make this system more practical for urban traffic management the detailed blockchain hierarchy is also designed.

In this study, Ahmed *et al.*, applied Gradient-weighted Class Activation Mapping (Grad-CAM) technique to enhance the comprehensibility and interpretability of the proposed deep learning architecture for radiological image analysis which is a color visualization technique (48). The design attains a 0.96 classification accuracy rate, yielding better outcomes. In this work authors tried predicting COVID-19 patients as early as possible. The ensemble technique and feature selection are combined in the suggested optimized union ensemble feature selection method. It uses the union approach to join subsets of characteristics that were acquired through separate feature selection processes. AUC, accuracy, and precision were among the performance metrics used to assess the machine learning classifiers (49). In this research work five stages were suggested. First, a median filter is used to preprocess the X-ray pictures in order to improve and eliminate noise. Second, to aid in quick diagnosis, robust invariant and high-level engineering features are extracted using five distinct feature extraction techniques: segmentation-based fractal texture analysis (SFTA), local binary pattern (LBP), grey-level co-occurrence matrix (GLCM), histogram of oriented gradients (HoG), and accelerated robust features. Subsequently, these characteristics are combined to close the gaps between them and produce optimal results (50).

Methodology

Motivation

U-Net is used because of its capacity to produce accurate segmentation output. The high-level and low-level data are combined using skip connections which enables accurate object boundary localization in a quick and effective manner. The fully convolutional design of U-Net allows for quick segmentation speeds and effective processing of huge pictures. Large data sets are required for model training in the discipline of deep learning. In terms of time, money, and hardware resources, it might be challenging to compile such vast amounts of data to answer an image classification challenge. Additionally, data labeling calls for the knowledge of multiple engineers and developers. This is especially true for extremely specialized domains like medical diagnostics. These issues are resolved by U-NET since it works well even with a little data set. Moreover, it provides greater accuracy than traditional models.

The second is an evaluation of performance among CNN and U-Net that demonstrated that U-Net is better suited to complete this task because it requires fewer hours of training. This is because it lacks a fully connected layer and provides a reasonably high degree of ground truth resemblance. The input data is first reduced in size by a traditional auto encoder design, followed by the subsequent layers. After that, decoding starts, the frame size progressively grows, and a linear representation of features is learned. The output size and the input size are equal at the finish of this architecture. Architecture like this is perfect for maintaining the original size. The issue is that it linearly compresses the input, preventing all of the details from being transmitted. With its U-shaped architecture, U-NET excels in this situation. By doing the de-convolution on the decoder side, the bottleneck issue that arises with an auto-encoder design is avoided, preventing feature loss.

Proposed Architecture

The research is completed in two phases. In the first phase, deep learning UV-Net model is used for covid-19 prediction. The results are stored in blockchain in the second phase.

Phase 1: High resolution chest X-ray pictures are preserved using the UV-Net architecture (51), which we have presented as an architecture to forecast COVID-19. Convolutional neural network architectures, like the popular U-Net, might not have been able to fully recover information because to the obliteration of high-resolution data and minute details by early maxpoolings and subsequent convolutional layers, which are essential for quantifying mitosis (52). In order to maintain the high-resolution details, using "V" blocks, the UV-Net design maintains dense features. Experiments are conducted on dataset obtained from the City Hospital, Vellore, Tamil Nadu.

Chest X-rays (CXR), the Covid-19 infection masks, and Lung Segmentation Mask serve as the model's input. The 256 x 256 input CXR images are converted into equivalent Gaussian images. Macenko stain normalization was applied to improve domain generalization and robustness (53).

