Capsule Networks for COVID-19 Detection with Explainable AI via Grad-CAM

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***Abstract* — COVID-19 is a serious epidemic disease that the world has encountered in recent years that has hugely impacted human health globally. The impacts of this deadly disease made an urge for early detection of the disease that can be detected from chest X-rays. Advanced AI techniques are developed to detect COVID-19 in chest X-rays; however, explainable models are needed to support clinical decision systems. In this work, we propose a methodology using Capsule Network with a customized dynamic routing algorithm combined with an explainable AI technique through Grad-CAM to improve the efficiency of COVID-19 detection. Relevant regions in the chest X-rays are highlighted using Grad-CAM visualization, providing insights for decision-making. The proposed model achieved the highest validation accuracy of 99.64%, training accuracy of 99.47%, Precision of 100%, Recall of 99%, F1-Score of 99%, AUC on training data of 99.54%, and on testing data of 99.89%. Integration of explainability methods provides a valuable tool for medical professionals.**

Keywords— Capsule Networks, Convolutional Neural Networks (CNN), COVID-19, Grad-CAM

I. INTRODUCTION

Severe acute respiratory syndrome Coronavirus 2 (SARS-CoV-2) is a deadly virus that causes coronavirus (COVID-19). Mild to moderate respiratory illness will be experienced by the people who are COVID-19 infected. The illness can be recovered without any special treatment; however, some cases can become serious and can result in the death of the patient [1]. On the 11th of March, 2021, the World Health Organization (WHO) declared COVID-19 a health emergency of global concern [2]. As of 15 September 2024, the total number of COVID-19 cases according to the WHO records stands at 776,281,230, and the total deaths reported are at 7,065,880 [3].

The Reverse Transcription Polymerase Chain Reaction (RT-PCR), is an older laboratory method used in diagnosing the presence of the COVID-19 virus. This process is time-consuming, ranging from a few hours to 1-2 days, may give some false negatives, and requires certain equipment that can be hardly available [4]. Radiographic imaging techniques have developed different methods to enhance the detection of coronavirus disease, especially chest imaging, which depicts the characteristics of COVID-19, which makes it much more efficient [5]. Neural networks have played a critical role in the automation of this process through the introduction of convolutional neural networks (CNN), a kind of neural network that is successfully employed in a variety of computer vision works, including object detection [6], image segmentation [7], and classification [8]. The efficiency of CNNs in image tasks encouraged researchers to apply CNN in radiology tasks [9] and also in automating COVID-19 detection via radiology images [10].

However, there is a need for explainability of the decisions made by CNNs to provide transparency of the model and to build trust towards model decisions. GradCAM is one of the Explainable AI techniques introduced by Selvaraju, et al [11] which uses gradients of any given target category flowing through the CNN layer and produces a localization map that highlights the relevant regions of the image to support the decision system of the model.

CNNs have some limitations, especially when it comes to the spatial relationships of objects in an image. Incorporating the max-pooling layer for downsampling the spatial dimension of the input enables some degree of translation invariance within CNNs, as features can be detected at any position without altering recognition. Nevertheless, the use of max-pooling has its drawbacks as far as some spatial information is likely to be lost. This loss of detail makes it difficult for the CNN to understand the spatial relations of the components of an image, which is necessary for medical imaging, as the spatial arrangement of certain structures, such as organs and lesions, has to be accurate for proper diagnosis.

To overcome the drawbacks of CNN Sara Sabour et al. [12] introduced the capsule network, which groups the neurons into capsules to better understand hierarchical relationships between objects and features in an image-preserving spatial information using dynamic routing between capsules.

This research develops a methodology to automate the process of COVID-19 detection in chest x-ray images:

- To make COVID-19 detection faster than traditional laboratory methods.
- To utilize the strengths of capsule networks in preserving hierarchical spatial information in chest x-ray images.
- To integrate the explainable AI method Gradient-weighted class activation map (Grad-CAM) to enhance and support the decision-making in disease prediction.

II. PREVIOUS WORKS

Sethy et al. [13] suggested a methodology related to how COVID-19 can be diagnosed from X-ray images, where an SVM classifier was used, using deep features extracted from X-ray images by pretrained CNN-based models. The ResNet50 deep feature extractor, followed by an SVM classifier, achieved the highest accuracy of 95.33%. Farah Shahid et al. [14] discussed the strengths of deep learning models like LSTM, BiLSTM, and GRU in the detection of COVID-19, and BiLSTM outperformed in their approach. Haque et al. [15] highlighted the capability of CNN-based models in the detection of COVID-19 in chest x-ray images. The authors employed the ResNet50 and VGG-pre trained.

