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SmartCovNet: An Intelligent ResNet-50 and Novel Neural Classifier Structure for COVID-19 Discovery Via CT Imageries

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Abstract

The COVID-19 pandemic has necessitated immediate attention towards the development of novel structures. The RT-PCR test is the widely used technique for diagnosis; however, it poses disadvantages such as longer delays and inconsistency in test results. We present a SmartCovNet framework to distinguish COVID and non-COVID cases using CT scan images. An integration of a pretrained ResNet-50 architecture with a novel neural network classifier is employed. The lung regions are highlighted by employing adaptive histogram equalization with contrast restriction. After extracting the features from ResNet-50, we pass them to the novel neural network classifier. SmartCovNet has achieved a classification accuracy of 99.53%, along with high specificity, sensitivity, and F1 score. The performance metrics indicate the effectiveness of SmartCovNet in the diagnosis of COVID infection.

Keywords: COVID-19, Deep Learning, ResNet-50, Feature Extraction, Neural Network, CT Images, Image Enhancement, Classification.

1. Introduction

The existing scenario in the present COVID-19 pandemic situation has led to a large load on the universal healthcare structure in the country, resulting in the absolute necessity for efficient and immediate diagnostic systems. Although the reverse transcription polymerase chain reaction (RT-PCR) test has been chosen as the most prominent mode of diagnosis, there has been an observation that the test is somewhat less sensitive. However, after recognizing that the RT-PCR test has been selected as the primary diagnostic method, some supportive systems in the form of chest computed tomography (CT) scans have gained immense attention [1]. The CT scan contains visible data points associated with the disease patterns for in lungs, including ground-glass opacities and consolidations in the context of a COVID-19 infection.

Deep learning techniques, particularly transfer learning, have tremendous applications in medical imaging. Various pre-built models, such as ResNet50, have been implemented for COVID-19 detection based on images. ResNet50 is considered highly specialized because it can utilize residuals, thereby overcoming issues such as vanishing gradients. This enables the development of discriminative models effectively for such tasks [2]. ResNet-50-type models, in some recent studies, have demonstrated high COVID-19 detection capabilities, even when small sets of training data are used—an advantage of this approach and technique. Methods

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such as Contrast-Limited Adaptive Histogram Equalization may be employed during preprocessing to enhance local contrast in the lungs of CT scans. In this respect, noise infection patterns may be reduced to enhance visibility. This method allows for the small features of the lungs to be visible so that deeper features in this approach can be used for higher-level classification. However, despite improvements, many past systems employ end-to-end CNN models without specifically designing lightweight and task-specific classifier networks. This could lead to wastage and overfitting, particularly when datasets are small. As an example, in our model SmartCovNet, ResNet-50 is used to extract a fixed number of features (via a global average pooling layer) and is connected to a specially designed all-associated network trained to perform binary classification. This is a hybrid design that balances model complexity, training accuracy, and efficiency.

Three main contributions are presented, including:

- Increasing the visibility of critical lung patterns by applying contrast enhancement preprocessing.
- Efficient use of ResNet-50's pre-trained features, preventing fine-tuning of the entire network to avoid overfitting.
- Custom lightweight neural classifier optimized for speed and accuracy on CT classification tasks.

2. Literature Review

Deep learning models using U-Net, ResNet and hybrid approaches with SVM classifiers are widely employed for COVID-19 detection. For example, teaching variational U-Net models have successfully segmented ground-glass opacities in CT scans, achieving a Dice score of ~86% on datasets of around 900 images [4]. Similarly, researchers utilizing standard U-Net architectures reported average Dice scores between 88% and 95% when identifying COVID-19 lesions in CT slices. Recent studies using transfer learning with ResNet-50 have shown that the model performs reliably on CT-based COVID-19 classification tasks, often achieving accuracies above 98%, which highlights its suitability for extracting meaningful lung features [5]. Additionally, CNN–SVM hybrids have proven effective in limited-data environments: a DenseNet model combined with SVM achieved 99.46% accuracy across over 2,400 CT images [6]. The table 1 below presents a comprehensive survey of existing literature on deep learning techniques for COVID-19 detection, highlighting the approaches, performance metrics, and limitations of each study.