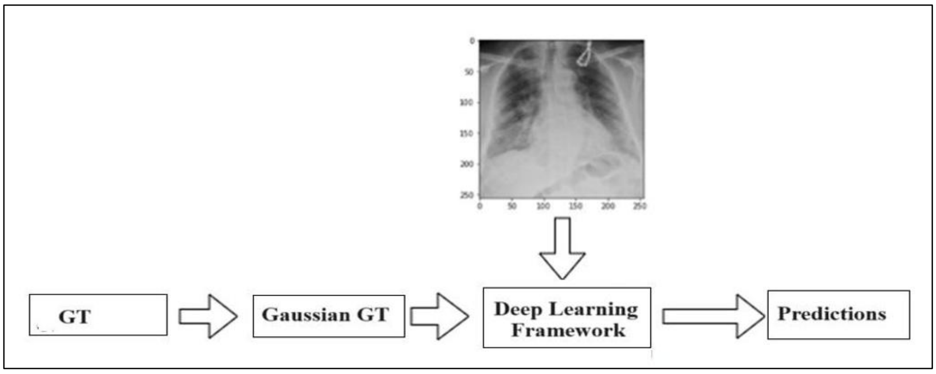

Figure 2: Pre-Processing and Working Process

Figure 2 shows the working process. The preprocessing steps includes Gaussian and Gaussian transform. The Gaussian function, which computes the values inside the kernel, is as follows:

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad [1]$$

Equation 1 is the 2D gaussian function where *x,y* represents the value for X and Ycoordinate and σ represents Standard Deviation.

In our research, we use the Huber loss, a loss function that is less susceptible to data outliers than the squared error loss and is used for robust regression which is shown in equation 2. The Mean

Squared Error (MSE) and Mean Absolute Error (MAE) are combined to bring the best of both worlds. The piecewise function listed below can be used to define it:

$$L_\delta(y, f(x)) = \{\tfrac{1}{2}(y - f((x))^2 \quad for|y - f(x)| \le \delta, \delta|y - f(x)| - \tfrac{1}{2}\delta^2 \quad otherwise \qquad [2]$$

To Predict COVID-19, we applied UV-Net architecture. Figure 3 depicts the entire design, replacing the U-Net's 3x3 convolutional layers with V-Blocks, which are motivated by the effectiveness of dense connections. Through four sequential phases, each V-Block forms a "V" shape by expanding an input having n channels into an output of 2n channels.