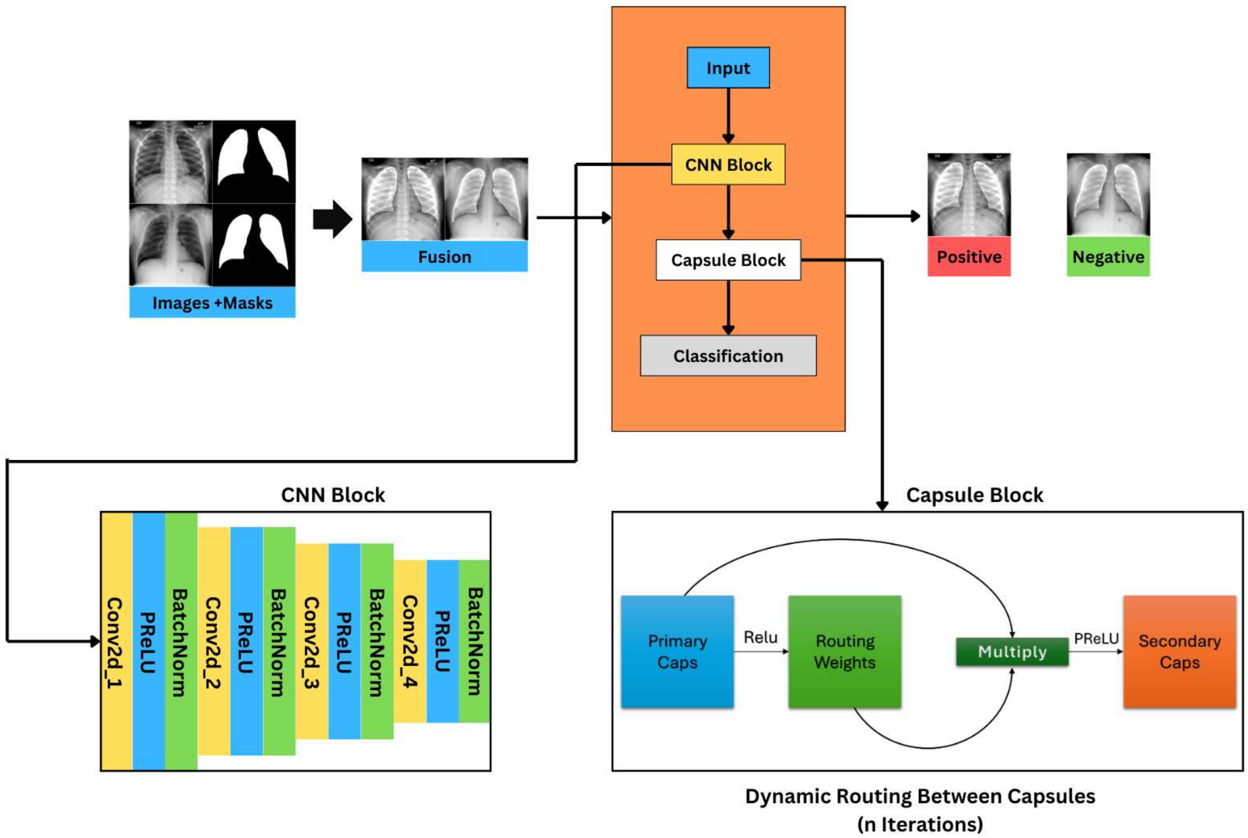

Fig. 1. The architecture of the proposed model

CNN models for feature extraction and classification tasks and the model proposed by the authors attained 98.3% accuracy. Muhammad Farooq and Abdul Hafeez [16] proposed the COVID-ResNet deep learning model, which is based on the ResNet50 architecture, and achieved an accuracy of 96.23%. The authors fine-tuned the model by resizing the images progressively. Ali Narin et al. [17] presented a method for the automatic detection of COVID-19 using pre-trained models based on CNN, which include ResNet50, ResNet101, ResNet152, InceptionV3, and Inception-ResNetV2. The ResNet50 model proposed by the authors achieved the highest accuracy of 99.7%. Linda Wang and Alexander Wong [18] introduced COVID-Net, a deep convolutional neural network for detection of COVID-19. The authors also introduced a new dataset for COVID-19 detection called COVID-19, which contains 13,975 chest X-ray images, and the model proposed by the authors achieved an accuracy of 93.3%. The authors used GSInquire, an explainability method proposed by Zhong Qiu Lin et al. [19], to provide more insights to clinicians in decision-making and to ensure transparency of the proposed system. Several studies [20–23] have shown that CNN plays a key role in the diagnosis of COVID-19.