Table 1. Literature Survey on Deep Learning-Based Methods for COVID-19 Detection Using Chest CT Scans

Author(s)	Method & Accuracy	Limitations
Kalane et al.[7]	U-Net, FCN, ResNet-50 + SVM ~96% (reported)	Performance on small datasets may drop
Mondal et al[8]	CNN, ResNet, COVIDNet, U-Net Review Paper	High model complexity, need for high-quality data
Albahli et al.[9]	Pre-trained DenseNet, InceptionV4 DenseNet ~92%	Overfitting on small image sets

Rehouma & Buchert[10]	U-Net, ResNet-18 + SVM Patch-based CNN ~90%	Limited to specific datasets
Subramanian et al[11]	U-Net for segmentation + ResNet Review paper	NA
A. Das[12]	Adaptive U-Net + Ensemble CNN 98.2 %	Model sensitivity to lung boundary variation
Lasker et al.[13]	36 CNN-based variants incl. ResNet ,Review Paper	Performance varies with preprocessing
Hamwi & Almustafa [14]	Pre-trained VGG + DenseNet (TL), ~98.81%	CT-only, data variety needed
Showkat & Qureshi[15]	ResNet (pre-trained TL) ~95%	No clinical trial validation
Das et al.[16]	U-Net, ResNet, SVM Review Paper	High training time, segmentation noise
Gürsoy & Kaya[17]	CNN (ResNet, AlexNet, Xception), SVM Varies (dataset-specific)	Generalization and overfitting risks
Sailunaz et al.[18]	U-Net++, Inf-Net, CNNs incl. ResNet	Dependence on CT and CXR modality
Bhosale & Patnaik[19]	Pre-trained CNN (ResNet) on CXR	Bias from imbalanced datasets
Poola & Pl[20]	Pre-trained ResNet-18, DenseNet, Inception ~99%	No unified comparison across models
Mozaffari et al.[21]	Model fusion of VGG, GoogleNet, CapsNet	Computation-intensive model fusion
Kathamuthu et al.[22]	TL with DenseNet, ResNet50	Needs validation on unseen datasets
Santosh et al.[23]	Comparative: AlexNet, ResNet, MobileNet, VGG, SENet	Primarily CT, no CXR generalization
Elangovan et al.[24]	Ensemble ConvNet-24 + Customized CNNs 98.30%	Lacks test on multicenter datasets
Hassan et al.[25]	Pre-trained VGG, ResNet, Inception + Custom DCNN ResNet-50 : 99.07% ,VGG-19: 98.07%,,VGG-16: 98.55% Inception V3 :96.23%	CT modality only
Talukder et al.[26]	Fine-tuned EfficientNet Xception :99.55%, InceptionResNetV2:97.32%, ResNet50 :99.11%, ResNet50V2: 99.55%, EfficientNetB0:99.11%	Limited comparison with other methods

From the above literature survey, it shows that deep learning representations have displayed noteworthy outcomes in classifying COVID-19 from chest CT scans; however, many current methods still face key limitations. Some of the models require large computing power, use pixel-level accuracy in deciding objects, or cannot be consistent across scans with different imaging configurations. Additionally, the greater the depth of the neural network, the higher the chances of overfitting with small or skewed datasets. These limitations underscore the need to develop detection structures that are both accurate and efficient and that do not require as much manual processing or professional involvement.

Here, we present SmartCovNet, a hybrid architecture integrating a set of powerful image processing tools with deep feature learning with ResNet-50 and classification with a novel neural network. The purpose of this pipeline is to achieve a balance between performance and practicality, namely, high diagnostic accuracy and low weight, while maintaining flexibility for clinical conditions with different imaging features.

3. Proposed Methodology

The developed SmartCovNet framework is an inherent COVID-19 detector of chest CT scan images based on a sequence of advanced image preprocessing methods, deep feature extraction via ResNet-50, and a powerful customized neural network classifier. The general workflow, as shown in Figure 1, comprises several steps: dataset preparation, image preprocessing, data augmentation, deep feature extraction, custom classification, evaluation, and region-of-interest (ROI) visualization. Each step is wisely customized to enhance diagnostic performance while maintaining computational efficiency.