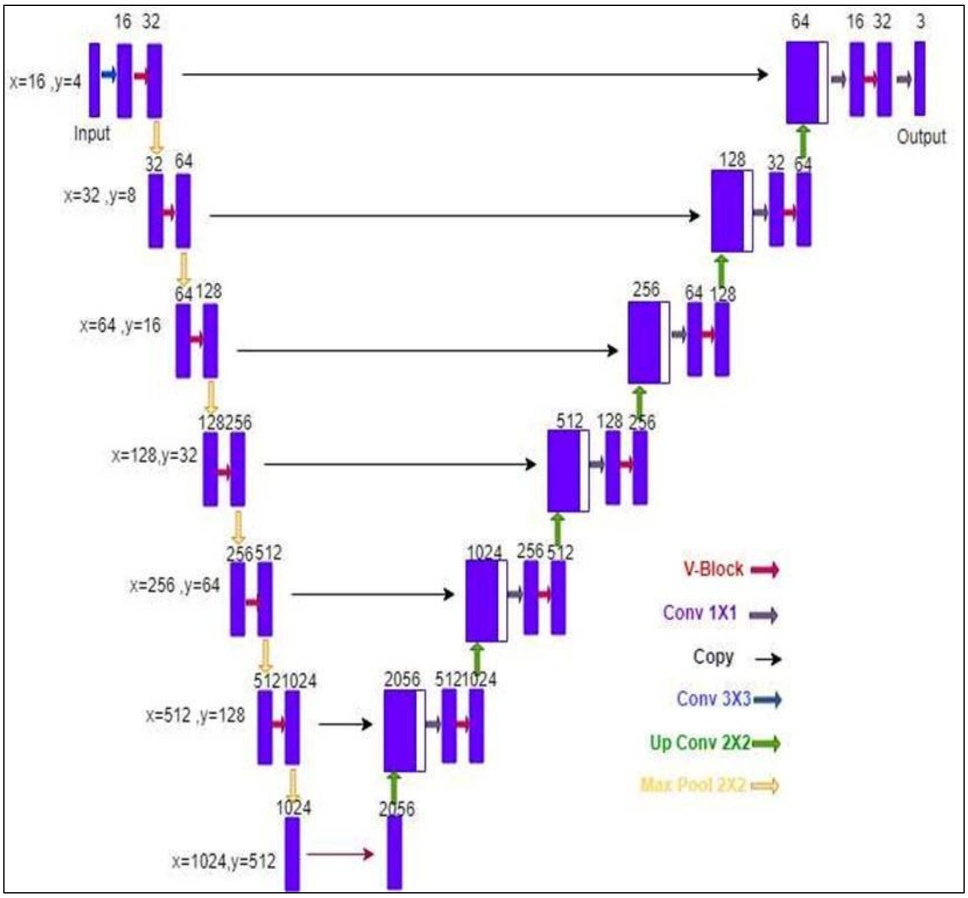

Figure 3: Architecture of UV-Net Using V-Block

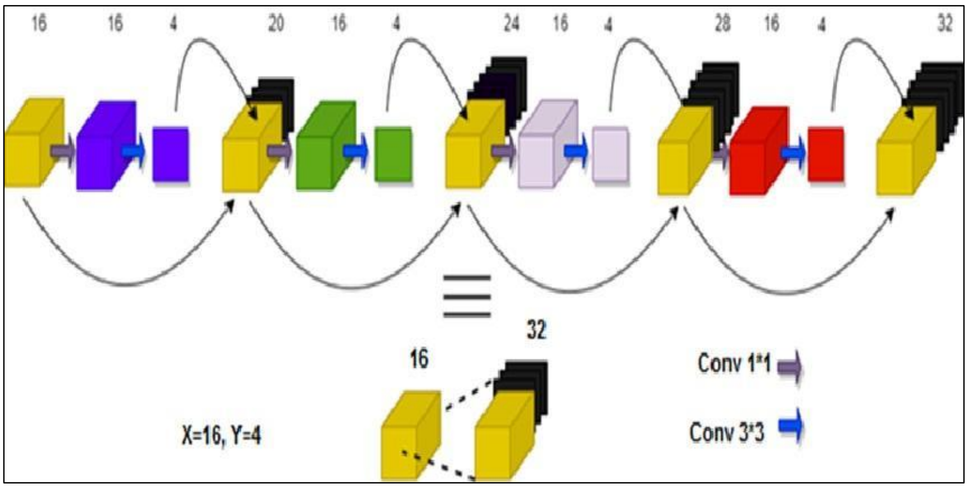

Figure 4: Example of V-Block When X = 16 and Y = 4

The quantity of input channels and output channels at the conclusion of each phase are the two hyperparameters, *x* and *y*, that are defined for each V-Block. The V-Block when $x = 16$ and y = 4 is shown in Figure 4. The input feature is processed in each phase using a 1x1 convolution with x = 16 filters before being translated to the output with y = 4 filters. Concatenating the output of the current phase with the input results in a matrix having 20 filters, which is passed to the second phase. To create an output using 2.x filters, this step is repeated for four times. The subsequent concatenations keep the features from earlier layers from being lost. This section displays the UV-Net test results for 33,920 images with a COVID-19 positive or negative result. Results of UV-Net tested on 33,920 unseen images that have COVID-19 positive or negative are presented in this section. Figure 4 displays the precision, recall and F1-score, from the UV-Net prediction. The obtained accuracy for the precision, recall and F1-score are 0.8702, 0.8928 and 0.9165.

Phase 2: A user interface is linked to the suggested model. Using the user interface, the doctor sends a test X-ray image to the suggested model. The UI receives the model's output. The user interface then gives an image to IPFS, which delivers back to the user interface the image's hash code. The hash code, which allows users to validate data, is recorded on the blockchain to guarantee the security the information saved in Interplanetary File System (IPFS). Lastly, the user interface creates a transaction using the patient's basic data and the hash code of the examined X-ray image. To handle the financial transaction in the BC, a "smart contract" is developed and set into use on the blockchain (54). Secure data transfers between many parties are directly and automatically governed by the smart contract.

Once the model predicted result is stored in the database, the same is reflected in the respective doctor's login. The doctor then analyses both the model result as well as the Chest X-Ray (CXR) to finally conclude and generate the result. Based on the doctor's decision the system generates an automated PDF which is digitally signed using the doctor's credentials. This PDF is then stored into the blockchain. Once generated, the PDF report can be viewed by the patient from his login. Secure patient sensitive healthcare data and records with a blockchain-powered security mechanism. Block chains are immutable, once records are added cannot be altered. If any attack is made to change records in the block chain, the whole blockchain will become invalid, and throw an error while verification: Block chain has been breached. In our work, we have implemented ethereum based blockchain, in which, whenever patient visits doctor his medical reports are uploaded in decentralized system of blockchain. Only a doctor can add a patient record and this is being verified by our smart contract and can be seen in our activity diagram (verification of designation). Patient and Insurance agent can view the records by entering specific patient id but are not allowed to add new records. A doctor can also view a patient record by entering the particular patient id. Hence it adds security features to patient records. Patient details will be displayed only when a valid patient id is entered. Blockchain adds an additional layer of security to record over normal database storage system, as they are immutable and adding a new block always validates complete blockchain. We used NodeJS, smart contracts (written in solidity), truffle, ganache and MetaMask to achieve this implementation.