Yadav, S., and Dhage, S. [24] proposed a time-efficient capsule network (TF-CapsNet), a novel approach to enhance disease detection from medical images like X-rays and MRIs with less computational complexity. Zhang, H., et al. [25] proposed a novel approach to detect COVID-19 in chest x-ray images: a hybrid model combining CNNs, capsule networks, and attention mechanisms. The proposed model achieved an accuracy of 98.54% for binary classification, including COVID or normal, and an accuracy of 96.71% for three-class classification, including COVID, pneumonia, or normal. Sharma, P., et al. [26] proposed a deep learning model for COVID-19 detection in chest x-rays called Conv-CapsNet and achieved an accuracy of 97.69% for binary classification, including COVID or normal, and 96.47% for multi-class classification, including COVID or no finings or pneumonia. Multiple studies [27–31] have demonstrated that capsule networks significantly enhanced COVID-19 detection. Harsh Panwar et al. [32] proposed a deep transfer learning algorithm for COVID-19 detection in X-rays and CT scans of the chest and also utilized Grad-CAM visualizations to make the proposed model explainable and interpretable.

III. Methodology

A. *Dataset Description*

The dataset contains chest X-ray images and respective lung masks of 4 categories: COVID, lung opacity, pneumonia, and normal. And is taken from Kaggle [33, 34]. It contains 3616 COVID images, 6012 lung opacity images, 1345 viral pneumonia images, and 10192 normal images. The present study focuses on developing a model for classifying a chest X-ray into COVID or Normal, so only COVID and Normal images and masks are taken for training the model.

B. *Preprocessing*

The dataset contains COVID-19 and normal chest x-ray images and respective lung masks in separate directories.