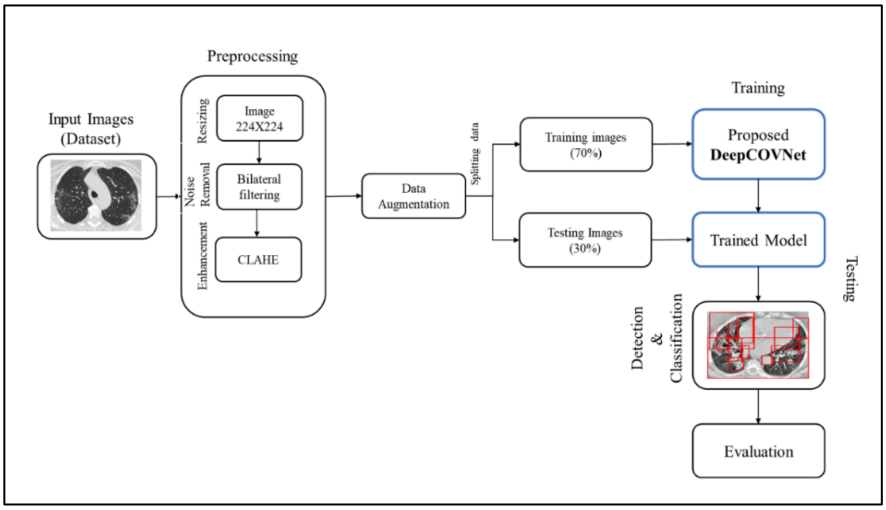

Figure 1. The Proposed Strategy for COVID_19 Detection and Categorization

3.1 Dataset Discerption

The proposed SmartCovNet structure used the SARS-CoV-2 CT Scan Dataset to train and conduct analysis because it is open and publicly available on Kaggle [27]. This dataset was created to ease the study of the automatic detection of COVID-19 from CT scan images. The dataset included a total of 2,480 pictures in two classes; one is COVID-19 and the other is the Non-COVID class. The images were taken from an extensive variety of patient collections and scanning parameters and compiled using freely available libraries and clinical case reports. All the images are in standard JPEG format and high resolution to derive deep features. The dataset is well-structured with distinct classes of COVID-19 and Non-COVID to perform preprocessing and feature extraction; however, it is necessary to mention that the SARS-CoV-2 CT Scan dataset does not contain patient identifiers; consequently, a rigorous split by patient is not ensured. All the images were sorted and uniformly partitioned class-wise first, and then divided to reduce the chances of slices from the same patient appearing in the training and testing sets. Due to the balanced composition the dataset would be an ideal benchmark to test the accuracy of the proposed SmartCovNet framework. The dataset is split into 70% for training and 30% for testing testing respectively. The sample input images of the SARS-Cov-2 dataset can be seen in the Figure 2.

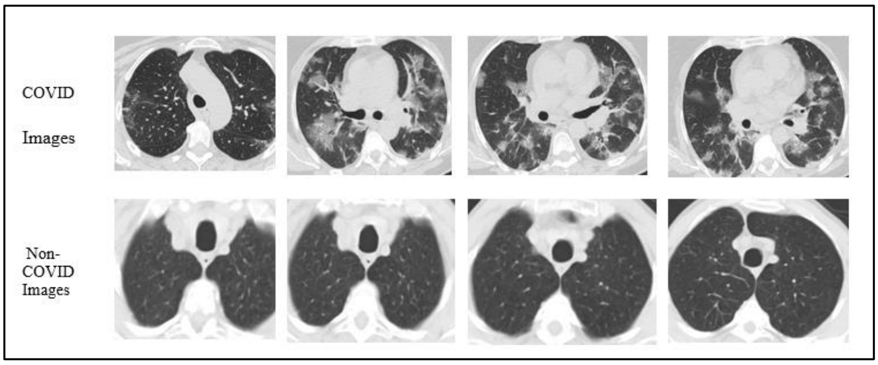

Figure 2. Shows the Sample Images of both COVID and Non-COVID Chest CT Scans

3.2 Image Preprocessing

High-quality preprocessing plays a critical role in extracting meaningful patterns from CT scans, particularly for COVID-19 detection, where identified, obscure areas and weak details can be easily hidden by noise or poor contrast. The SmartCovNet pipeline we propose consists of three steps in the preprocessing approach, which include: bilateral filtering to eliminate noise, Contrast Limited Adaptive Histogram Equalization (CLAHE) for the improvement of local contrasts, and sharpening to structure The three preprocessing techniques bilateral filtering, CLAHE, and image sharpening were deliberately selected to address key challenges in chest CT imaging, such as noise contamination, low local contrast, and weak boundary definition of infection regions. Bilateral filtering effectively suppresses noise while preserving important anatomical edges, CLAHE enhances local contrast to make subtle lung abnormalities, like ground-glass opacities more visible without amplifying noise, and sharpening further emphasizes structural boundaries. Together, this combination ensures improved feature visibility and discriminative quality for deep feature extraction while maintaining computational efficiency.

SmartCovNet achieves robustness against noise and intensity variations by integrating bilateral filtering, CLAHE, and sharpening in the preprocessing stage. Bilateral filtering suppresses noise while preserving edges, CLAHE enhances local contrast across varying intensity ranges, and sharpening highlights subtle structural details. Together, these steps normalize image appearance and ensure stable feature extraction across CT scans acquired under different conditions.

