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A Blockchain-Enabled Machine Learning Mask Detection Method for Prevention of Pandemic Diseases

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Abstract During the COVID-19 pandemic, finding effective methods to prevent the spread of infectious diseases has become critical. One important measure for reducing the transmission of airborne viruses is wearing face masks but enforcing mask-wearing regulations can be difficult in many settings. Real-time and accurate monitoring of mask usage is needed to address this challenge. To do so, we propose a method for mask detection using a Convolutional Neural Network (CNN) and Blockchain Technology. Our system involves training a CNN model on a Dataset of images of people with and without masks and then deploying it on IoT-enabled devices for real-time monitoring. The use of Blockchain Technology ensures the security and privacy of the data and enables the efficient sharing of resources among network participants. Our proposed system achieved 99 percent accuracy through CNN training and was transformed into a Blockchain-enabled network mechanism with QR validation of every node for authentication. This approach can potentially be an effective tool for promoting compliance with mask-wearing regulations and reducing the risk of infection. We present a framework for implementing this technique and discuss its potential benefits and challenges.

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1 Introduction

As the COVID-19 pandemic continues, there is a growing need for automated systems to detect face mask usage in public spaces. One promising solution is face mask detection using machine learning algorithms. This project proposes a system that uses a machine learning algorithm and a Blockchain framework for added security to detect face masks in real-time from a live video stream. The system captures video feed from a camera and analyzes the footage using a pretrained machine learning model to detect whether individuals are wearing face masks. The resulting data is uploaded to a Blockchain network, providing a secure and tamper-proof way to store the data and creating an immutable ledger that tracks face mask usage in public spaces.

The system also incorporates security measures such as encryption and access control to ensure that only authorized users can access the data. Furthermore, leveraging Blockchain technology eliminates the need for a centralized authority to manage the data, providing an added layer of security and transparency. Overall, the proposed face mask detection live streaming system has the potential to be an effective tool for promoting compliance with face mask mandates, which is crucial for mitigating the spread of COVID-19 and other infectious diseases in public spaces. Furthermore, by incorporating Blockchain technology, the system can provide a secure and transparent means of tracking face mask usage, which could be helpful for public health officials, policymakers, and other stakeholders[1].

Many studies are found in the literature where face mask detection is discussed with many image-processing techniques[18],[20], [21]. And some other studies also conducted live camera streaming and Face detection, but it's just for one placement at fixed points. Many gaps are analyzed to manage fully crowded events and face detection, and many studies have experience with different methods. We, in this study, have two perspectives. Detect facemasks in live mode using a Blockchain-enabled network because it's at high risk when connected to different edged computing devices and IoT-based infrastructure like blue tooth connected devices, e.g., live cameras, drone cameras, etc. [22],[23] . This study composed objectives: design a trained machine learning model and frame the security with blockchain-enabled systems with edged computing devices.

Convolutional Neural Networks (CNNs) will be used in the current endeavor to develop a trained machine learning model for detecting face masks. In the context of the COVID-19 pandemic, the trained model [20],[23–25] will be able to determine whether or not someone is wearing a face mask. The CNN model can be trained to attain high accuracy and efficiency by selecting an acceptable dataset, preparing the data, and doing so. For real-time face mask identification, the trained model can be installed on edge computing devices like the Raspberry Pi or Nvidia Jetson. Since machine learning models can be vulnerable to adversarial attacks and model stealing, their use for face mask detection also raises issues with data security and privacy. As a result, it's crucial to incorporate security measures into the architecture of machine learning models to guarantee the privacy, availability, and integrity of data.

Machine learning models can be made more secure by using edge computing and Blockchain-enabled systems. With the help of distributed ledger technology, data can be accessed and stored securely and autonomously, allowing for secure data transfer and thwarting unauthorized access [26–31]. On the other side, edge computing tools enable data processing at the network's edge, lowering latency and enhancing data privacy. A safe and effective infrastructure for machine learning applications can be created by integrating blockchain-enabled systems with edge computing hardware. Machine learning models can be trained on a big dataset without sacrificing data privacy, for instance, using a blockchain-enabled edge computing network to share data securely and decentralized between devices[32–35].

2 Literature Review

CNN-based face mask detection systems and their integration into Blockchain-IoT-enabled networks is an emerging area of research with promising results. These systems can improve the security and transparency of face mask compliance monitoring in public spaces. Here is a brief literature review on face mask detection using CNN methods and implementation into Blockchain-IoT-enabled networks in Table-1

2.1 Video Restoration

These recent publications demonstrate the potential of CNN-based video restoration techniques for improving video quality. By training on large-scale datasets and incorporating both spatial and temporal in-