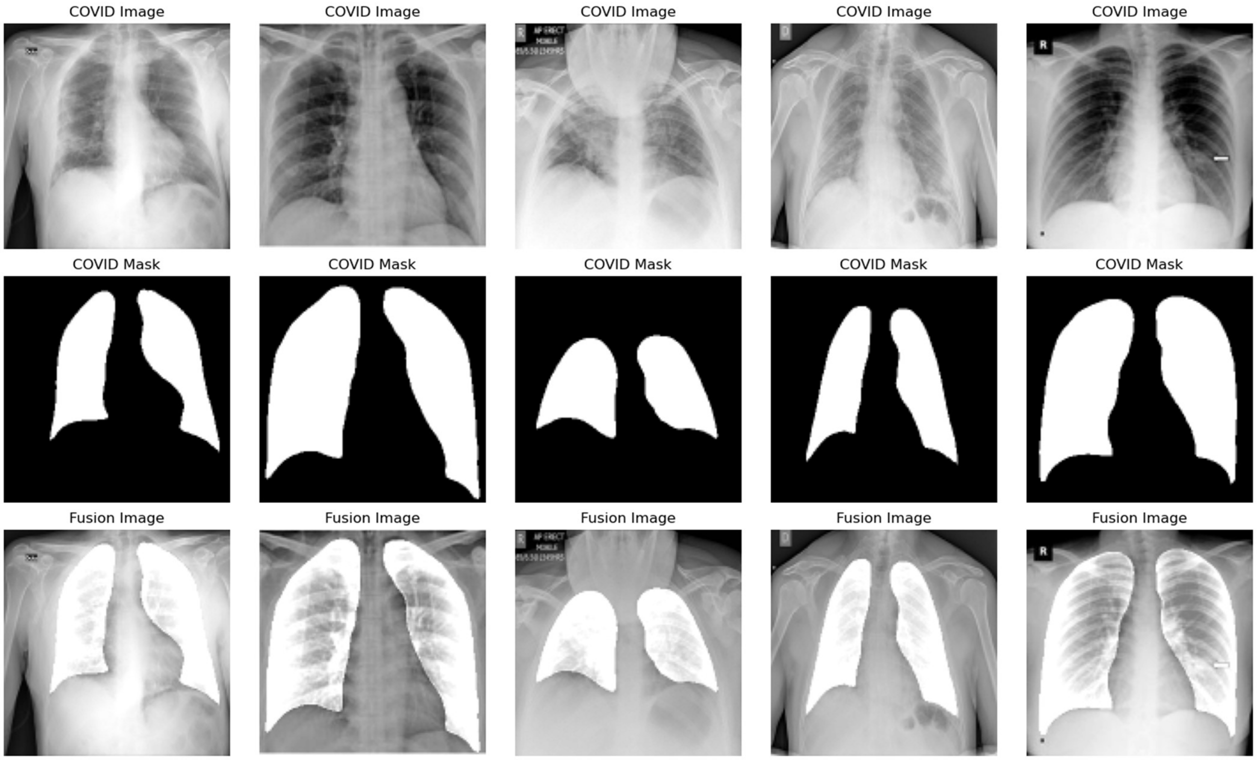

Fig. 2. Sample COVID-19 images.

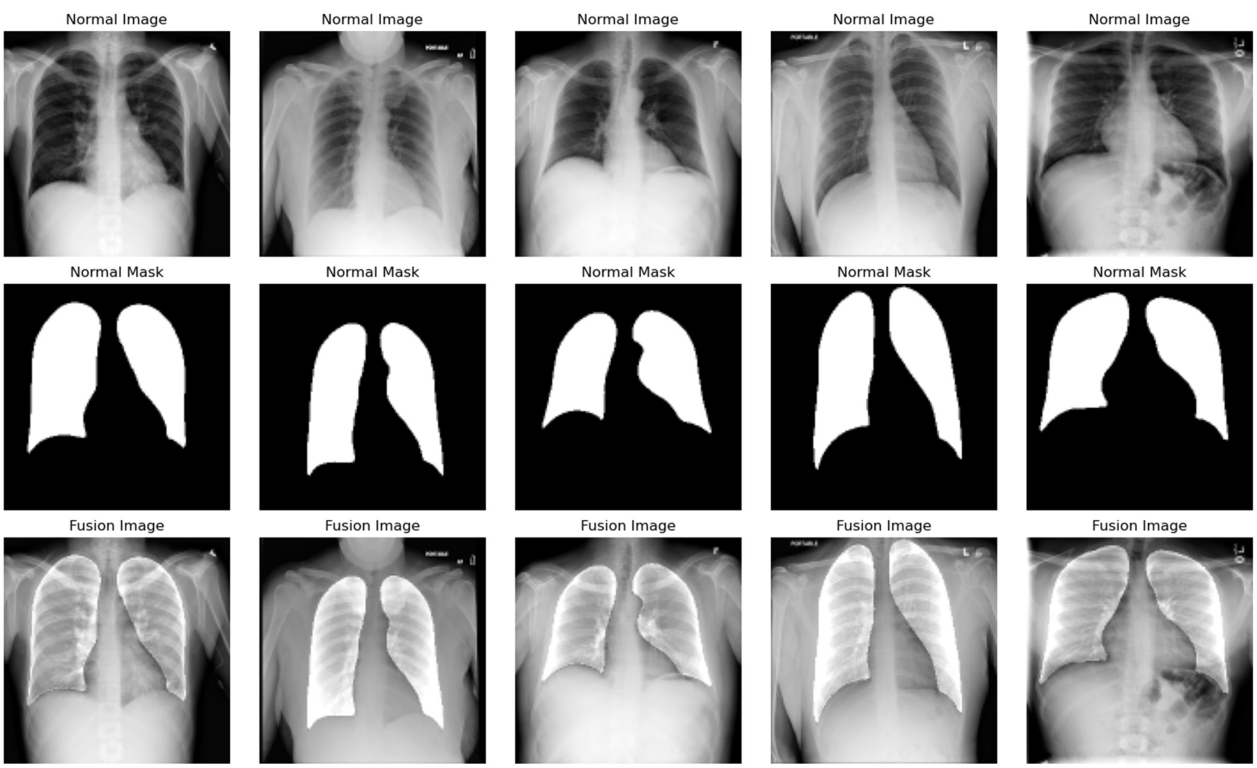

Fig. 3. Sample Normal images.

