biocybernetics and biomedical engineering 43 (2023) 352–368

Available at www.sciencedirect.com
ScienceDirect
journal homepage: www.elsevier.com/locate/bbe

Original Research Article

SCovNet: A skip connection-based feature union deep learning technique with statistical approach analysis for the detection of COVID-19

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A R T I C L E I N F O

Article history:
Received 25 October 2022
Received in revised form
21 December 2022
Accepted 30 January 2023
Available online 15 February 2023

Keywords:
COVID-19
CNN
Deep learning
Image augmentation
Skip connection
X-ray Images

A B S T R A C T

Background and Objective: The global population has been heavily impacted by the COVID-19 pandemic of coronavirus. Infections are spreading quickly around the world, and new spikes (Delta, Delta Plus, and Omicron) are still being made. The real-time reverse transcription-polymerase chain reaction (RT-PCR) is the method most often used to find viral RNA in a nasopharyngeal swab. However, these diagnostic approaches require human involvement and consume more time per prediction. Moreover, the existing conventional test mainly suffers from false negatives, so there is a chance for the virus to spread quickly. Therefore, a rapid and early diagnosis of COVID-19 patients is needed to overcome these problems.
Methods: Existing approaches based on deep learning for COVID detection are suffering from unbalanced datasets, poor performance, and gradient vanishing problems. A customized skip connection-based network with a feature union approach has been developed in this work to overcome some of the issues mentioned above. Gradient information from chest X-ray (CXR) images to subsequent layers is bypassed through skip connections. In the script's title, "SCovNet" refers to a skip-connection-based feature union network for detecting COVID-19 in a short notation. The performance of the proposed model was tested with two publicly available CXR image databases, including balanced and unbalanced datasets.
Results: A modified skip connection-based CNN model was suggested for a small unbalanced dataset (Kaggle) and achieved remarkable performance. In addition, the proposed

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https://doi.org/10.1016/j.bbe.2023.01.005

model was also tested with a large GitHub database of CXR images and obtained an overall best accuracy of 98.67% with an impressive low false-negative rate of 0.0074.

Conclusions: The results of the experiments show that the proposed method works better than current methods at finding early signs of COVID-19. As an additional point of interest, we must mention the innovative hierarchical classification strategy provided for this work, which considered both balanced and unbalanced datasets to get the best COVID-19 identification rate.

1. Introduction

Coronavirus disease (COVID-19), a new Coronavirus, was first reported as a group of deadly respiratory illnesses in Wuhan, China, in December 2019. The COVID-19 virus appears to have reached pandemic proportions and is spreading at an alarmingly rapid pace [1]. A patient infected with COVID-19 may have various symptoms and signs, including fever, dry cough, headache, and sore throat, which can lead to pneumonia, multi-organ failure, respiratory problems, and even death [2]. The majority of tests performed in India and throughout the world are reverse transcription-polymerase chain reaction (RT-PCR), which uses nasal and throat swabs to indicate the existence of the virus [3,4]. Although the RT-PCR test can detect the virus in asymptomatic people, the test results may produce false negatives [5]. In private medical laboratories, the RT-PCR test might take up to 8 h for a valid diagnosis and is quite expensive in some countries [6]. Due to the significant increase in confirmed and suspected new COVID-19 cases, computer-based diagnosis is required. Currently, artificial intelligence (AI) may play a significant role in COVID-19 imaging identification. COVID-19 mainly affects the respiratory system such that a Chest X-ray (CXR) scan may play an important role in the early detection and diagnosis of infection [7]. Radiographic image, Computed tomography (CT) scan analysis with deep learning techniques may provide an accurate solution with low cost and fewer time [8,9].

A chest radiography image-based screening system provides various advantages for COVID-19 detection over conventional procedures such as rapid diagnostic tests (RDT) and RT-PCR. It may be quick, assess numerous cases at once, and have a higher level of availability with accurate detection of lung diseases [10,11]. Most significantly, such a system can be extremely valuable in hospitals with limited testing equipment and resources. Furthermore, because radiography is so important in today's healthcare systems, radiology imaging equipment is available in every hospital, making radiography-based approaches easier and more accessible. At present, Deep learning (DL) approaches have been utilised to significantly improve image processing performance in the medical imaging area [12,13]. DL has been proven its effectiveness in brain tumour classification [14], MRI image analysis [15], skin cancer, lung infection [16] and retinal images [17]. Therefore, initial days of the epidemic DL based methods were extensively applied to radiographic images to detect COVID-19. X-ray is a commonly available tool that saves time in detecting various problems in the patient that are not visible to the naked eye. Moreover, the results of a chest X-ray (CXR) can also be used to diagnose an infection within the body. In addition, the integration of AI approaches to CXR results will have a significant impact on radiologists by providing them with technology for more accurate diagnosis and prognosis.

As of now, professionals from all across the world are working hard to fight against the disease. Many researchers and academicians published different articles describing methods for detecting COVID-19 using CXR images [18–22]. Using image processing on chest X-ray images, Hasoon et al. suggested a method for classifying and early detecting COVID-19. The authors used several pre-processing techniques, such as noise reduction, contrast enhancement, and morphological operation, to improve the quality of the images they used. Furthermore, suitable features were detected, segmented, and extracted using Region of Interest (ROI) based techniques. Finally, six different machine learning classifiers were used to evaluate the COVID-19 detection classification ability, and they reported an average accuracy of 98.66%. In paper [11], the authors utilised the concept of normalised images to extract enriched features that were then fed into image categorisation systems based on deep learning. Transfer learning-based Convolutional Neural Network (CNN) methods such as Visual Geometry Group (VGG) - 19, MobileNetV2, Inception, Xception, and Inception residual network (ResNet) V2 were applied to classify COVID-19 from pneumonia and healthy CXR image datasets. All the classification algorithms tested different bases, and MobileNetV2 reported the overall highest accuracy of 96.70%.

Narin et al. [23] introduced three different pre-trained deep learning algorithms (ResNet50, InceptionV3 and Inception-ResNetV20) to detect COVID-19 from CXR images. With five-fold cross-validation, classifications were performed on four classes (COVID-19, normal, pneumonia (bacterial), and pneumonia (viral)). Finally, the authors reported an overall greatest accuracy of 97% with ResNet50. Authors in [24] presented a tailored deep learning model (COVID-Net) for diagnosing COVID-19 from CXR images. This study also used a large private, publicly available open-source benchmark database (COVIDx) with X-ray images. Further, the proposed model was evaluated with three classes and found to be accurate in 83.50% cases. Ahmed *et al.* [25] utilized chest radiograph images (CRI) for the detection of new coronavirus disease 2019 (COVID-19). The suggested system is based on Squeeze-

Net for extracting deep features and SVM for classification. CT scan pictures were used by Abdulkareem *et al.* [26] to diagnose COVID-19 infection in its earliest stages. In order to create a diagnostic system for COVID-19, researchers used a convolutional neural network (CNN), stacked autoencoder, and deep neural network. Prior to using the three CT image approaches to distinguish between normal and COVID-19 instances, the classification process in this system is modified. The adopted deep learning model was trained on a huge and complex CT imaging dataset, and the results showed an accuracy of 88.30%.

The application of artificial intelligence techniques on X-ray imaging was presented by the authors in the paper [29]. Many deep learning techniques were utilised in this study and reported an accuracy of 87.02% for three different classes (COVID, Normal and Pneumonia). Most recent studies used CXR images to diagnose COVID-19, highlighting the importance of CXR image processing as an acceptable tool for clinicians and radiographers. Arman et al.[30]collected frontal CXR images from multiple sources and created a large database for experimentation. Moreover, a new COVID-CXNet is developed utilising transfer learning and the CheXNet methodology. This sophisticated model can detect and localise new coronavirus pneumonia based on important features with an accuracy of 87.88%. In order to diagnose COVID-19, Nagi*et al.* [31] examined the effectiveness of a large chest X-ray image dataset using a variety of deep learning models and compared their results. The size of the dataset that was employed is approximately 4.25 times larger than the largest COVID-19 chest X-ray image dataset that was utilised in the earlier investigations. During the course of the research, the authors created a customized CNN model and evaluated its performance in comparison to that of other current deep learning models. In addition to this, researchers assessed the overall performance of each of the deep learning models using the more extensive COVID-19 chest X-ray image dataset.