Table 1. Advancements in Face detection with CNN & Deep Learning Methods

S No.	Authors	Problem	Methodology
1	Zhang et al.(2021) [2],	Face detection	MTCNN method
2	Liu et al.(2021)[3]	Object detection	SSD for face detection
3	Redmon et al. (2016)[4]	Object detection	YOLO – uses single-step CNN for real-time face detection application method
4	Deng et al. (2019)[5]	Face detection	RetinaFace- face detection algorithm using the multi-task function to detect faces, landmarks, and gender
5	Zhou et al. (2018)[6]	Face Detection -Review	a CNN to detect object centers and regresses the object size and orientation from the center point
6	Anil Kumar & Mohan Bansal (2023)[7]	Real-time face mask detection	CNN- Caffe model a face detector,MobileNetV2 for mask identification
7	L. M. I. Leo Joseph et al. (2021)[8]	Facial Detection	CNN model to detect face masks - Real-Time dataset
8	Danqing Xu & Yiquan Wu (2020)[9**?**, 10]	Multi-Scale Remote Sensing Target Detection	YOLO-V3; Convolutional Neural Network ; DenseNet
9	Pooja S et al.(2021)[11]	object detection, Blockchain, and IoT technologies	a secure face mask detection and monitoring system that uses a CNN-based
10	Xin Tao et al. (2017)[12]	" sub-pixel motion compensation "	(SPMC) layer in a CNN framework
11	L. Yaroslavsky (2001)[13]	Noise-suppression capability-Adaptive transform domain - image restoration methods	DCT domain (SWDCT) image-denoising algorithms
12	Matias Tassano Julie Delon, and Thomas Veit (2019)[14]	DVDNET- Deep video denoising	CNN denoisers and another algorithm
13	Caballero et al. (2017)[15]	Video Super-Resolution	Video, super-resolution method-CNN-based architecture
14	Qiao et al. (2020) [16]	face detection method	R-CNN-based face detection method
15	Wu et al. (2019)[17], [18],[9]	face detection & recognition	CNN-based architecture
16	Chen et al. (2019) [19] [4]	showed high detection accuracy on challenging Dataset and outperformed traditional face detection methods	an improved CNN-based face detection algorithm
17	Zhao et al. (2018)[6][19]	present a real-time face-detection method	a multi-task learning framework with CNN

formation, these methods have shown significant improvements over traditional methods. Video restoration using trained CNN models is an active area of research. Here are some recent publications on this topic in Table 1:

2.2 Face Detection

Face detection using CNN is a popular and active area of research. These recent studies demonstrate the potential of CNN-based face detection methods for iNmproving accuracy and efficiency. By training on large-scale datasets and incorporating multi-task learning or improved network architectures, these methods have shown significant Here are some recent publications on this topic in table 2 :
The choice of dataset and CNN architecture for mask detection can vary depending on the application and performance requirements. However, recent studies have shown that CNN models can achieve high accuracy for mask detection tasks using various architectures and datasets. The choice of the dataset of face masks can significantly impact CNN performance. Here are some standard datasets used in recent studies on this topic in Table 3 :

Face detection applications use many strategies to train the model for accuracy and performance. Since the CNN is a classifier to experiment, in terms of model architectures, some recent studies have carried out the face detection following:

1. "MobileNetV2" [1, 47, 48]: This model is a lightweight CNN architecture optimized for mobile devices. It has been used in recent studies for mask detection and achieved high accuracy.
2. ResNet-50” [42]: This model is a deep CNN architecture widely used for image classification and object detection tasks. It has also been used in recent studies for mask detection and achieved high accuracy.
3. “Inception-v3” [49]]: This model is a deep CNN architecture designed for image recognition tasks. It has been used in recent studies for mask detection and achieved high accuracy.

3 Methodology

The proposed methodology for face detection using CNN is explained below:

3.1 Design

The design is a high-level methodology for developing a face mask detection CNN model and integrating it with an IoT-enabled blockchain security mechanism. This design methodology can be adapted and customized based on the specific requirements in fig1 as follows:

1. Define the problem and requirements: Determine the face mask detection system and the requirements for accuracy, speed, and security. Consider the environmental factors, such as lighting conditions and camera positioning.
2. Collect and preprocess the data: Obtain a suitable dataset of face images with and without masks. Preprocess the data by resizing, normalizing, and augmenting the images to improve the training data, including quality and quantity.
3. Train the CNN model: Design a suitable CNN Face mask detector and train the model using the preprocessed data. Use transfer learning to leverage existing pre-trained models for faster and more efficient training.
4. Deploy the model to an IoT device: Deploy the trained model to an IoT device, such as a camera or a mobile phone, to enable real-time face mask detection in the field.
5. Integrate with a Blockchain security mechanism: Integrate the IoT device with a Blockchain network to provide secure storage and transfer of face mask detection data. Use smart contracts to enforce the rules and policies for data access and sharing.
6. Test and optimize the system: Test the system in a real-world setting and fine-tune the model and security mechanisms based on the feedback and performance data.