Experimental Analysis

Dataset

The dataset is obtained from a City Hospital, Vellore, Tamil Nadu, India containing 33,920 chest X-ray images including:

- 11,956 Covid cases
- 11,263 Non-Covid infections (Bacterial or Viral Pneumonia)
- 10,701 Normal cases

The original dataset contained 45,342 subjects and includes separate validation and test sets. A cleaned version of the dataset in which several husband bad training images have been removed. A preprocessing is done to generate a pseudo color image which plays an important role in improving accuracy of covid-19 prediction. The new dataset contains 33,920 images from over each of the chest x-ray image contains a Meta data file which has patient id, image path and label. Images may be added over time to improve the dataset. The chest x-ray images are distributed as follows in Table 1. Ground-truth lung segmentation masks are performed for the entire dataset. The dataset is split into 60% training, 20% validation and 20% testing respectively. The results are given in the sections below.

Table 1: Dataset Statistics

Type	COVID-19 Negative	COVID-19 Positive	Total
Train	11487	8865	20,352
Validation	3747	3103	7068
Test	3500	3218	6500

Results

We provide a detailed analysis of experimental studies accomplished for evaluating our classification framework in this section. We present both qualitative and quantitative results and also compare with the baseline. We also provide an overview of popular metrics used for evaluating proposed model and also discuss about hyper-parameters used in our study. Figures 5 and 6 show the lungs mask predicted by the proposed system and the ground truth of the input images. The images obtained from the dataset are segmented manually to train and test the model and then determine the ground truth. A binary ground truth is determined for each slice, using the information of pulmonary region from Radiotherapy Structure file.