The research in [32] has resulted in the development of a cloud-based Smartphone application that can determine the early prognosis of COVID-19-infected patients and also forecast the mortality risk of patients based on their symptoms. In addition, the authors used a heuristic approach to identify the most significant symptoms that are required for generating such predictions. Symptoms such as difficulty breathing, fever, dry cough, and headache are utilized for COVID-19 prediction. Furthermore, factors such as age, sex, fever, diabetes, and hypertension are considered when assessing mortality risk. Table 1 shows an overview of the recent studies on the detection of COVID-19.

The inputs, number of classes, techniques, and experimental findings from various earlier works are also discussed in Table 1. Several of the studies used CXR imaging to find COVID-19, while the rest used CT scan analysis. The majority of recent works used deep learning-based methods, including ResNet, VGG, GoogleNet, *etc.* (Pre-trained networks), and some customized CNN-based models. Researchers could have gathered the data for the studies in different places and with different kinds of imaging equipment. Pre-processing, data splitting (training, validation, and test), and tuning of hyperparameters are some of the experimental settings that can affect the performance of these methods.

Early detection of SARS-CoV-2 is critical to preventing the virus from spreading to others. Along with this work, authors developed a deep learning approach for automatically detecting COVID-19 using CXR images of patients who are infected with COVID-19 and those who are not infected. Moreover, deep learning has been shown clinically beneficial for segmenting COVID-19 lung lesions [33]. The use of chest imaging modalities as main, secondary, or supplemental diagnoses is growing and will continue to evolve; moreover, the incorporation of AI algorithms can also aid in the prediction of clinical improvement to combat COVID-19.

Saeed et al. [34] presented a mathematical framework for COVID-19 diagnosis that makes use of a novel agile fuzzy-like arrangement: the complex fuzzy hypersoft set, which is a hybrid of the complex fuzzy set and the Hypersoft. A study connecting COVID-19 symptoms to medications lends credence to the authors' proposed approach. In addition, researchers provide a generalised mapping that can be used by a professional to extract the patient's health record and estimate the time it will take for the infection to clear up.

Currently, a significant number of experiments are being conducted on COVID-19 detection and diagnosis using deep learning techniques, with the goal of determining which model is the most effective. Mohammed et al. [35] provided an integrated technique for selecting the best deep learning model for COVID-19 diagnosis, which was based on an innovative crow swarm optimization algorithm.

This article proposes a reliable skip- a connection-based feature union deep neural network with the combination of CXR image processing tools for the early detection of COVID-19 symptoms, building on previous work to overcome certain limitations related to data environment issues (balanced and unbalanced) and performance. The concept for creating a customised SCovNet network is derived from residual networks (ResNet). ResNet was created to design deep networks without the "vanishing gradient" problem and for cost savings. A ResNet is a feed-forward network containing residual connections. The operations in these residual blocks vary depending on the residual network design. Residual connections and Inception blocks are commonly employed in current architectures like Inception-v4, ResNeXt, etc. The proposed model provides better detection based on computational cost, speed, and performance. We employed different layered skip-connection-based CNN networks with appropriate feature union strategy and customized learning for efficient classification results. In point of fact, we have used our proposed algorithm for the processing of simple CXR images in order to detect COVID-19. The analysis using the CXR model requires less data, fewer computer resources, and less time to compute when compared to the analysis using the CT scan. The major contributions of the proposed work are summarised as follows:

- A novel deep skip-connection-based CNN (SCovNet) with feature union strategy is proposed to efficiently utilise training parameters on CXR image processing for identifying COVID-19 and customized the architecture of the proposed residual CNN models in various aspects to improve the performance of the classification algorithm.
- The proposed system utilises pre-processing steps that include the normalisation, segmentation and augmentation of several transformation processes for

Table 1 – Review of the literature works.

S.No	Author(s)	Modality	Classes	Technique	Performance (Accuracy in %)
1	Yoo SH et al. [60]	CXR	COVID-19 and Normal	Deep Learning based Decision Tree	95
2	De Moura et al. [61]	CXR	COVID-19, Pneumonia, and normal	Densely Convolutional Network	90.27
3	Pandit et al. [62]	CXR	COVID-19 and Normal	VGG16	96
4	Karar et al. [63]	CXR	COVID-19, Pneumonia, and Normal	ResNet50V2	91.67 (Pneumonia) 99 (COVID-19)
5	Shamsi et al. [64]	CXR and CT scan	COVID-19 and Normal	DenseNet121(Transfer Learning) with SVM classifier	85.90
6	Chouat et al. [58]	CXR and CT scan	COVID-19 and Normal	ResNet50 and InceptionV3	90.50 (CXR) 87 (CT)
7	Rahhal et al. [43]	CXR and CT scan	COVID-19, Pneumonia and Normal	Deep Learning with Siamese encoder	94.62
8	Heidari et al. [65]	CT scan	COVID-19 and Normal	Block chain based CNN	99.40 (F1 score)
9	Ouyang et al. [66]	CT scan	COVID-19, Pneumonia and Normal	3D- CNN	0.944 (AUC)
10	Bassi et al. [27]	CXR	COVID-19 and Normal	Pre-trained ImageNet with Twice transfer Learning	98.7
11	Mahmoudi et al. [28]	CT scan	COVID-19, Pneumonia and Normal	3- layered customized CNN architecture	98

extracting more appropriate information from the existing database.

- Compared to traditional deep learning techniques, the proposed skip-connection-based feature union learning scheme enhances the network training process in performance and convergence time.
- A reliable training strategy was employed in conjunction with several permutations, including cross-validation and data augmentation techniques to boost the method's universal efficacy and prevent over-fitting.
- The balanced and unbalanced datasets are utilised to assess the network's generalization capabilities. A slightly modified structure of SCovNet is proposed for small unbalanced datasets to improve performance.
- Different evaluation matrices and compare the proposed system with various state-of-the-art schemes to demonstrate its efficiency in this work. The McNemar Chi-Square method was conducted to test the experiment's statistical significance and reliability. The part of the code is available in the author's GitHub repository [36].

The rest of the paper is organized as follows. Section 2 presents the detailed proposed methodology, including the information about datasets, proposed CNN architecture, fine-tuning and statistical analysis. Experimental works, results and performance parameters are explained in Section 3. Section 4 provides discussions on the results, including comparisons with similar works. Finally, Section 5 provides the overall conclusion of the work.

2. Proposed methodology

The proposed work mainly concentrated on AI-based tools for radiographic image processing in the detection of the SARS-CoV-2 virus. Early accurate detection of the SARS-CoV-2 virus and monitoring are integrated into the proposed methodology. Most of the work mainly focused on false-negative cases (symptomatic non-COVID) to restrict the further spreading of the disease. The proposed work for early detection of COVID-19 is carried out in three major stages: dataset preparation, CXR image processing, and the deep learning model depicted in Fig. 1 for the detection of the SARS-CoV-2 virus. Brief descriptions of the database, preprocessing methods for radiographic images, data splitting, and cross-validation are provided to elucidate these processes further.