Table 2. Literature for face detection and Machine learning

S No.	Authors	Methodology-Problems	Technique	Parameters -Analysis
1	Calistus N. Ngonghala et al. 2023[36]	Viral impacts analysis	Medicine	Vaccinations, different variants of COVID-19 analyzed
2	A.K. Sharadhi et al. 2022[37]	face mask recognizer	convolutional neural network Mobile Net V2	98 percent, Image processing - Computer vision
3	Heidari et al., 2022 [25]	COVID-19 detection(chest CT images)	lightweight CNN - blockchain	Transfer Learning (TL) technique to initialize by layers
4	Meiling Fang et al. 2021 [38]	Collaborative Real Mask Attack Database (CRMA)	PAD algorithms	Performance /effect analysis of masked attacks by Face PAD algorithms
5	Minghui Li et al. 2021[3]	Significance analysis of COVID-19 -pandemic face mask - classifications	The human body infects using healthy types of shows -reviewed all organs	Analysis of toxic effects - face mask-derived MPs / NPs
6	P. Gupta, V. Sharma, & S.Varma 2022[39]	Mask detection and recognizing human actions & novel algorithm	a video surveillance algorithm for face mask detection	Multi-CNN prediction model for suspicious activities
7	Preeti Nagrath et al., 2021 [40]	Face detection	OPEN-CV DNN	accuracy - 0.9264 & F1- 0.93
8	Aldert Vrij,Maria Hartwig 2021[23]	Medical-face mask Survey - analysis	Literature reviewed	Analyzed how to wear medical face masks
9	TM Saravanan et al. 2022[22]	Face mask detection	Novel approach- CNN	96.50 per accuracy
10	Elliot Mbunge et al. 2021[41]	to detect COVID-19 face masks	DCNN models review	Parameters- Inception-v4, Mask-RCNN, Faster-RCNN, YOLO-v3, Xception, DenseNet, used to detect face masks
11	Mohamed Loey et al., 2021[42]	Face mask detection	Decision tree, SVM, Ensemble algorithms	SVM @ 99.64 perc in RMFD,SMFD @ 99.49 perc, & LFW @ 100 perc accuracy
12	Mostafa M. Mohamed et al. 2022 [43]	Face mask recognition through voice	Mask Augsburg Speech Corpus (MASC), Baseline schemes applied to solve a problem	Results of performance - Unweighted Average Recall (UAR.) – 71.8 perc , 80.1 perc.,& 82.6 percent
13	Peishu Wu et al. 2022 [18]	face mask detection method	FMD-Yolo	FMD-Yolo precision AP50 of 92.0 percent, 88.4 percent
14	Adnane Cabani et al. 2021[20]	Masked Face-Net – A dataset	A dataset of correctly/poorly masked face images	137016 images available at https://github.com/cabani/MaskedFace-Net
15	Xiangjie Kong et al. 2021[24]	Mask Identification	Real-Time Deep Learning	ECMask 1) video restoration, 2) face detection & 3) mask identification
16	Bensenane Hamdan, Keche Mokhtar 2017[21]	Detection of spoofing by 3D mask	A Review	performance evaluated by public 3D Mask Attack Database (3DMAD)
17	Preeti Nagrath et al., 2021[1]	Face mask detection system	SSDMNV2 - Single Shot Multibox Detector as a face detector and MobilenetV2 framework	0.9264 accuracy with F1 0.93 results
18	Andrea Pazienza & Daniele Monte 2022[44]	Monitoring Equipment Mask Environment	(ME)2-Monitoring Equipment	94.80 percent model accuracy

Table 3. Dataset literature for face Mask Detection

S No.	Source of Dataset Data details-images	Popular Dataset
1	Kaggle repository[45]	Face Mask Detection Dataset -Kaggle & 12000 images
2	Mohamed Loey et al.[42]	COVID-19 Coronavirus Face Mask Collection Dataset & Large dataset, Masked Faces (MAFA),35806 masked face images
3	Kaggle repository[46]	Dataset -Kaggle & 850 face mask images of 03 classes
4	Qin , 2020[16]	Kaggle, Mask detection dataset & 3835 images

7. Maintain and update the system: Regularly maintain and update the system to ensure continued performance and security and to incorporate new features and capabilities as needed.

3.2 IoT- Edge Devices

An edged IoT-enabled device for facemask detection using a trained CNN model [10, 44, 50]. This high-level design can be customized and expanded based on the specific requirements and constraints of the facemask detection system. In additionally, it is crucial to ensure the system complies with data privacy regulations and security standards [24], which can be expressed in fig2 as follows:

1. Hardware Selection: Select an edged IoT device suitable for running a CNN model, such as a Raspberry Pi or Nvidia Jetson Nano. Consider the device's computing power, memory, and power consumption.
2. Software Installation: Install the operating system and required software on the device, including the CNN model, a web server, and an MQTT broker.
3. Face mask Detection Model: Train a CNN model using a suitable dataset for facemask detection and then optimize the model for deployment on an edged IoT device.
4. Real-time Image Capture: Connect a camera module to the edged IoT device and configure the device to capture images in real-time. You may use a USB camera, Raspberry Pi camera, or an IP camera that supports video streaming.
5. Face Mask Detection: Run the trained CNN on the captured images to detect whether the person is wearing a face mask. Apply face detection, face alignment, and classification techniques to increase CNN accuracy.
6. Alert System: Based on the output from the facemask detection model, trigger an alert to notify the concerned person or send an email, text message, or push notification
7. Integration with Blockchain: Integrate the edged IoT device with the Blockchain network to enable secure storage and transfer of facemask detection data. Use a smart contract to enforce the rules and policies for data access and sharing.

3.3 Video Data Restoration and Transformation

The CNN model trains the video data restoration and transformation for a facemask detector. This process can be refined and optimized based on the specific requirements and constraints of the video data restoration and transformation system [36, 44, 51–53] . Additionally, it is essential to ensure that the[6, 9, 50, 53, 54] system complies with data privacy regulations and security standards; it involves the following phases :