Algorithm 1: Customized Dynamic Routing

1. **Procedure** DYNAMIC ROUTING ($\hat{u}_{i|j}$, n, l)
2. $\forall$, primary Caps i in the layer l and Secondary Caps j in layer $(l+1)$:
3. $X \leftarrow \hat{u}_{i|j}$
4. *for* n iterations *do*
5. $\forall$, primary Caps i in the layer l: $C_{ij} \leftarrow ReLU(\sum XW_{ij} + b_{ij})$.
6. $\forall$, secondary Caps j in the layer $(l+1)$: $\epsilon_{i|j} \leftarrow C_{ij} \odot X$
7. $\forall$, secondary Caps j in the layer $(l+1)$: $X \leftarrow PReLU(\epsilon_{i|j})$.
8. *end for*
9. **return** X
10. *end* **Procedure**

Each X-ray image and respective lung mask are loaded using the OpenCV module and fused using the added Weighted. Function of OpenCV with a 0.5 alpha value. This method generates a fusion of X-ray and lung masks, which overlays the lung regions of the mask onto the X-ray, enhancing visualization of the COVID-affected area. The fused images are saved in a separate directory for training the model. Fig. 2. and Fig. 3. visualize the sample X-ray images, lung masks, and fused images.

C. Convolution Block

As shown in Fig. 1., the convolutional block contains 4 fully connected CNN layers to extract the features from the input images. The PReLU activation function is used for each CNN layer with a stride of 2, padding of the same, a kernel size of 3x3, and batch normalization after each CNN layer. L2 regularization is applied in the first CNN layer to add a penalty term to incorrectly classified instances. These extracted features are sent to capsules after applying the Squash function (1) to understand the hierarchical spatial information in the images.

D. Capsule Block

The features extracted by CNN layers are grouped to form primary capsules, which represent the entities of the objects in the image, like orientation and various instantiation parameters. Primary layer capsules try to predict the output of the next layer capsule, called secondary layer capsules. This process of predicting the output of secondary layer capsules is called dynamic routing. Now secondary level capsules evaluate the predicted outputs of primary level capsules with actual outputs. The primary capsules that predict the output correctly are given more weight, and those capsules that are predicted incorrectly are given less weight. This mechanism is called routing by agreement between capsules. This routing mechanism can be iterated a certain no. of times to enhance the performance of the Capsule Network. The output of a capsule network is a vector rather than scalar like in the case of traditional CNN; however, the length of the vector is the probability of the presence of the object in the image, and the length of the vector can be greater than 1 so the Squash function (1) is used to squash the length of the vector to be between 0 and 1. The marginal loss function (2) is used to boost the correct classifications and penalize the incorrect classifications. Algorithm 1 explains the routing mechanism implemented in this research.

$$squash(x) = \frac{\|x\|^2}{1 + \|x\|^2} \times \frac{x}{\|x\| + \epsilon} \ldots (1)$$

$$\begin{aligned} loss = y_{true} \times \max\left(0, 0.9 - y_{pred}\right)^2 \\ + 0.45 \times (1 - y_{true}) \\ \times \max\left(0, y_{pred} - 0.1\right)^2 \ldots (2) \end{aligned}$$

E. GradCAM Visualization

The GradCAM visualizations introduced by Selvaraju et al. [11] explain the proposed model's decision system. Fig.3 and Fig. 4 describe the GradCAMs generated by the proposed model.

IV. RESULTS

The model is trained with 90% of the data, using Adam optimizer with a learning rate 1e-3 on the fused images for 5 iterative routings and 50 epochs, and tested with the remaining 10% of the data. Table -1 and Table 2 describe the metrics of the model and Fig.2 illustrates the learning curves of the model when trained for n(1-5) no. of routings. With 2 routings, training accuracy, and validation accuracy are aligned closely showing smooth curves and stable performance of the model and achieving an accuracy of 99.42 on both training and testing data. With 4 routings, the model achieved the highest validation accuracy of 99.64%, training accuracy of 99.47%, Precision of 100%, Recall of 99%, F1-Score of 99%, AUC on training data of 99.54%, and on testing data of 99.89%. The training time taken by the model with 4 routings is 281.56 seconds and 0.48 seconds for testing. With less training time, the model achieved high accuracy showing model effectiveness and robustness which makes it suitable for practical applications where both accuracy and training speed are essential. GradCAM visualizations enhanced model transparency and explainability and also provided visual explanations. The comparison of the proposed model with existing models is presented in Table -3. The proposed model outperformed existing models and provided a visual interpretation of the results obtained.