2.1. *Database preparation*

CXR images are the basic tools for detecting any respiratory issues in humans. X-ray images are generally less sensitive than other scans for preliminarily targeting COVID-19. Two different databases are used in this work to validate the proposed model. The first one is a large GitHub CXR database [37] which was created by Joseph Paul Cohen to identify COVID-19 https://github.com/ieee8023/covid-chestxray-dataset. The database contains 845 COVID-19 CXR images of individuals, and the University of Montreal's Ethics Committee approved this database. Metadata are supplied for each sample, providing the patient's ID and, in most cases, the location and additional remarks containing a reference to the doctor who uploaded the CXR image. Some of the prepared sample CXR images are shown in Fig. 2. The other COVID-19 CXR images are collected from the Kaggle repository https://www.kaggle.com/alifrahman/covid19-chest-xray-image-dataset. It contains 69 COVID-19 and 25 non-COVID (normal healthy) X-ray images. From two databases, 914 COVID-19 and 433 normal CXR images are prepared for further experimentation.

2.2. Radiographic image pre-processing

In machine learning, the input dataset must be gone through the pre-processing stage before the experimentation. Image pre-processing reduces the complexity of data and improves the accuracy of the results. This approach helps to simplify data in various phases to provide a clean dataset to the network. In this work, data pre-processing is done in three stages; Data augmentation is a technique for extracting more information from an existing dataset. In this work, it generates perturbed duplicates of the existing images, such as translation (± 10% in the x & y-axis), rotation (± 5°), reflection (x & y with 50% probability) and shear (both horizontal & vertical). The augmented data are processed to the image pre-processing block for complexity reduction and maintain unified data fed to the network model.

Moreover, the X-ray images (6% top area) were cropped to remove frequently found textual information in CXR images. The pre-processed CXR images shown in Fig. 3 are then sent into a segmentation block, which looks for abnormalities in CXR. Generally, segmentation is fundamental for analyzing and detecting COVID-19 from radiographic images. In segmentation, edge information might be helpful to highlight regions of interest (ROI). After being pre-processed, the CXR pictures are then input into two convolutional layers responsible for the extracting of low-resolution features. The high-resolution features are then extracted by inserting these features into three convolutional layers. In this work, regions of interest (ROIs) were extracted from chest X-rays to get information regarding edges specifically. In addition to early detection, we allow this block to detect condition severity through further radiographic image analysis.

2.3. Skip-connection based deep learning model for the detection

AI-related technology has demonstrated its great potential in the healthcare and medical sectors, and it is changing the way healthcare services are utilised in hospitals. At present, deep learning plays a vital role in medical imaging systems. It helps radiologists make more exact diagnoses by providing a quantitative analysis of concerning lesions and a better workflow [29].

In general deep learning techniques, we usually stack more layers to handle a complex problem for improving accuracy performance. The idea behind introducing extra layers is to extract complex features from the input data. Adding more layers to the network increases the train/test error and complexity and lowers performance. This issue of training deep-layer networks was solved by introducing residual networks. The residual CNN network, generally called 'ResNet', is a specific neural network introduced by Kaiming He et al. in 2015 [38]. The network includes residual blocks with skip connection that bypasses several layers depending on the model. Meanwhile, skip connection is a type of identity mapping in which the previous layer's input is immediately added to the output of the next layer. This work presents a novel skip-connection-based deep CNN network to efficiently utilise training parameters on CXR image processing for identifying COVID-19.

Fig. 4 shows deep CNN with bypassed skip connection, and some layers are skipped over-activation. Let *x* is the input of the layer *L-1* and *g(x)* be the output; the residual block output can be summarised as:

$$y = g(x) + x \tag{1}$$

This method appears to have a minor flaw when the input dimensions differ from the output's, which can occur with convolutional and pooling layers. The modified output with dimensions as:

$$y = g(x, W_a) + W_b x \tag{2}$$

where W_a denotes the CNN layer's parameter and denotes the convolution configuration that may be used to make the input and output dimensions similar. The residual network served as the source of inspiration for the basic concept underlying the development of the customised SCovNet network.

In order to create a SCovNet architectural layer, each layer needs its own set of criteria. The model includes a convolution layer, batch normalisation layer, and activation layer, followed by a pooling layer. The convolution layer is commonly used in feature learning models. Following the convolution layer, batch normalisation is used, and the activation layer employs the ReLU activation function. The pooling layers were used only at the start of feature learning or at the preceding convolution stage of the classification layer. The detailed proposed architecture of skip-connection-based feature union deep CNN with customized layers network is shown in Fig. 5.

In this work, the authors developed a comprehensive skip-connection-based CNN model using a feature union strategy to process features efficiently. The proposed study primarily focused on integrating features from different skip-connection-based networks into a single set of appropriate features (feature union), which was then fed into the SCovNet. By adjusting the relevant classification parameters, the proposed network's customized section can produce significant improvements. This section features layers including the pooling layer, fully-connected layer, soft-max layer, and dense output layer. The precise benefit of the technique of feature union is the acceleration of feature processing and, consequently, the efficient processing of data.

The dense layer is updated with a newclass-output layer for classifying only two classes (COVID and Normal) with size (1×1×2). Furthermore, the soft-max layer is updated with a new soft-max layer of the same size (1×1×2). In addition, the fully connected layer was also updated with a new_{f_c} layer with

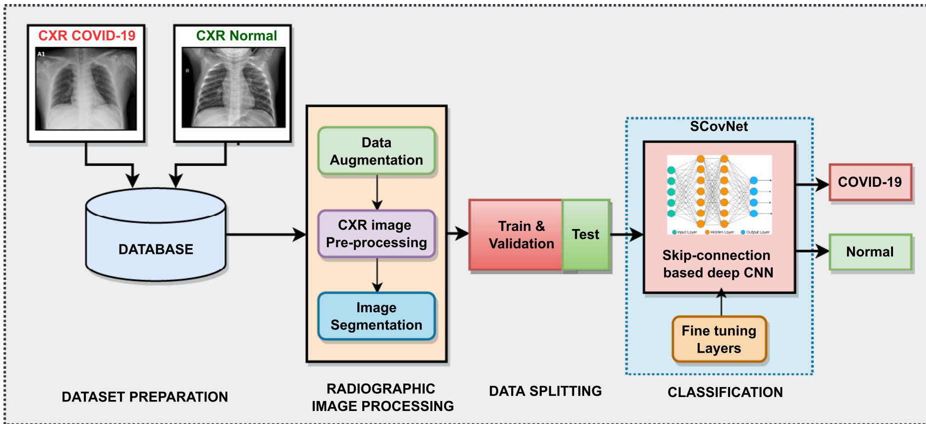
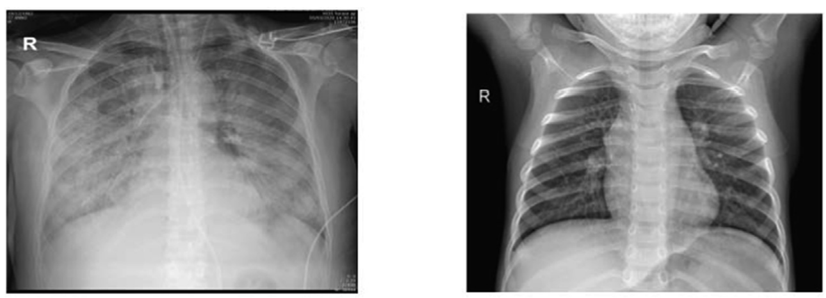


Fig. 1 – Proposed methodology for detection of COVID patient.



(a) COVID-19 (b) Normal healthy

Fig. 2 – (a) and (b) are the COVID-infected and Normal CXR Images.

Fig. 3 – CXR images after data augmentation.

size (1×1×512). In this study, a slightly modified SCovNet architecture was applied to the Kaggle dataset. The Kaggle dataset is small and unbalanced, resulting in incredibly limited training data. Small datasets need a greater number of fully connected layers than large ones [39]. In the fully connected layer, every neuron from the previous layer is linked to every neuron in the following layer, and each value helps to forecast how well a value matches a specific class. To address the issue, a first fully connected layer of size 1024 is added to the next fully connected layer of size 512 for processing the Kaggle dataset. However, the additional fully connected layer is unnecessary for analysing huge GitHub datasets.