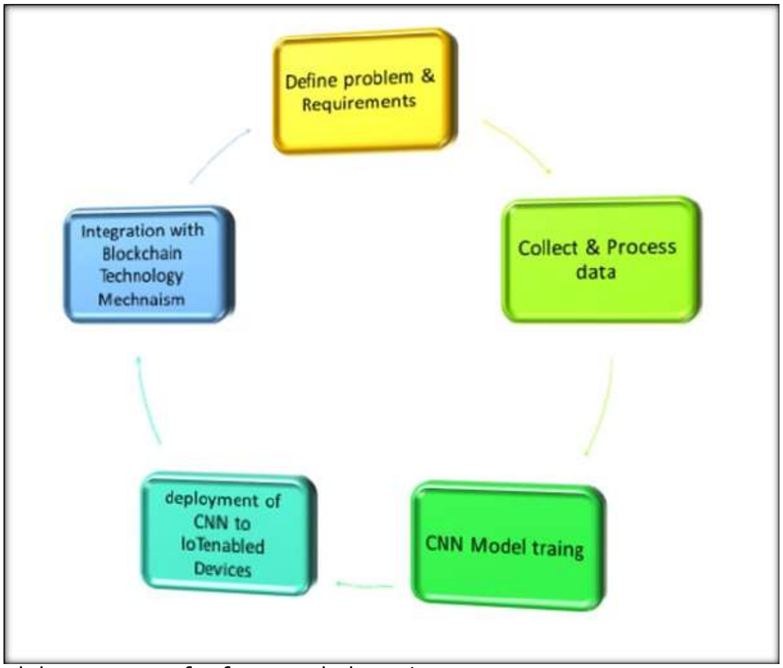

Figure 1. Design methodology process for face mask detection

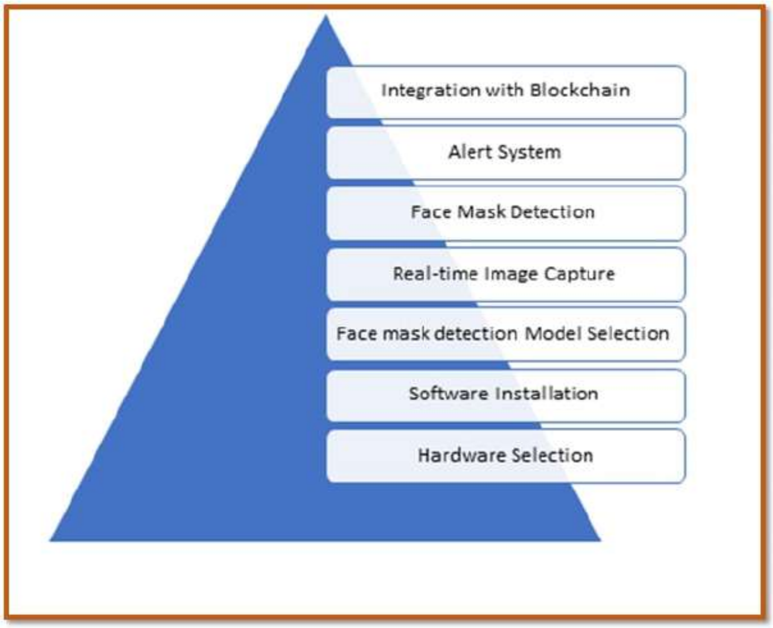

Figure 2. An edged IoT-enabled device for facemask detection using a trained CNN model

1. Video Data Collection: the data that needs to be restored and transformed, videos captured in different lighting conditions, low-resolution videos, or videos with noise.
2. Video Preprocessing: Preprocess the video data to make it suitable for input to the trained CNN model, i.e., resizing, normalization, and color space conversion.
3. Frame Extraction: Extract individual frames from the preprocessed video to apply the trained CNN model.
4. Face mask Detection: Apply the trained CNN model to each video frame to detect wearing a face mask. Apply image processing techniques to increase the model's accuracy.
5. Video Transformation: Based on the output of the facemask detection model, transform the video frames to enhance the visibility of facemasks, involving image enhancement, image restoration, and super-resolution techniques.
6. Video Reconstruction: Reconstruct the transformed frames back into a video, to be done by concatenating the transformed frames back in order.
7. Video Postprocessing: Postprocess the reconstructed video data to improve its quality, including denoising, color correction, and contrast adjustment.
8. Video Storage and Transfer: Store the restored and transformed video data on a blockchain-enabled storage system to ensure secure storage and sharing.

3.4 Detail of Proposed CNN Model Design

The processing model of a facemask detection CNN model typically involves the following steps, mentioned in Figure 3-5, [11, 22, 24, 35, 36, 44, 53] :

1. Input Data Preprocessing: Preprocess the input data to ensure it is suitable for the CNN model; include operations such as image resizing, normalization, and color space conversion
2. Convolution and Pooling Layers: The input data is then passed through a series of convolutional and pooling layers to extract features from the input image.
3. Fully Connected Layers: The output of the convolutional and pooling layers is flattened and passed through one or more fully connected layers to perform classification.
4. Softmax Activation: A softmax activation function is applied to the output of the final fully connected layer to produce a probability distribution over the possible classes. In the case of facemask detection, the two possible courses are "with a mask" and "without a mask."
5. Model Training: The CNN trained on a large dataset of images labeled "with mask" or "without a mask." Labeled classes
6. Inference: Once the CNN model has been trained, it can classify new images as "with a mask" or "without a mask." In the case of facemask detection, this would involve passing the input image through the model and producing a binary classification output.
7. Postprocessing: A step to improve the accuracy of facemask detection— it's a technique for non-maximum suppression or thresholding. CNN is a supervised learning algorithm that needs a large, labeled image dataset. It learns to recognize to classify new images as either "with a mask" or "without a mask." The trained model can be integrated into an IoT-enabled system and combined with blockchain technology to provide a secure and decentralized mechanism for facemask detection in various settings.

3.5 CNN Model Training and Testing process

The process of preparing and using training and testing data for a facemask detection CNN model typically involves the following steps[1, 9, 20, 22, 51]:

1. Data Collection: The first step in building a facemask detection CNN model is to collect a large dataset of images labeled images in two classes of the mask. This dataset can be gathered from various sources, such as online repositories or in-house data collection.