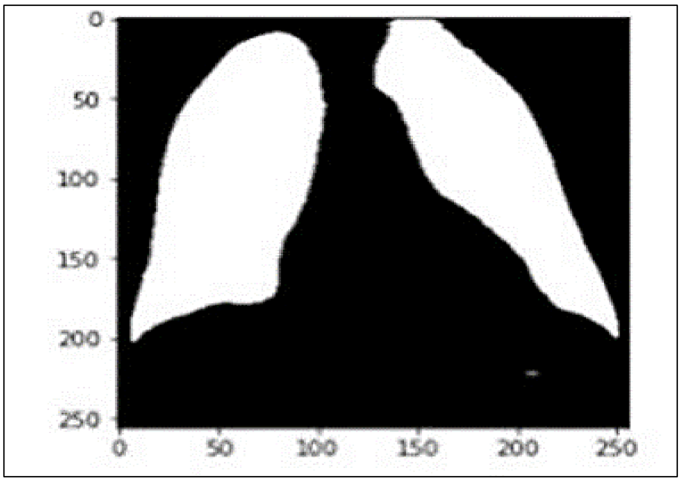

Figure 5: Lungs Mask Predicted by U Net

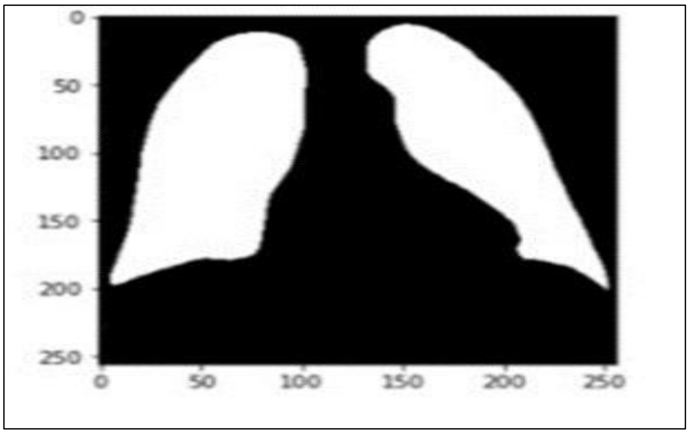

Figure 6: Ground Truth Lungs

Table 2: Convolution Kernels in the Networks

Encoder/Decoder	$X^{0,0}$/ $X^{0,4}$	$X^{1,0}$/ $X^{1,,3}$	$X^{2,0}$/ $X^{2,2}$	$X^{3,0}$/$X^{3,1}$	$X^{4,0}$/ $X^{4,1}$
U-Net	32	64	128	256	512
V-Net	35	70	140	280	560

Table 2 shows the kernel details of U-Net and V-Net. A 3*3 size convolutional layer is deployed and a skip pathway ($X^{I,J}$) is used where k= $32*2^{i}$. A 1 X 1 convolutional layer is implemented and a sigmoid activation is added to all the target points: { $x^{0,j}$ | j € {1,2,34}}. Therefore, the UV-Net creates four segmentation maps for an input image to determine the final segmentation map by an averaging technique.

Hyperparameter Searching

The U-Net and V-Net are validated with the 10-fold cross-validation and evaluated with 256 various hyperparameter configurations. The original number of feature maps in the fixed model configurations is not necessary for the networks. Therefore, U-Net and V-Net are tested for 64 hyperparameter configurations.

Table 3: Hyperparameter Configurations of Various Networks

Hyperparameters	Value 1	Value 2	Value 3	Value 4
Input Image Size	[64,112,128]	[48,80,96]	[32,48,64]	[16,32,48]
Learning degree	10^{-2}	10^{-3}	10^{-4}	10^{-5}
Mass decay	0	10^{-2}	10^{-4}	10^{-6}
Primary Networks	4	8	16	32

Table 3 summarises the four hyperparameters analyzed for this study producing 256 hyperparameter combinations. All the input images are resampled with various isotropic vowel sizes of 1,1.5 and 2 mm/voxel respectively. The initial input feature channels specify the network size, but there is a constraint on GPU memory for the input images.

Table 4: Hyperparameter Values for the Segmented Networks

Network	Input Image	Primary Learning degree	Weight decay	Primary networks	[10^{th},50^{th}, 90^{th}] percentile
VNet	[32,48,16]	10^{-4}	10^{-4}	N/A	0.87 [0.87,0.85,0.84]
UNet	[48,64,32]	10^{-2}	10^{-6}	8	0.89 [0.67,0.85,0.88]

Table 4 shows the hyperparameter values for the segmented networks of UNet and VNet respectively.

Training

Figure 7 shows the Covid-19 infection mask determined by the proposed model. The slice number varies uniformly between 25 to 50 for the x and y axis. Figure 8 shows the ground truth infection of the lungs. The ground truth is performed on the entire dataset and a sample is shown in Figure 8. Figure 9 shows the COVID-19 prediction output with a precision, recall and F-Score of 0.91, 0.87 and 0.89 respectively. Figure 10 shows the lung segmentation performed by the proposed model. The segmentation task is improved with the proposed UV-Net model which aims to enhance the performance of the original network (i.e. UV-Net). Figure 11 shows the model prediction snapshot. Figure 12 shows a sample test report generated.