2.4. *Fine-tuning and selection of the hyper-parameters for the proposed network*

In this work, ten-fold cross-validation is conducted with the GitHub database only, as it has a decent number of images for proper training, validation, and testing of the model. The entire dataset is split into 70% for training with validation and the remaining 30% for testing the model. The detailed portions of the training, cross-validation and testing dataset are shown in Fig. 6.

The training and validation dataset is divided into ten equal portions, and nine of them were utilized as training

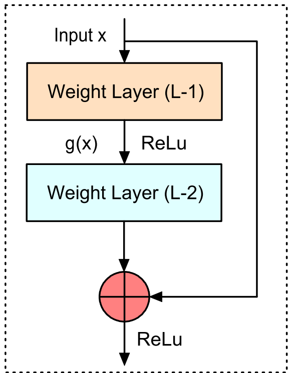


Fig. 4 – Skip-connection structure.

data in turn. One was utilized as test data for testing. The average value accuracy (*Acc*) of the ten-portion test results is calculated to estimate the model accuracy. It is used as a performance indicator for the current 10-fold cross-validation model. Therefore, the best way is to build multiple models using different training and test sets and compute the mean performance accuracy and standard deviation. The average performance indicators of the 10-fold cross-validation are listed in Table 2. Several folds, including Fold2, Fold3, Fold6, and Fold10, met 100% performance criteria during testing. A 10-fold cross-validation technique yielded an average accuracy of 99.29%, a sensitivity of 99.08%, a specificity of 99.31%, and a precision of 99.57%.

In the current work, a customized skip-connection-based feature union deep CNN model was designed to classify COVID-19. Initially, three different layered improved modified residual network models such as SCovNet-18, SCovNet-50 and SCovNet-101, were utilised and thereby, a customized learning strategy was implemented for better classification. Fine-tuning involves updating CNN layer architecture by retraining it to learn new class labels (COVID/NON-COVID). The training accuracy and validation approach used to fine-tune the SCovNet-101 model is depicted in Fig. 7.

The proposed skip-connection-based deep CNN model is optimised by choosing appropriate hyper-parameter values. The learning rate, number of epochs, and batch size are the most important factors for customising the CNN model. The epoch is an essential training parameter; it specifies the number of times the learning algorithm has traversed the whole training dataset. The best-suited hyper-parameters result in enhanced classification performance. After conducting several experiments, the Adaptive Moment Estimation (ADAM) training method is adopted with a finalized learning rate of 0.0001, the number of epochs 30 and batch size 8 for achieving the highest performance of the CNN model in detection. The designed deep learning model (SCovNet) performed with a considerable average time of 1159 *seconds* for training.

2.5. *Details about Statistical approaches to validate the proposed methods*

In addition to the regular performance metrics such as accuracy (Acc), sensitivity (Sen), specificity (Spe), and positive predictivity (Ppr), different statistical approaches are also used in this work. At first, the McNemar Chi-Square technique is used to evaluate the performance of a given approach. The McNemar test is a non-parametric statistical test for paired comparisons that may be used to assess the effectiveness of two classification models. The overall concept was developed by Quinn McNemar in 1947 [40] and is also termed the chi-squared test. McNemar Chi-Square statistic test is performed as follows [41]: In fact, numerous different statistical hypothesis testing frameworks are utilized to compare the performance of classification models. In brief, if the 95% confidence intervals of the two models' accuracies do not overlap, we may reject the null hypothesis that their performance is identical at $\alpha = 0.05$. (5 % probability). This allows us to conclude that one of the models is more accurate than the other. The McNemar test mainly compares two models by its generated confusion matrices from machine learning classifiers. The detailed analysis is presented in the experimental results section.

2.6. *Possible Uncertainties of the proposed deep learning model*

The following are the four factors that are the most important contributors to the level of uncertainty in a DNN‘s predictions:

- The variability that occurs in real-world settings
- The errors that are built into measurement systems
- The errors that are present in the architecture specification of the DNN
- The errors that are present in the training procedure of the DNN and the errors that are brought on by the presence of unknown data.

The data uncertainty can be reduced by extracting additional features from the input data (or) using deep architecture to extract deep features from the input image data. The proposed architecture is designed in a different way with the help of skip connections to reduce the effect of uncertainties. The authors are able to minimise the calibration error to 1.33% with 98.67% performance accuracy.

3. Experimental results

In this section, the experimental results of the proposed methods for diagnosing COVID-19 from CXR images are reported. The proposed model is tested and processed using MATLAB 2021b software with deep learning toolboxes. The supported MATLAB codes are executed with an Intel i5 processor (10th gen.), 8 GB RAM, and NVIDIA RTX 2060 graphics card as hardware. The CXR images were obtained from two distinct sources such as GitHub and Kaggle, with specialised doctors annotating the images. The CXR images were first reduced to 224×224 pixels for compliance with the CNN models. In this work, a random 70 % of the image dataset was used for training purposes, while the remaining 30% was used to evaluate the suggested model. The two databases were utilized separately for experimental purposes.

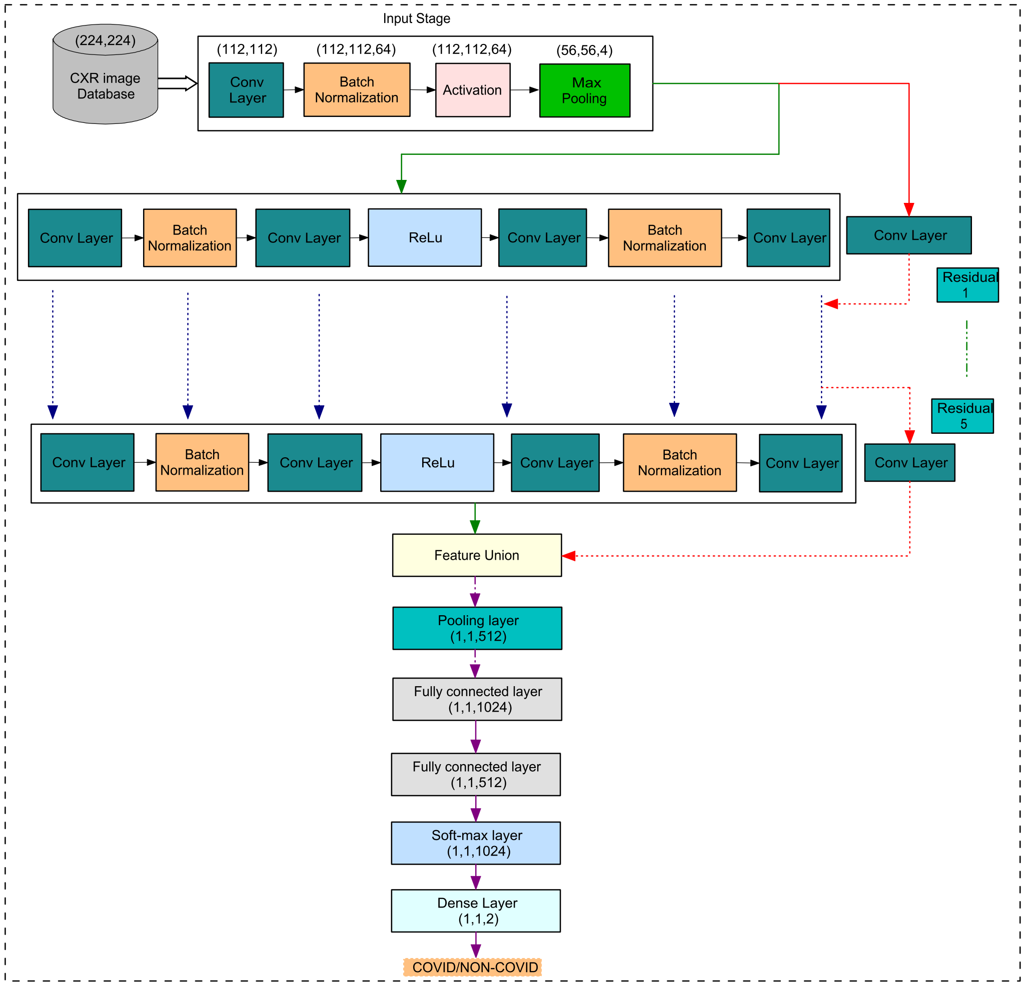


Fig. 5 – Proposed customized skip-connection based feature union deep CNN architecture for COVID-19 detection.