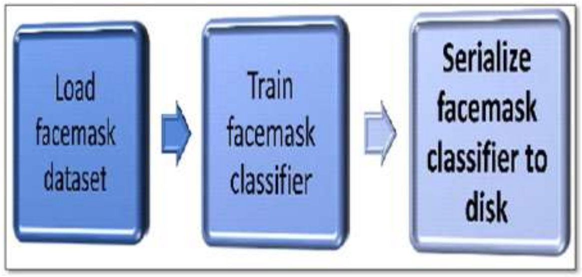

Figure 3. Describe the Phase-I processing of the CNN model for training

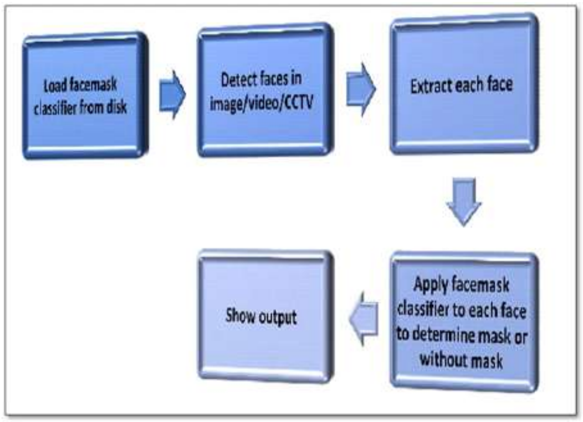

Figure 4. Describe Phase II of the CNN model for the Training process

2. Data Preprocessing: Once the data has been collected, it must be preprocessed to ensure it is suitable for use in the CNN model
3. Splitting the Data: The dataset is divided into two groups, 30 percent for training and 70 percent for testing of CNN model.
4. Data Augmentation: To avoid overfitting, use data augmentation techniques such as image flipping, rotation, and zooming to increase the size of the training set.
5. Training/testing the Model: The training set trains the CNN model. During training, the model learns to recognize the features of facemasks and the absence of facemasks by adjusting the weights of the model using a gradient-based optimization algorithm. We have to train our machine using those datasets using CNN Based Classification Algorithm. In the Training process, the techniques and Algorithms which we will use are Deep Learning, Keras, TensorFlow, and OpenCV to train our model. We will use MobileNetV2 Architecture for the image classifier, and it also has a feature of sending emails or notifications. After the module's integration into our system, we will check it's working correctly on images/videos or any other integrated devices. We check out whether faces are either detected or not. OpenCV framework uses for the integration of devices and video streaming. It helps us to connect any device to our model. After integration, the Mask Detection module extract faces from videos/images and highlight faces with colored square boxes.
6. Evaluating the Model: Once the model has been trained, it is considered using the testing set. The model's performance is measured in accuracy, precision, recall, and F1-score.
7. Fine-Tuning the Model: If the model's performance is not satisfactory, it may be necessary to fine-tune the model by adjusting hyperparameters such as the learning rate, batch size, and the number of epochs.
8. Deployment:Trained CNN model applied to primary data in an IoT-enabled system for facemask detection. This application uses PHP for its server-side code and HTML and CSS for the interface. PHP language is combined with CodeIgniter. PHP framework to make development easier and faster.

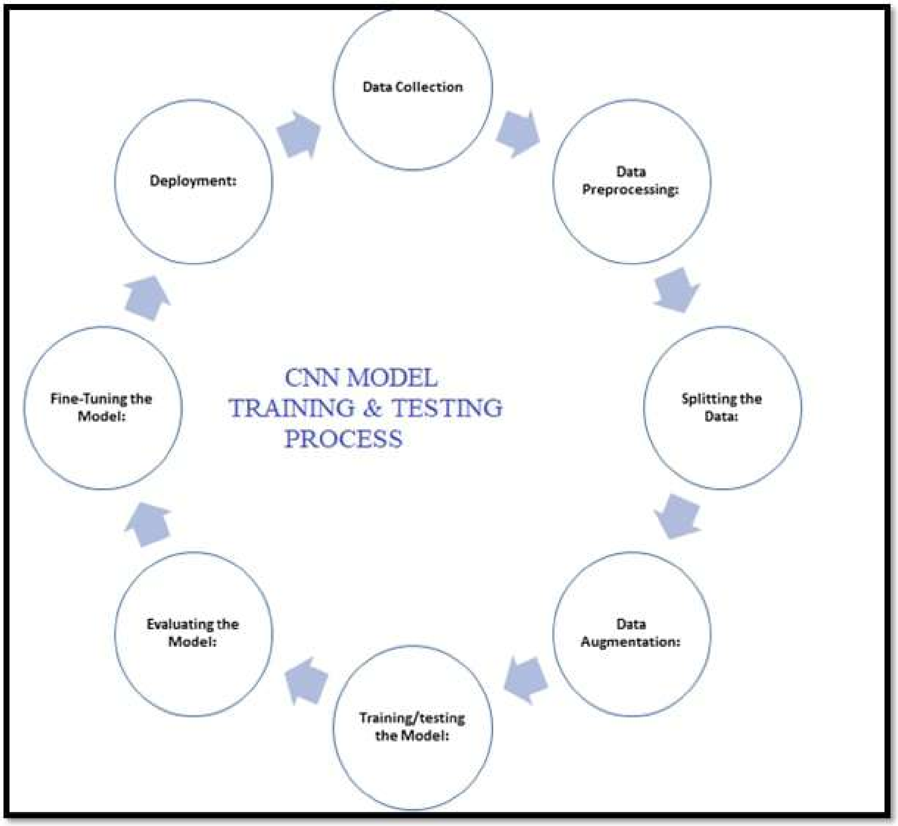

Figure 5. CNN model Training and Testing process

But we used MERN full stack development with the market. React for the front end, the most usable library of JavaScript focuses most on UI, which comprises REACT. The final output displays with or without a face mask. OpenCV framework is used for visualizing our production.