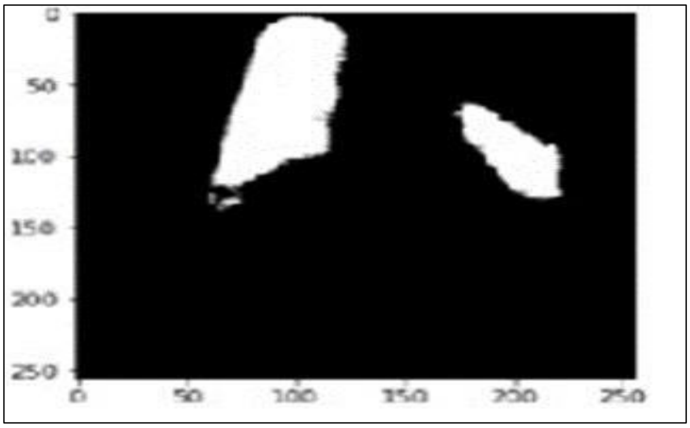

Figure 7: Covid 19 Infection Mask Predicted By UV Net Model

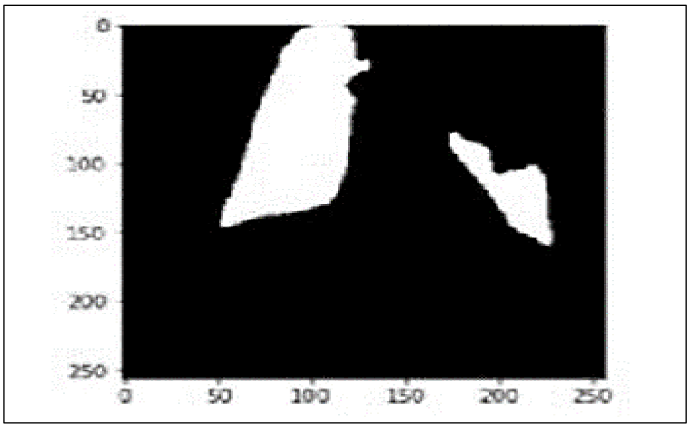

Figure 8: Ground Truth Infection

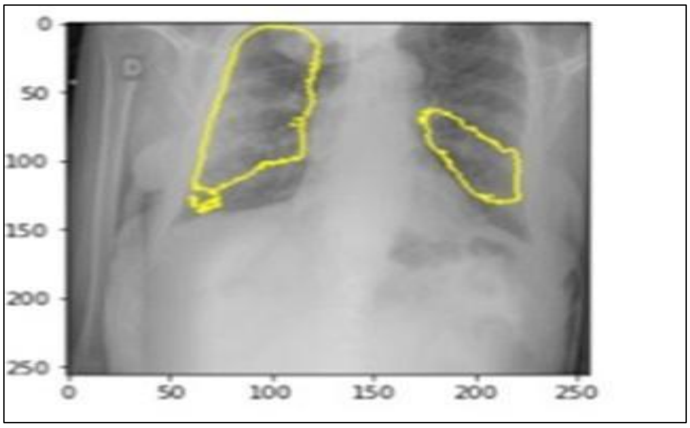

Figure 9: Covid -19 Prediction Output

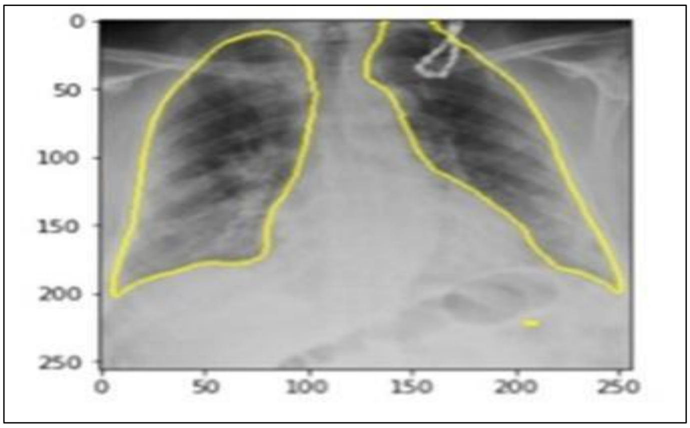

Figure 10: Segmentation of Lungs

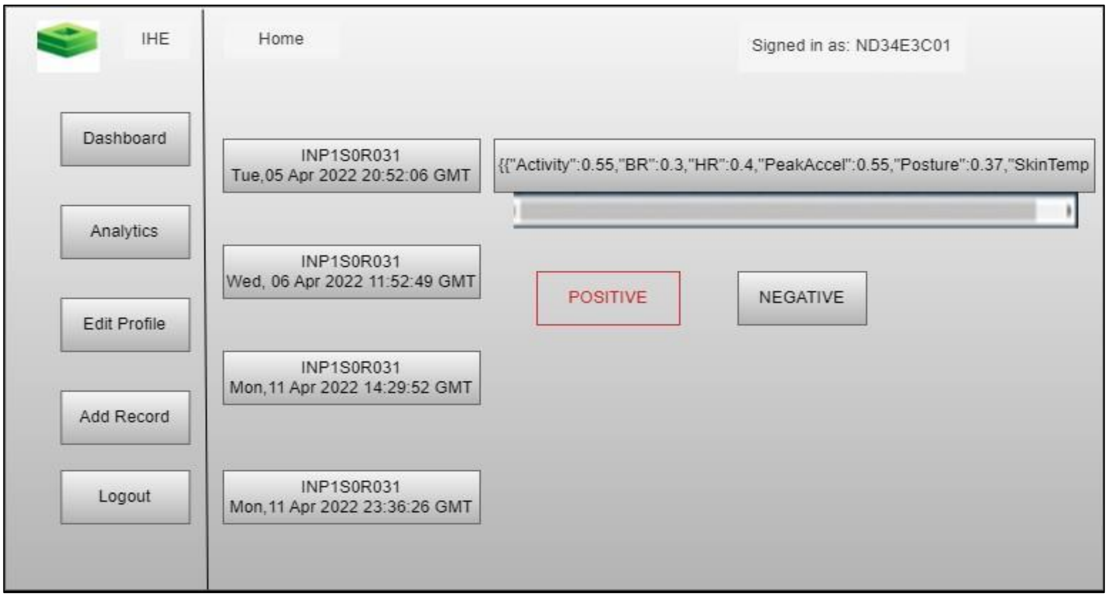

Figure 11: Model Prediction Snapshot in the Blockchain Dashboard

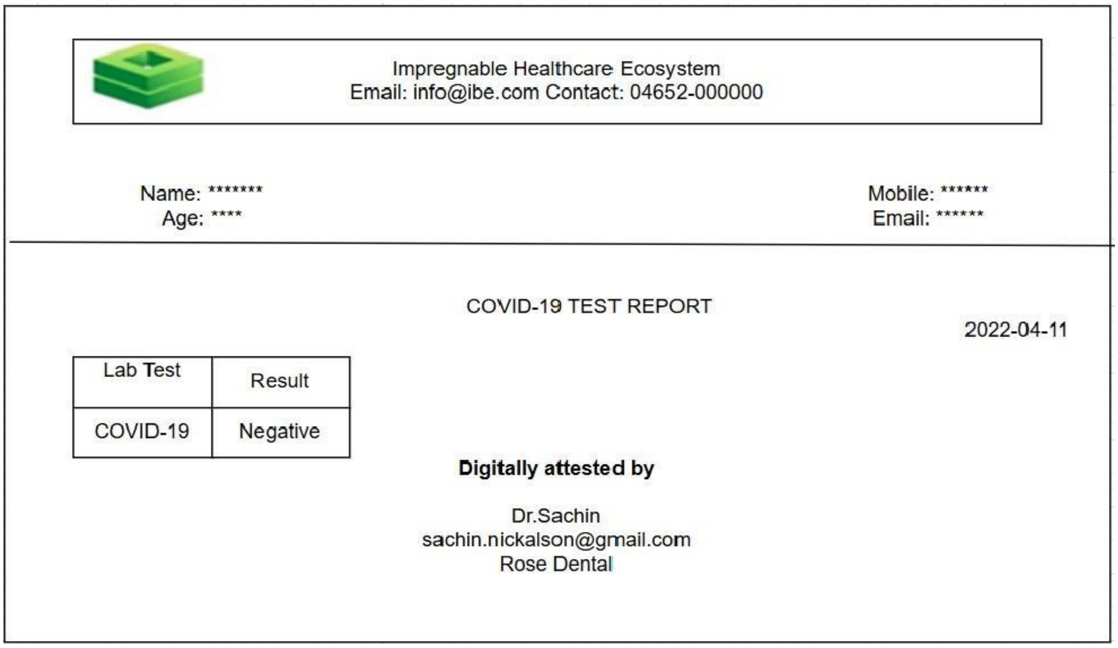

Figure 12: Covid-19 Test Report

Evaluation Metrics

Three widely adopted metrics for evaluating the performance of covid-19 image classification models, are the Precision, Recall and F-Score. Table 5 represents the comparison of the various performance metrics on various existing models such as U-Net and V-Net and the proposed model. Thus, it is observed that the proposed work outperforms the existing networks of U-Net and V-net respectively.