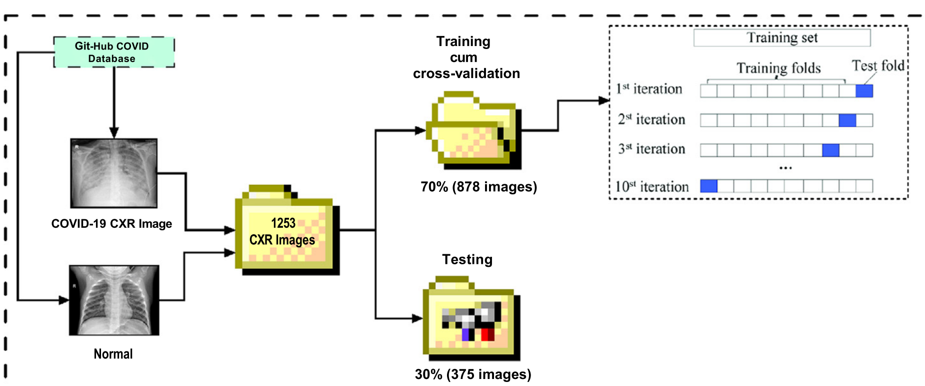


Fig. 6 – Splitting of Git-Hub CXR database for training, validation, and testing.

Table 3 gives the overview of the data split for the experimentation. After successfully pre-processing the CXR images, the images are applied to the proposed network. The optimal hyper-parameters result in improved classification efficiency of the proposed network. The appropriate set of training parameters for the proposed SCovNet was determined through a series of experiments and are presented in Table 4.

In the event of an unbalanced small dataset, a modified version of the ResNet structure, that is, SCovNet, was used for testing. Performance metrics such as accuracy, specificity sensitivity, precision, F1-score and Matthews's correlation coefficient are calculated using classifier-generated confusion matrix [42–46]. The accurately detected cases in the confusion matrix's diagonal region are used to calculate the effectiveness of the deep learning classifier [44,45].

Table 2 – Performance indicators for 10-fold cross-validation.

Parameter	Avg.±SD
Accuracy(%)	99.292 ± 0.873
Sensitivity (%)	99.08 ± 1.315
Specificity(%)	99.31 ± 1.232
Precision(%)	99.57 ± 0.820

Table 3 – Data splitting for experimentation.

Database	Class	CXR Images (Total)	Training & Validation	Test
GitHub	COVID	845	592	253
	NORMAL	408	286	122
Kaggle	COVID	68	41	10
	NORMAL	25	15	10

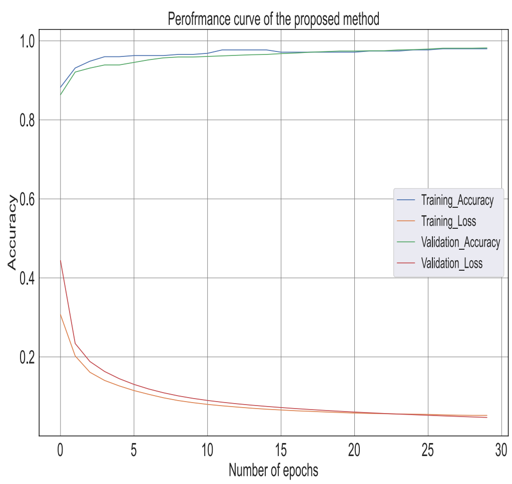


Fig. 7 – Training and validation curve for COVID-19 classification.

The confusion matrices generated on the Kaggle database for three different layered modified CNN networks, such as SCovNet (18-layered), SCovNet (50-layers) and SCovNet (101-layers), are shown in Fig. 8. Each column in the confusion matrix indicates the output class (actual class), while each row represents the target class (predicted class) [45]. The associated performance parameters are reported in Table 5.

The performance of the different layered SCovNet model for COVID-19 classification shows considerable performance over increasing the number of layers (fc1 and fc2) for the Kaggle (unbalanced) database. The suggested model produced a remarkable performance with an accuracy of 100% for detecting COVID-19 from CXR images. To test the generalisation capability of the proposed model, a large GitHub database of CXR images is also used for experimentation. The generated confusion matrices for different layered SCovNet are shown in Fig. 9. The associated classification performance parameters for a large GitHub database are reported in Table 6.

The results show that the layered structure of the SCovNet-101 network is capable of efficiently detecting COVID-19 with a low false-negative rate of 0.00746 and an average accuracy of 98.67%. The associated Receiver Operating Characteristic (ROC) and precision-recall curves for classification are shown in Fig. 10. Precision-recall curves are appropriate for imbalanced datasets, whereas ROC curves are suitable for balanced datasets. In the proposed work, the authors used both balanced and unbalanced datasets. Hence both ROC and precision-recall curves are shown in Fig. 10.

The area under the ROC curve is 0.989, which is approximately equal to 0.99. The AUC reflects the model skill. Larger y-axis values on ROC indicate more true positives and fewer false negatives. Precision is the number of true positives divided by the total number of true positives, and it measures a model's ability to predict positive class.

The authors performed the McNemar Chi-Square test between classifier models such as 18-layer (Model-1), 50-layer (Model 2) and 101-layer (Model 3) to test the statistical significance and reported in Table 7, and Table 8.

For case-I *(Model 1 and Model 3)* the McNemar Chi-Square statistic computed as follows:

$$\chi^2 = \frac{(B - C)^2}{(B + C)} \tag{3}$$

From the above equation, χ^2 is calculated as 3.76. The significance threshold level set to be α= 0.05 (5 % probability) and also calculated the p-value of the obtained Chi-Squared distribution is 0.05. The obtained p-value in case-1 is equal to the standard significance level ($p \leqslant 0.05$), such that we reject the null hypothesis and conclude that Model-3 (Layer-101) performs better than Mode-1 (Layer-18). For case-II *(Model 2 and Model 3)* similarly calculated McNemar Chi-Square statistic as χ^2 = 2.27 and computed the p-value of the obtained Chi-Squared distribution is 0.13, which is greater than the standard significance level ($p > 0.05$) so that there is no evidence to reject the null hypothesis. This means the performances of the two models *(Model 2 and Model 3)* are equal. Lastly, based on the McNemar statistical test, Model 3 (Layer-101) provided in this work performs better than most of the existing models.

3.1. *Validation of the specific portion significance of the network architecture using ablation study*

The authors used the ablation study to analyze the performance of the proposed SCovNet. An ablation study can help determine which parts of a network's architecture are most important for better performance classification. Residual paths or skip connections are important in the image classification for this network.

The authors incorporated five residual paths into the deep learning architecture. The detailed ablation study performance of the proposed network is shown in Table 9. The following important points were observed from the ablation study:

1. It's clear that the network doesn't work well without skipped connections.

2. After adding the forward skip connection to bypass the gradient information to the next layers, the performance is slightly better.
3. Even if we include backward skip-connections without forward skip-connections, performance does not significantly change.
4. In order to get the best performance out of the network architecture, it is determined that five skip connections are required.
5. These skip connections are provided with the gradient information to the further layers without losing gradient information.