A facemask detection-CNN model's training and testing process is critical to accurately classify new images as "with a mask" or "without a mask." It involves collecting and preprocessing a large dataset of images, splitting the data into training and testing sets, and using data augmentation techniques to prevent overfitting and evaluation.

4 Results and Discussion

The results and discussion of a CNN model for facemask detection using a given dataset can provide insight into its performance and potential for real-world applications. The following metrics are commonly used to evaluate the performance of a facemask detection CNN model[23, 37, 42, 47]:

1. Accuracy: The percentage of correctly classified images out of the total images.
2. Precision: The percentage of the result evaluated in precision by true positive (TP) predictions out of the total number of positive predictions (TP + false positives (FP)).
3. Recall: The percentage of true positive (TP) predictions out of the total number of actual positive samples (TP + false negatives (FN)).
4. F1-Score: The harmonic mean of precision and recall.
5. AUC-ROC: The area under the receiver operating characteristic (ROC) curve analyzed by the standards scales between the actual and false positive rates.

	precision	recall	f1-score	support
with_mask	1.00	0.99	0.99	1000
without_mask	0.99	1.00	0.99	1000
accuracy			0.99	2000
macro avg	0.99	0.99	0.99	2000
weighted avg	0.99	0.99	0.99	2000

Figure 6. CNN Model Analysis-confusion matrix

```
[INFO] training head...
2021-11-20 22:53:20.248688: I tensorflow/compiler/mlir/
mlir_graph_optimization_pass.cc:185] None of the MLIR
Optimization Passes are enabled (registered 2)
Epoch 1/20
2021-11-20 22:54:05.238905: W tensorflow/core/framework/
cpu_allocator_impl.cc:80] Allocation of 154140672 exceeds 10%
of free system memory.
2021-11-20 22:54:05.388873: W tensorflow/core/framework/
cpu_allocator_impl.cc:80] Allocation of 156905472 exceeds 10%
of free system memory.
  1/250 [..............................] - ETA: 3:04:37 - loss
: 0.8875 - accuracy: 0.50002021-11-20 22:54:11.616929: W
tensorflow/core/framework/cpu_allocator_impl.cc:80] Allocation
of 154140672 exceeds 10% of free system memory.
```

Figure 7. Training Model 01

The results and discussion of a facemask detection CNN model in Figures 6-11 include the values of these metrics for the training and testing sets. The model's performance can be further analyzed by looking at the confusion matrix result in Fig 3, which shows the number of true positive, false positive, true negative, and false pessimistic predictions. In the study further, we found that high accuracy, precision, recall, and F1-score, along with a high AUC-ROC value, indicate a well-performing facemask detection CNN model in figures 3-9. It is important to note that the performance of a facemask detection CNN model can vary depending on the specific dataset used, the training process, and the model architecture. It is finally concluded that the live camera results displayed in Fig 10 demonstrate the accuracy of the proposed model with live data.

4.1 CNN Model Results and Analysis

The following results of the custom build model of the CNN implementation to seek the analysis of trainig and testing of the model, showed in figures [6- 12] .

5 Blockchain framework design and CNN integration

A proposed blockchain framework for a facemask detection CNN model-oriented system can provide enhanced security, privacy, and accountability for the system[27, 29, 30] . The blockchain can store and manage the data generated [36, 40]by the CNN model, such as the results of facemask detection and any associated metadata[25, 42, 47, 55]. The following are some critical components of a proposed blockchain framework for a facemask detection CNN model-oriented system in fig12:

```
2021-11-20 22:54:11.682763: W tensorflow/core/framework/
cpu_allocator_impl.cc:80] Allocation of 156905472 exceeds 10%
of free system memory.
  2/250 [..............................] - ETA: 17:53 - loss: 0
.8674 - accuracy: 0.5000  2021-11-20 22:54:16.892244: W
tensorflow/core/framework/cpu_allocator_impl.cc:80] Allocation
of 154140672 exceeds 10% of free system memory.
250/250 [==============================] - ETA: 0s - loss: 0.
2388 - accuracy: 0.9185WARNING:tensorflow:Your input ran out of
 data; interrupting training. Make sure that your dataset or
generator can generate at least `steps_per_epoch * epochs`
batches (in this case, 62 batches). You may need to use the
repeat() function when building your dataset.
250/250 [==============================] - 2430s 10s/step -
loss: 0.2388 - accuracy: 0.9185 - val_loss: 0.0649 -
val_accuracy: 0.9855
Epoch 2/20
250/250 [==============================] - 2505s 10s/step -
loss: 0.0869 - accuracy: 0.9753
Epoch 3/20
250/250 [==============================] - 2239s 9s/step - loss
: 0.0670 - accuracy: 0.9789
Epoch 4/20
250/250 [==============================] - 1557s 6s/step - loss
: 0.0548 - accuracy: 0.9824
Epoch 5/20
250/250 [==============================] - 4371s 18s/step -
loss: 0.0466 - accuracy: 0.9868
Epoch 6/20
250/250 [==============================] - 1004s 4s/step - loss
: 0.0414 - accuracy: 0.9877
Epoch 7/20
250/250 [==============================] - 36970s 148s/step -
loss: 0.0345 - accuracy: 0.9890
Epoch 8/20
250/250 [==============================] - 1430s 6s/step - loss
: 0.0342 - accuracy: 0.9894
Epoch 9/20
250/250 [==============================] - 952s 4s/step - loss
: 0.0333 - accuracy: 0.9896
Epoch 10/20
250/250 [==============================] - 5300s 21s/step -
loss: 0.0295 - accuracy: 0.9896
Epoch 11/20
250/250 [==============================] - 1385s 6s/step - loss
: 0.0295 - accuracy: 0.9901
Epoch 12/20
250/250 [==============================] - 1285s 5s/step - loss
: 0.0263 - accuracy: 0.9906
```