V. CONCLUSION

In this research, we presented a capsule network with a customized routing algorithm for COVID-19 detection to provide faster and more accurate results than traditional laboratory methods. The proposed model performed well with 4 routings and also outperformed existing methods for

TABLE I. PERFORMANCE METRICS OF THE MODEL

No. of Routings	Training Accuracy	Testing Accuracy	Precision	Recall	F1-Score	AUC	
						Training	Testing
1	99.51	99.06	100	96	98	99.43	99.33
2	99.42	99.42	100	98	99	99.43	99.14
3	99.36	99.13	98	98	98	99.31	99.46
4	**99.47**	**99.64**	**100**	**99**	**99**	**99.54**	**99.89**
5	99.35	99.28	100	97	99	99.47	99.75

TABLE II. EFFICIENCY METRICS OF THE MODEL

No. of Routings	Training Time	Testing Time	Trainable Parameters	Training Data (90%)	Testing Data (10%)
1	238.33	0.37	1,316,610	12427	1381
2	242.36	0.38	1,337,154	12427	1381
3	287.26	0.43	1,357,698	12427	1381
4	**281.56**	**0.48**	**1,378,242**	**12427**	**1381**
5	271.14	0.42	1,398,786	12427	1381

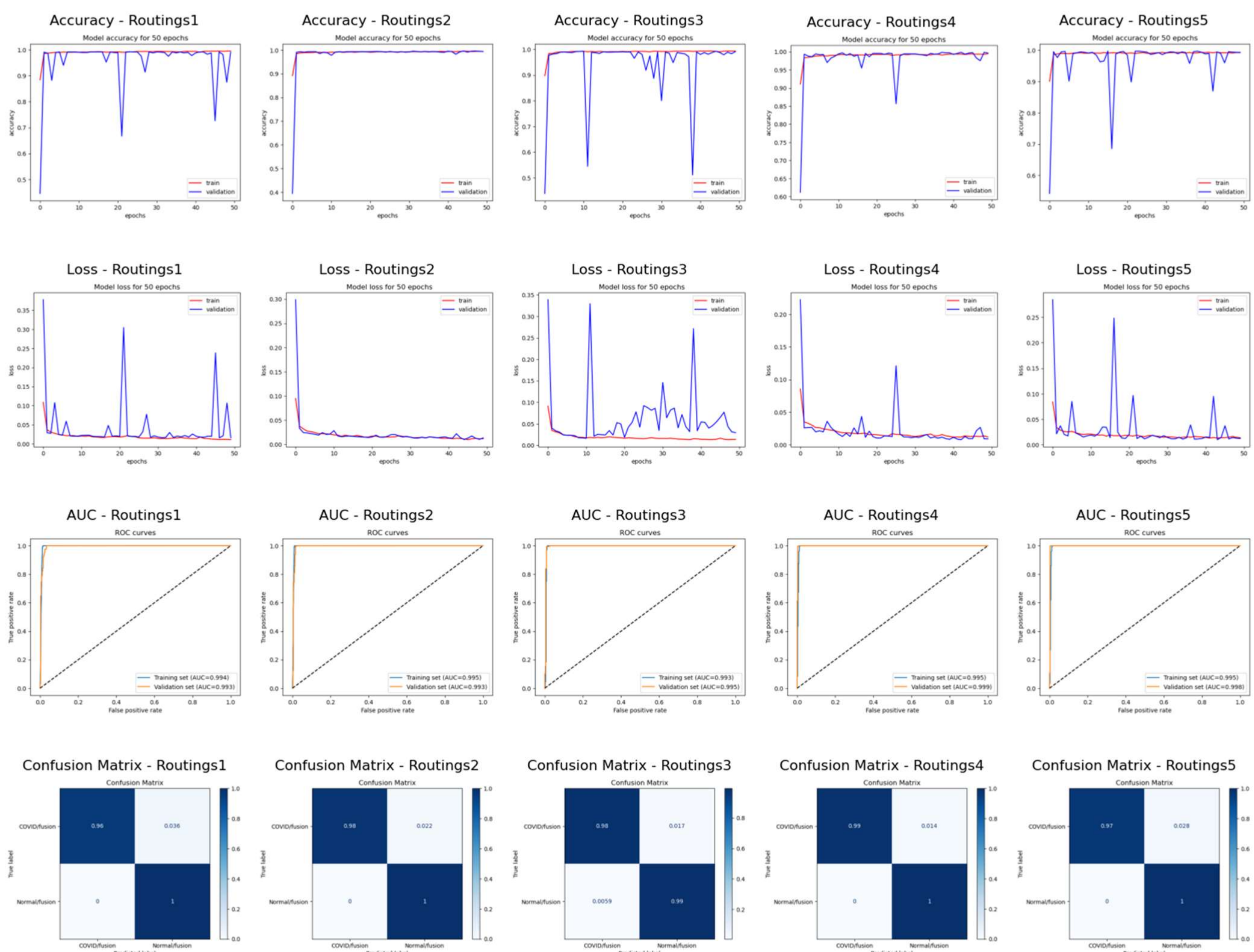

Fig. 4. Learning curves of the proposed model

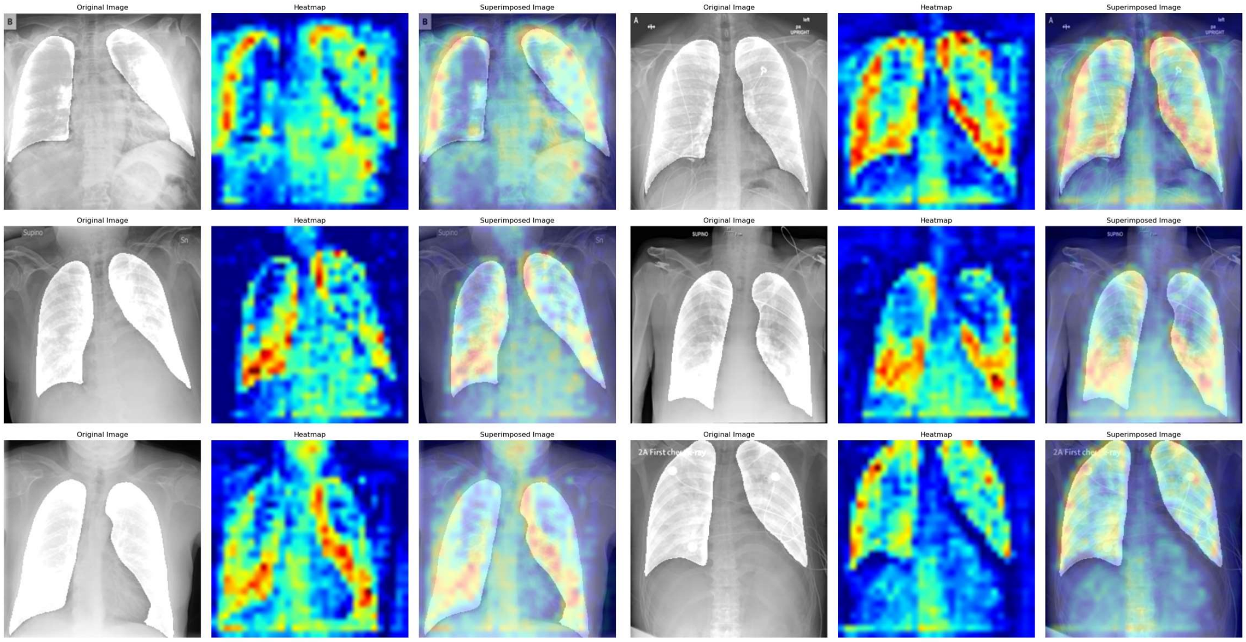

Fig. 5. Original image, heatmap, and GradCAM visualizations of COVID-19 images generated by the proposed model with 4 routings.