Table 4 – Various parameters for hyper-tuning of the proposed SCovNet.

Hyperparameter	Assigned value
Model Name	SCovNet
Learning rate	0.0001
Number of epochs	30
Batch size	8
Input size	224×224
Input labels	2
Augmentation used	Translation (± 10% in the x y-axis), rotation (± 5°) reflection (x y with 50% probability) and shear (both horizontal vertical)
Loss function	Cross Entropy
Optimizer	Adam
Training time	1159 Seconds Avg.

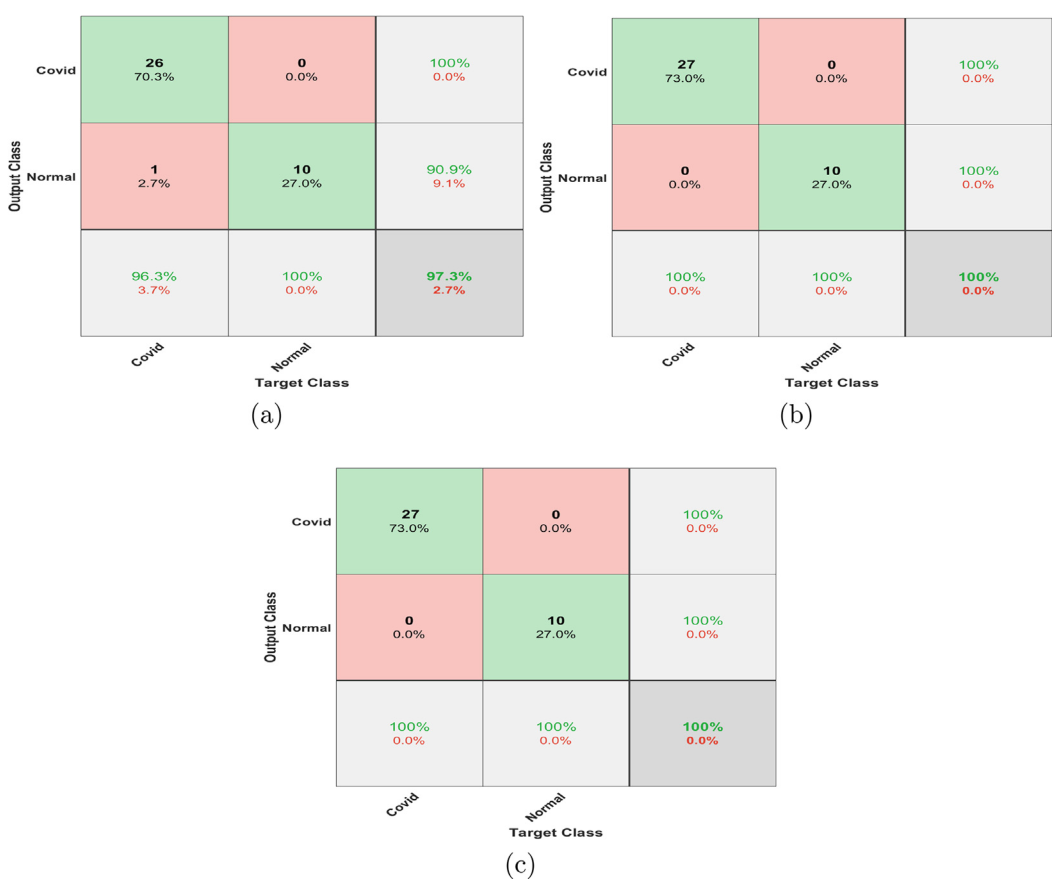


Fig. 8 – Confusion matrices of SCovNet Classification: (a) 18-layered; (b) 50-layered; (c) 101-layered for the Kaggle database, respectively.

Table 5 – Performance parameters (Kaggle database).

Parameter	SCovNet		
	18-Layer	50-Layer	101-Layer
Accuracy (%)	97.30	100.0	100.0
Sensitivity (%)	96.30	100.0	100.0
Specificity (%)	100.0	100.0	100.0
Precision (%)	100.0	100.0	100.0
Negative Predicted Value (%)	90.91	100.0	100.0
False Positive Rate	0	0	0
False Negative Rate	0.0370	0	0
F1 Score (%)	98.11	100.0	100.0
MCC	0.9356	1.0	1.0
AUC	0.99	1.0	1.0

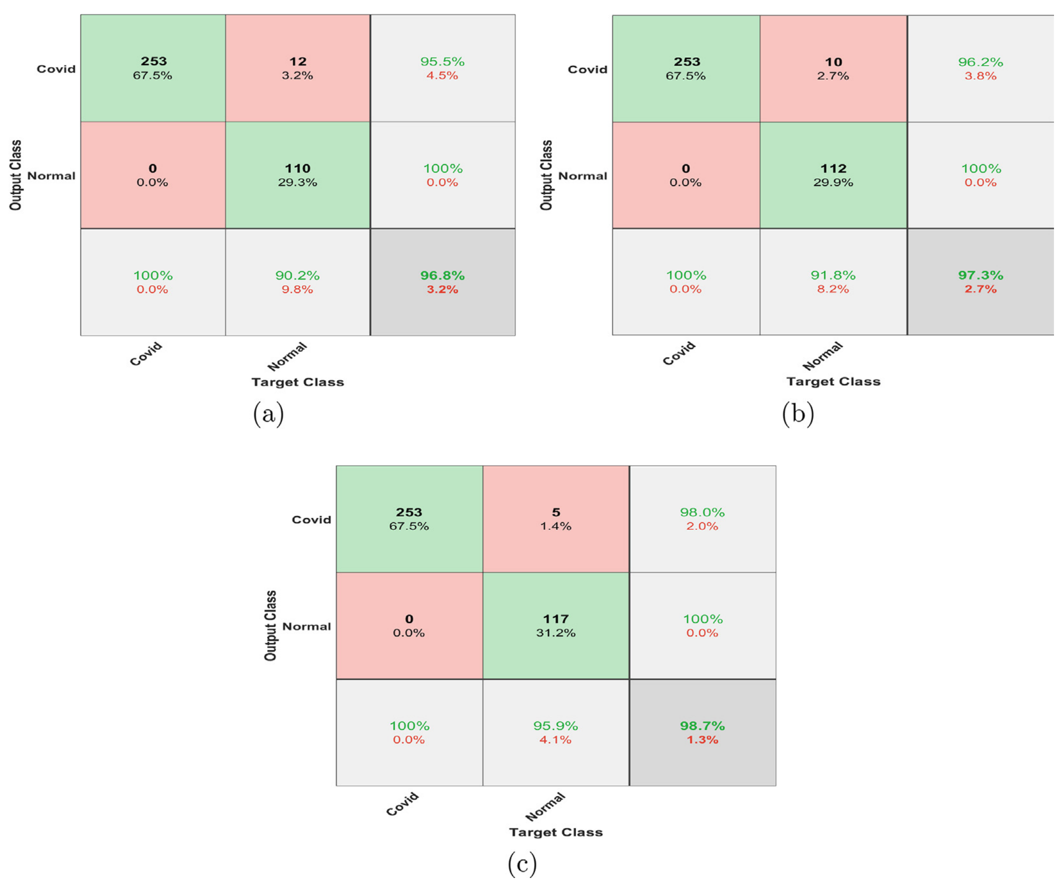


Fig. 9 – Confusion matrices of SCovNet Classification: (a) 18-layered; (b) 50-layered; (c) 101-layered for GitHub database respectively.