Figure 8. Training Model 02

```
Epoch 13/28
```

Figure 9. Training Model 03

```
250/250 [==============================] - 6205s 25s/step -
loss: 0.0242 - accuracy: 0.9918
Epoch 14/20
250/250 [==============================] - 2943s 12s/step -
loss: 0.0254 - accuracy: 0.9920
Epoch 15/20
250/250 [==============================] - 1991s 8s/step - loss
: 0.0236 - accuracy: 0.9920
Epoch 16/20
250/250 [==============================] - 2267s 9s/step - loss
: 0.0240 - accuracy: 0.9923
Epoch 17/20
250/250 [==============================] - 2134s 9s/step - loss
: 0.0242 - accuracy: 0.9924
Epoch 18/20
250/250 [==============================] - 1596s 6s/step - loss
: 0.0219 - accuracy: 0.9933
Epoch 19/20
250/250 [==============================] - 1477s 6s/step - loss
: 0.0256 - accuracy: 0.9910
Epoch 20/20
250/250 [==============================] - 1380s 6s/step - loss
: 0.0228 - accuracy: 0.9929
```

Figure 10. Training Model 04

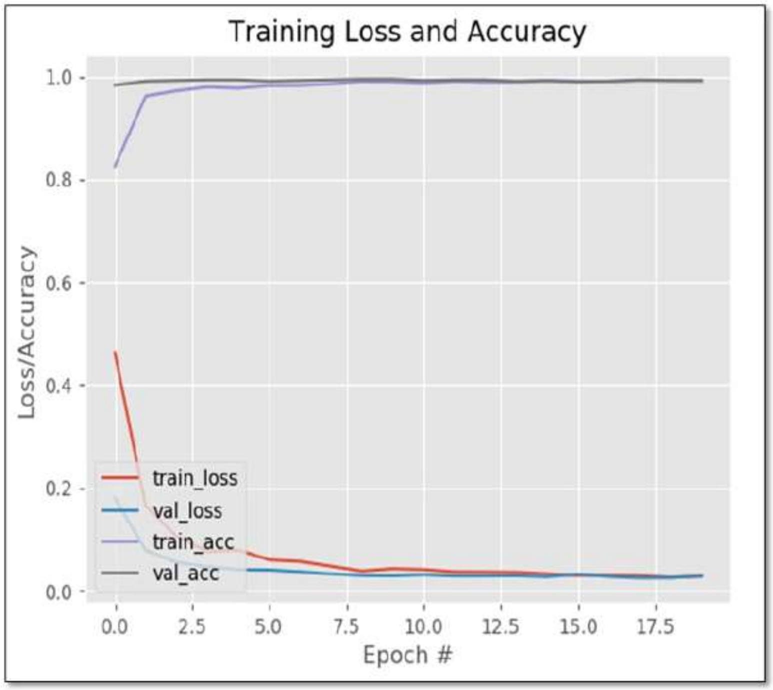

Figure 11. Training Model CNN -Los and Accuracy

Figure 12. Describe the output result analysis with live camera extraction

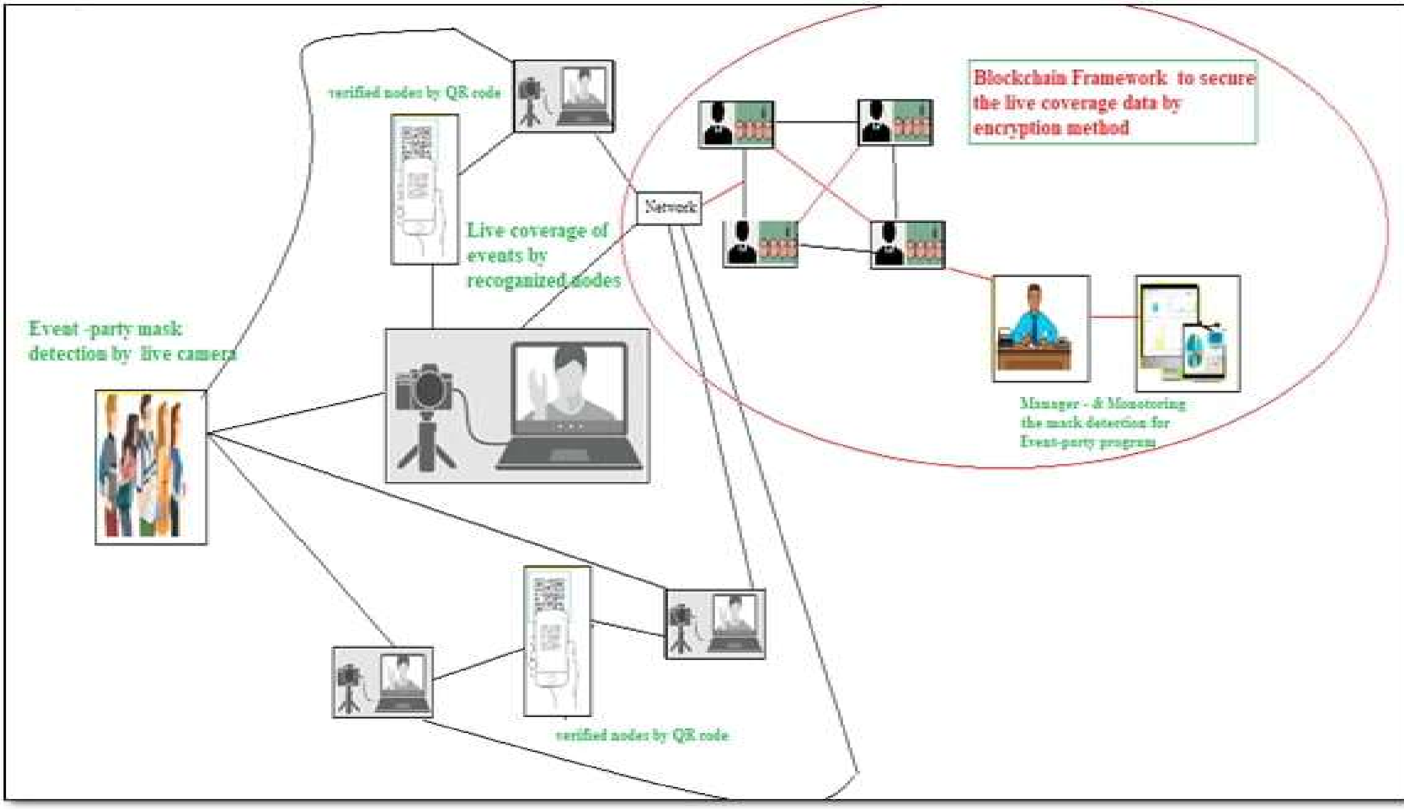

Figure 13. Proposed Blockchain Framework for face Mask detection in live data to secure the network data

5.0.1 Distributed Ledger:

A distributed ledger is a decentralized database maintained by a network of nodes. In the context of a facemask detection CNN model-oriented system, the distributed ledger can store and manage the data generated by the CNN model.

5.0.2 Smart Contracts:

Smart contracts are self-executing contracts with the terms of the agreement between buyer and seller being directly written into lines of code. In the context of a facemask detection CNN model-oriented system, smart contracts can be used to automate storing and managing of the data generated by the CNN model.

5.0.3 Consensus Mechanism:

The consensus mechanism is a protocol to achieve agreement among nodes in a distributed system. In the context of a facemask detection CNN model-oriented system, the consensus mechanism can be used to ensure the integrity of the data stored on the blockchain.

5.0.4 Privacy and Security:

The blockchain can provide enhanced privacy and security for the facemask detection CNN model-oriented system by enabling secure, tamper-resistant storage of data and facilitating access control through digital signatures and other cryptographic mechanisms.

5.0.5 Decentralization:

The decentralized nature of the blockchain can provide enhanced resilience and fault tolerance for the facemask detection CNN model-oriented system and enable more efficient and cost-effective sharing of data and resources among network participants.