Table 5: Comparison of the Performance Metrics on Various Existing Models and the Proposed Model

Algorithm	Precision	Recall	F-Score
U-Net	0.8312	0.7991	0.8148
V-Net	0.8429	0.7951	0.8183
Proposed UV-Net	0.9165	0.8702	0.8928

Discussion

While the idea of combining blockchain technology with UV-NET is innovative, there hasn't been much discussion of it in comparison to other blockchain-based applications in the fields of urban planning and healthcare. This might be because blockchain technology is still in its early stages and developing in these domains. Blockchain-powered healthcare systems have demonstrated potential to improve security and scalability through hybrid deep learning. But rather than integrating these systems with UV-NET, the emphasis has been on building them. By using blockchain technology, patient data is secure and decentralized in nature. All data is available in blockchain-based Electronic Health Records. Thus, medical supply authenticity may be tracked and verified (55).

Since COVID-19-related data is sensitive, a strong privacy-preserving solution is required. Blockchain technology can successfully solve this need. The decentralized, immutable, and secure architecture of blockchain technology can be used to protect patient data via access restriction, hiding information, and encryption. Secure data sharing and analysis are made possible by blockchain-based technologies like Homomorphic Encryption and Zero-Knowledge Proofs, which conceal sensitive data. Additionally, data integrity and accountability are guaranteed by blockchain's visible and auditable nature. To protect electronic health records, for example, Medibloc's blockchain-based technology (56) makes use of decentralized storage and robust encryption. COVID-19 data may be securely handled through the use of blockchain technology, assuring confidentiality, integrity. This will eventually uphold public confidence and support data-driven research.

The proposed work of storing Electronic Medical Records (EMR) for covid-19 patients has very limited privacy issues as there is no unauthorized access of outsiders in the blockchain environment. Only doctors are accessed to the patient records which prevents any tampering of data, data theft or breaches. This is focused on the current work. In addition, various scalability, security, and privacy concerns, like transaction linkability, crypto-key management (e.g., recovery), on-chain data privacy, or compliance with privacy rules (e.g. GDPR), might affect blockchains. Novel privacy-preserving blockchain solutions based on crypto-privacy techniques are emerging to address these issues, providing users with mechanisms to adopt a Self-Sovereign Identity (SSI) model, which enables them to become anonymous and take control of their personal data during digital transactions of any kind in the register (57). This can be addressed in the future work.

Conclusion

The pandemic has primarily changed how cities are governed in the near future. It is very important to take necessary actions in the coming years to develop post-COVID cities in a sustainable manner. Therefore, in this research, a block chain-based approach integrating deep learning models is proposed for secure access and storage of COVID-19 patient's health records in Vellore city. As patients' data is highly sensitive, blockchain is an appropriate solution for healthcare issues such as interoperability of EHR, trust sharing between healthcare providers, confidentiality, auditability and access control grant to patients if required. Blockchain is secure as they are immutable and adding a new block always validates the complete blockchain. Our proposed architecture is an integration of UV-Net model which has been significantly optimized for effective COVID-19 prediction. Experiments demonstrate that the proposed model obtained a precision, recall and F-score of 0.91, 0.87 and 0.89 respectively and results are stored in blockchain. Blockchain could play a tactical role in future digital healthcare: precisely, it may work to enhance COVID19-safe clinical practice. In addition, blockchain combined with Artificial Intelligence approaches can be useful for Internet of Medical Things (IoMT) to prevent the spread of COVID-19 infectious diseases. New features like location sharing and contact tracing can be integrated in the proposed system.

Abbreviations

AI: Artificial Intelligence, HER: Electronic Health Records, CNN: Convolutional Neural Network, IoT: Internet of Things, MIoT: Medical IoT, IIoT: Industrial IoT, CIoT: Cognitive IoT, BIoT: Block chain with IoT, CXR: Chest X-ray, GDCNN: Genetic Deep Learning Convolutional Neural Network, GVE: Gland Volume Errors, TRE: Target Registration Errors, Grad-CAM: Gradient-weighted Class Activation Mapping, SFTA: Segmentation-based Fractal Texture Analysis, LBP: Local Binary

Pattern, GLCM: Grey-Level Co-occurrence Matrix, HoG: Histogram of oriented Gradients, IPFS: Interplanetary File System.

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All Authors contributed equally.

Conflict of Interest
The authors declare that there is no conflict of interest pertaining to this review paper.

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