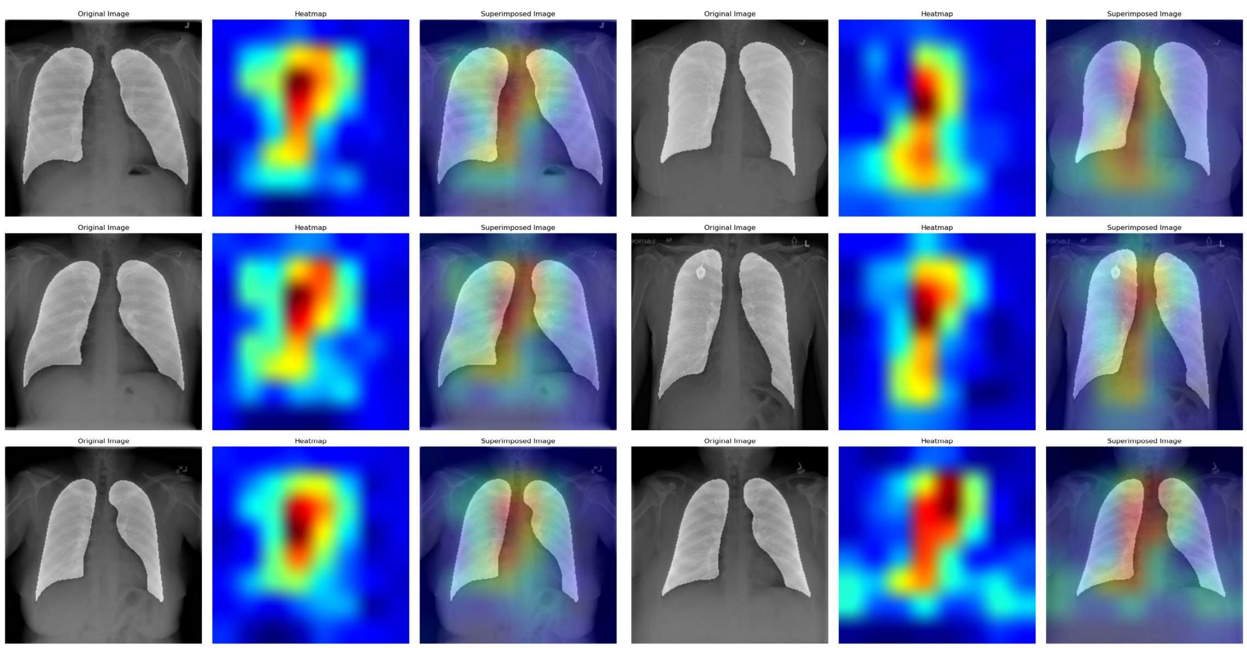

Fig. 6. Original image, heatmap, and GradCAM visualizations of Normal images generated by the proposed model with 4 routings.

COVID-19 detection. Also, the integration of GradCAMs enhanced model transparency and explainability. The proposed model achieved the highest validation accuracy of 99.64%, training accuracy of 99.47%, Precision of 100%, Recall of 99%, F1-Score of 99%, AUC on training data of 99.54%, and on testing data of 99.89%. The proposed model took 281.56 seconds for training and 0.48 seconds for testing. With less training time, the model achieved high accuracy showing model effectiveness and robustness which makes it suitable for practical applications where both accuracy and training speed are essential.

The future scope of this research can involve expanding the model to work on other medical imaging techniques such as CT scans, MRI scans, etc. The model can be used for real-time detection of COVID-19 in chest x-rays and new explainable AI technologies can also be integrated to provide a more detailed explanation of the decision system of the model. Cross-validation with additional train-test splits and experimenting with different image sizes can be included in the future scope.

TABLE III. COMPARISON OF THE PROPOSED MODEL WITH EXISTING MODELS

Authors	Approach	Accuracy
Hao Quan, et al [30] (2021)	CNN +CapsNet	90.7
P.K. Gupta, et al [29] (2022)	CNN +CapsNet	91
Pinesh Arvindbhai Darji, et al [31] (2021)	UNet + CNN + CapsNet	93.2
Linda Wang and Alexander Wong [18] (2020)	CNN	93.3
Harsh Panwar, et al [32] (2020)	Transfer Learning + GradCAM	95.61
Muhammad Farooq and Abdul Hafeez [16] (2020)	ResNet50	96.23
Hafeez, U., et al [22] (2023)	CNN	97
Sharma, P., et al. [26] (2023)	CNN +CapsNet	97.69
Parnian Afshar, et al [28] (2020)	CNN +CapsNet	98.3
Haque et al. [15] (2020)	ResNet50 and VGG	98.3
Zhang, H., et al [25] (2024)	CNN + Attention Mechanism + CapsNet	98.54
Haval I. Hussein, et al [23] (2023)	CNN	98.55
Sethy, et al [13] (2020)	ResNet50 plus SVM	98.66
Mohsen, S., et al [21] (2024)	CNN	99
Proposed Model	**CNN + CapsNet + GradCAM**	**99.6**

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