4. Comparision of proposed method performance with earlier state-of-the-art techniques

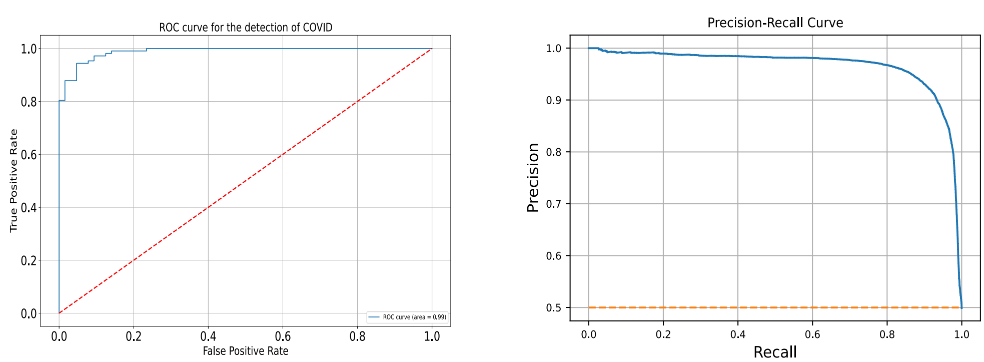
The proposed model's performance is compared to that of previous state-of-the-art methods in a more comprehensible manner in Table 10. Abbas et al.[47] proposed a novel deep CNN approach which is a combination of Decompose, Transfer and Compose *(DeTrac)* for the detection of COVID-19 from the Chest X-ray images. Experimentation is performed between three different classes of COVID-19, normal and SARS CXR images. The authors reported the highest accuracy of 93.10 % and sensitivity of 87.09% with VGG19 in DeTrac. Ismael *et al.* [48] presented different deep learning-based techniques, including deep feature extraction, fine-tuning of pre-trained convolutional neural networks (CNN), and end-to-end training of a designed CNN model, which have been utilised to identify COVID-19 and normal (healthy) chest X-ray images. Several pre-trained models were employed to extract deep features, and machine learning classification algorithms were applied to complete classification tasks. From the experiments, authors reported an overall accuracy of 95.79% and an F1-score of 95.92% with ResNet50 with SVM classifier (end-to-end training).

Shankar et al. [49] suggested an intelligent COVID-19 detection model that combines a barnacle mating optimization (BMO) method with a cascaded recurrent neural network (CRNN) model (BMO-CRNN). In this work, the BMO method is used to perform hyperparameter tuning on CRNN in order to improve the classification algorithm's performance. The experiment yielded impressive findings, with 97.31% accuracy and 97.01% average sensitivity, as reported by the authors. Das *et al.* [51] proposed Deep Convolutional Neural Network-based method for detecting COVID-19-positive patients from chest X-ray images. To predict a class value, authors introduced a new method called weighted average ensembling is used to combine the models. COVID-19 and healthy were classified with an overall accuracy of 91.62% and 0.917 Area Under ROC curve (AUC) as per the researcher's report. Bhattacharya *et al.* [52] proposed a new way to use chest X-rays to find COVID-19 and pneumonia. The proposed approach can be split into three stages. In the first stage, CXR images are segmented using a conditional adversarial network (C-GAN). In the second stage, deep neural networks are trained to extract discriminatory features. Several Machine Learning approaches were utilised for classification in the third stage, with the combination of VGG19 and Random Forest achieving 96.60% overall accuracy and 97.40% sensitivity.

Muhammad et al. [53] presented a self-augmentation approach for data augmentation that uses reconstruction-independent component analysis (RICA) to do the augmentation in the feature space rather than in the data space. A unified architecture including a CNN, a feature augmentation technique, and a bidirectional LSTM is suggested (BiLSTM). The authors conducted experiments on two classes, including COVID-19 and healthy CXR images, and revealed that ResNet50 with BiLSTM had the greatest overall accuracy of 93.77% and 87.71% precision. The Deep Neural Network (DNN) was utilized by authors in [54] for the automated detection of COVID-19 from CXR images. In this technique, for the purpose of extracting features from X-ray images that were acquired from the chests of the patients, DenseNet was used. After the features were extracted, they were used as input for the Extreme Gradient Boosting (XGBoost) method, which was used to complete the classification process. Experimentation

Table 6 – Performance parameters (GitHub database).

Parameter	SCovNet		
	18-Layer	50-Layer	101-Layer
Accuracy (%)	96.80	97.33	98.67
Sensitivity (%)	100	100	98.81
Specificity (%)	90.16	91.80	98.36
Precision (%)	95.47	96.20	99.21
Negative Predicted Value (%)	100	100	97.56
False Positive Rate	0.0984	0.0820	0.0164
False Negative Rate	0.0119	0.0105	0
F1 Score (%)	97.68	98.06	99.01
MCC	0.9278	0.9397	0.9697
AUC	0.981	0.985	0.990



(a) (b)

Fig. 10 – A curves of: (a) Receiver operating characteristic (ROC) for the proposed SCovNet model; (b) Precision-Recall curve of the proposed SCovNet deep learning model.

Table 7 – McNemar test for Model 1 Vs Model 3.

	Model 3 (Number of correctly predicted cases)	Model 3 (Number of correctly predicted cases)
Model 1 (Number of correctly predicted cases)	360	3 (B)
Model 1 (Number of correctly predicted cases)	10 (C)	2

Table 8 – McNemar test for Model 2 Vs Model 3.

	Model 3 (Number of correctly predicted cases)	Model 3 (Number of correctly predicted cases)
Model 2 (Number of correctly predicted cases)	362	3 (B)
Model 2 (Number of correctly predicted cases)	8 (C)	2

Table 9 – Ablation Study of the proposed SCovNet on Git-Hub database

Acc (in %)	Sen (in %)	Spe (in %)	Pre (in %)	NPV (in %)	Residual Path-1	Residual Path-2	Residual Path-3	Residual Path-4	Residual Path-5
75.36	74.21	69.85	70.82	66.32	No	No	No	No	No
77.65	77.14	74.12	76.52	73.22	Yes	No	No	No	No
82.12	82.98	80.32	78.98	80.65	Yes	Yes	Yes	No	No
95.69	94.99	95.25	95.68	95.15	Yes	Yes	Yes	Yes	No
78.36	76.45	77.95	78.21	75.96	Yes	Yes	No	No	No
77.25	77.12	75.85	76.65	76.98	No	No	Yes	Yes	No
76..65	74.85	75.85	76.21	76.87	No	No	No	Yes	Yes
93.85	93.65	92.87	91.87	91.99	Yes	Yes	Yes	Yes	No
90.65	89.84	88.95	90.85	91.35	No	No	Yes	Yes	Yes
95.02	94.85	93.85	95.00	94.85	No	Yes	Yes	Yes	Yes
98.67	98.81	98.36	99.21	97.56	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

was performed on three classes, including COVID-19, Pneumonia and Normal and reported an overall highest accuracy of 89.33%. The authors [55] conducted a comparative investigation of fine-tuned deep-learning architectures to enhance the detection and classification of COVID-19 patients from other pneumonia groups. Experiments were conducted on three types of data, including COVID-19, normal, and Pneumonia, and the focus of this research was to differentiate pneumonia categories from COVID-19. DenseNet121 obtained the maximum accuracy of 97% and 98.66% F1-score, according to the authors. Gouda et al. [57] proposed a deep learning approach for classifying CXR images based on an ensemble that uses several runs of a modified version of the Resnet-50. The suggested network was tested on 930 images from three classes, including COVID-19, healthy and Pneumonia. The authors reported an overall average accuracy of 98.05% and 0.998 AUC with ResNet50 *(run-2)*.