A proposed blockchain framework in Fig.13 for a facemask detection CNN model-oriented system can provide enhanced security, privacy, and accountability and enable more efficient and cost-effective sharing of data and resources among network participants. However, the implementation of a framework requires careful consideration

Proposed Blockchain framework for Mask detection in live data to secure the network data

6 Conclusion

Blockchain-enabled technique using the CNN method for mask detection can effectively prevent the spread of pandemic diseases. By leveraging the power of machine learning and Blockchain technology, this technique can provide accurate, real-time detection of face masks and enable secure, tamper-resistant storage and data sharing. CNN model for mask detection is verified at high accuracy and robust performance, even in complex and dynamic environments. The use of Blockchain Technology can provide enhanced security, privacy, and accountability for the system and enable more efficient and cost-effective sharing of data and resources among network participants. Additionally, IoT-enabled devices can extend the reach and impact of the system by enabling real-time monitoring and data collection from remote locations. However, implementing a Blockchain-enabled technique using the CNN method for mask detection requires careful consideration of technical and organizational challenges, including data privacy and security, computational complexity, and integration with existing systems and infrastructure. Further research and development are needed to fully realize the potential of this approach and address these challenges. A Blockchain-enabled technique using CNN method for mask detection can be a powerful tool in the fight against pandemics and other infectious diseases and holds promise for improving public health and safety in the future.

Author Contributions

Anwar Ali Sathio: Writing,Reviewing,Conceptualization, Methodology, Software **Dr Shafique Ahmad Awan**: Data curation, Writing- Original draft preparation. **Ali Orangzeb Panhwar**: Visualization, Investigation. **Ali Muhammad Aamir**: Supervision: **Ariz Muhammad Brohi**: Conversion, Reviewing and Editing :**Asadullah Buledi**: investigation and review

Compliance with Ethical Standards

It is declare that all authors don't have any conflict of interest. It is also declare that this article does not contain any studies with human participants or animals performed by any of the authors. Furthermore, informed consent was obtained from all individual participants included in the study.

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