The availability of annotated COVID-19 X-ray images is a key difficulty, resulting in a few misclassifications and perhaps some scattering in gradient-based localisations outside the feature map. Our suggested skip-connection-based feature union deep CNN technique effectively worked with the available COVID-19 CXR images. Furthermore, this model may be more accurate and robust by including new data. The suggested system is extremely adjustable, and the skip-connection-based feature union deep CNN may be fine-tuned using additional COVID-19 X-rays throughout the learning phase. Moreover, we proposed a novel hierarchical classification technique for detecting COVID-19 with a good accuracy rate for small unbalanced datasets, implying that the study might be beneficial for screening patients with mild COVID-19 symptoms. This script uses an early stopping strategy to assess model performance on a validation set and terminate training when performance deteriorates. As a result, performance measures have a slight divergence of 0.5, which is negligible for the new testing data.

Recently, certain state-of-the-art (SOTA) models provide improved detection accuracy but they have one or more drawbacks. SOTA deep learning networks can be identified by their accuracy, speed, or other characteristics [59]. In most computer vision applications, these measures are traded off. A fast DNN is not accurate enough. Occasionally, we can design a model with good performance metrics. It would still lack latency and throughput for applications like picture categorization and detection.

The utilisation of chest radiographs in the diagnostic process provides professionals with important information. Many studies have focused on the automated classification of chest X-rays for this condition using artificial intelligence. The exciting and promising results of deep learning models in detecting COVID-19 from radiography images suggest that deep learning plays a significant role in combating this pandemic. Overall, the outcomes of the proposed models in this work are encouraging. However, some of the findings from these studies include slight inaccuracies that need to be fixed before they can be used in clinical practice. The study's limitations may be alleviated by doing a more in-depth analysis with a more complete and high-quality image dataset. As more data for training becomes available, the performance can be enhanced even further. Despite the promising results, SCovNet still requires clinical investigation and testing; with increased accuracy and sensitivity for COVID-19 instances, SCovNet can still be useful for radiologists and health professionals to obtain a deeper understanding of essential features related to COVID-19 cases.

Table 10 – Performance of the proposed work with other similar studies.

S.No	Study	No. of CXR images ((Classes)	Model	Accuracy (%)	F1-Score (%)	Sensitivity (%)	Any other performance parameter
1	Narin et al. [2021] [23]	204 (COVID-19 and Normal)	ResNet50	96.10	83.50	91.81	96.6 (Specificity)
2	Ahmed et al. [2021] [25]	75 (COVID-19, Pneumonia and Normal)	SqueezeNet with SVM	94.40	94.41	94.45	0.981 (AUC)
3	Abbas et al. [2021] [47]	196 (COVID-19, SARS and Normal)	VGG19	93.10	-	87.09	85.18 (Specificity)
4	Ismael et al. [2021][48]	380 (COVID-19 and Normal)	ResNet50 with SVM	95.79	95.92	94.0	0.998(AUC)
5	Shankar et al. [2021] [49]	247 (COVID-19 and Normal)	BMO-CRNN	97.31	97.73	97.01	98.15 (Specificity)
6	Mohammed et al. [2021][50]	1200 (COVID-19, Pneumonia and Normal)	VGG16	98.72	97.59	98.78	96.43 (Precision)
7	Das et al. [2021] [51]	1006 (COVID-19 and Normal)	Ensemble Learning	91.62	91.71	95.09	0.917(AUC)
8	Bhattacharyya et al. [2022] [52]	930 (COVID-19 and Normal)	VGG19 with RF	96.60	-	95.0	97.4 (Specificity)
9	Muhammad et al. [2022] [53]	625 (COVID-19 and Normal)	ResNet50 + BiLSTM	93.77	93.45	99.80	87.71 (Precision)
10	Nasiri et al. [2022] [54]	1125 (COVID-19, Pneumonia and Normal)	DarkCovidNet	89.70	91.20	95.20	92.50(Precision)
11	Aggarwal et al. [2022] [55]	959 (COVID-19, Pneumonia and Normal)	DenseNet121	97.0	98.66	97.33	98.66(Specificity)
12	Ieracitano et al. [2022] [56]	120 (Portable CXR) (COVID-19 and Normal)	CovNNet with Fuzzy edge detection	80.9 ± 6.2%	85.2 ± 4.5%	82.5 ± 11.9%	78.6 ± 6.9% (Specificity)
13	Gouda et al. [2022] [57]	930 (COVID-19, Pneumonia and Normal)	ResNet50 (multiple runs)	98.05	98.65	98.39	0.998(AUC)
14	Chouat et al. [2022] [58]	1000 (COVID-19 and Normal)	VGG19	94.0	94.50	94.50	91.50(Precision)
15	Proposed Method*	1253 (COVID-19 and Normal)	SCovNet (18-layered)	96.80	97.68	100	0.981(AUC) 95.47 (Precision)
16	Proposed Method*	1253 (COVID-19 and Normal)	SCovNet (50-layered)	97.33	98.06	100	0.985(AUC) 96.20 (Precision)
17	Proposed Method*	1253 (COVID-19 and Normal)	SCovNet (101-layered)	98.67	99.01	98.81	0.991 (AUC) 0.00746(Avg. FNR)

5. Conclusions

The consistent increase in COVID-19 cases is straining the resources of several countries. Therefore, it is crucial to record each confirmed case during this health crisis. In most cases, analysing lung issues required a chest X-ray (COVID-19, normal). In this research, multiple layered deep CNN models were used to detect COVID-19 at an early stage with a satisfactory degree of accuracy. The primary goal of this research is to develop a deep learning-based technique with radiographic image processing techniques to identify COVID-positive cases with the help of CXR images. A skip-connection-based feature union deep CNN architecture extracts the in-depth features from the CXR images. The proposed model utilises an effective learning mechanism with fine-tuning layer parameters for COVID detection. Different sizes of databases are utilised in this work to verify the generalisation capability of the proposed network. The proposed SCovNet detects COVID cases with 100% accuracy on a small imbalanced Kaggle dataset, and the SCovNet model with a 101-layered structure achieved an accuracy of 98.70% for a large GitHub database. In addition, the McNemar Chi-square test was carried out as part of the research to analyse the efficacy of the various methodologies considered. These findings will assist medical professionals in selecting appropriate models for the many different image analysis approaches, which will be critical when time and resources are limited in a pandemic scenario like the one we are currently experiencing.

The experimental results show that the proposed technique works better compared to recent works in the literature. Since our work and that of others in the literature are not always evaluated using the same dataset and the same conditions, it would be unfair to compare the identification rates obtained by the two directly. However, we may make the observation that the best identification rate achieved here (0.9921 precision) is the best nominal rate ever recorded for the objective of COVID-19 identification in an unbalanced environment with two classes. The best recognition rate for COVID-19 was achieved by using a novel hierarchical classification approach described in this work, which took into account multiple types of image-processing approaches. While it is not the goal of this work to establish a conclusive diagnosis of COVID-19, the good identification rate achieved for COVID-19 can be highly valuable in aiding the screening of patients in the emergency medical support systems, which have been badly impacted by the pandemic breakthrough.

This research can assist radiologists and healthcare professionals in accurately diagnosing COVID cases. In the course of our future work, one of our goals is to expand the database so that we can implement more complex deep Learning strategies with the appropriate level of depth into the samples. In addition, by using a more comprehensive database, researchers can do extensive cross-validation tests on our suggested method, giving us a more complete view of how our solution fits into the situation.

CRediT authorship contribution statement

Kiran Kumar Patro: Conceptualization, Software, Validation, Writing - original draft, Writing – review & editing. **Allam Jaya Prakash:** Conceptualization, Methodology, Validation, Investigation, Writing – review & editing, Visualization, Supervision. **Mohamed Hammad:** Methodology, Formal analysis, Writing – review & editing, Visualization. **Ryszard Tadeusiewicz:** Resources, Supervision. **Paweł Pławiak:** Software, Formal analysis, Investigation, Resources, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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