3.2.1 Image Resizing and Normalization

Any CT scan is resized to a size of 224 x 224 pixels to match the size that the feature extraction network is expected to be fed. Intensity normalization is used to normalize pixel values and minimize variations between images from different scanners. As convolutional neural networks usually receive 3-channel input in RGB format, grayscale CT images are duplicated to three channels that are all the same. This action guarantees consistency of inputs and still preserves the structural integrity of the medical images.

3.2.2 Bilateral Filtering for Noise Reduction

CT images are usually affected by the noise due to Gaussian effects or scanner artifacts, which may cause blurring of clinically significant features. Bilateral filtering [28] is used as an edge-preserving denoising technique that denoises noise while maintaining fine anatomical edges. In contrast to Gaussian smoothing, which tends to smooth edges, bilateral filtering capitalizes on the spatial distance and pixel intensity similarity to selectively smooth edges. This maintains the sharpness of critical structures like lung borders, lesion boundaries, and small opacities.

3.2.3 Contrast Limited Adaptive Histogram Equalization (CLAHE)

CLAHE is employed to boost local contrast in small contextual areas (tiles) to increase the visibility of fine lung patterns. In contrast the traditional histogram equalization which generally uses a global intensity adjustment, CLAHE eliminates excess amplification of noise by implementing a contrast limiting threshold. Such a local solution reveals ground-glass opacities and initial signs of infection that are critical for the accurate recognition of COVID-19.

Recent research validates the efficacy of CLAHE in the imaging pipeline in medicine. For example, Islam et al. [29] obtained more than 99% accuracy in the classification of CT-based detection of COVID-19 by combining deep learning with CLAHE for preprocessing. Similarly, Saifullah and Dreżewski [30] reported that combining CLAHE with histogram equalization enhanced the visibility of lung structures and improved segmentation performance, showing measurable gains in Dice and SSIM scores on CT-scan datasets.

3.2.4 Sharpening for Edge and Detail Enhancement

After the contrast enhancement, a sharpening filter is used to emphasize edges and structural features. This operation enhances the intensity change, which improves the visibility of areas of infection and lung-outlined structures. Through sharpening, the classifier attains more fine-grained anatomical structures, thus enabling it to concentrate on clinically important ROIs without missing early infection indications. The input and output of the preprocessed images are presented in Figures 3 and 4.

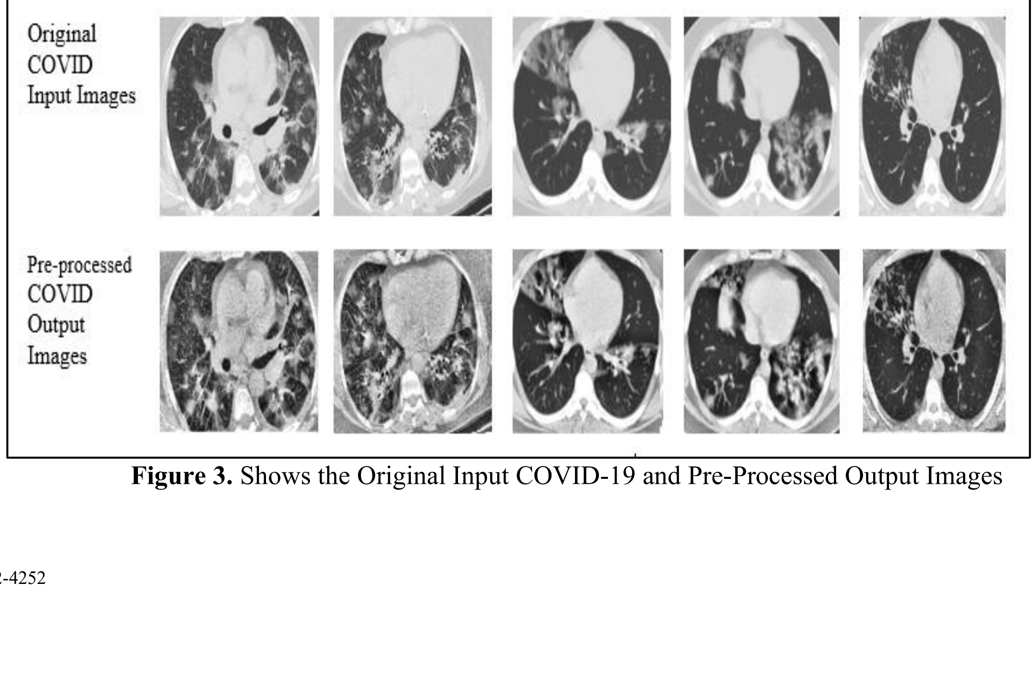

Figure 3. Shows the Original Input COVID-19 and Pre-Processed Output Images

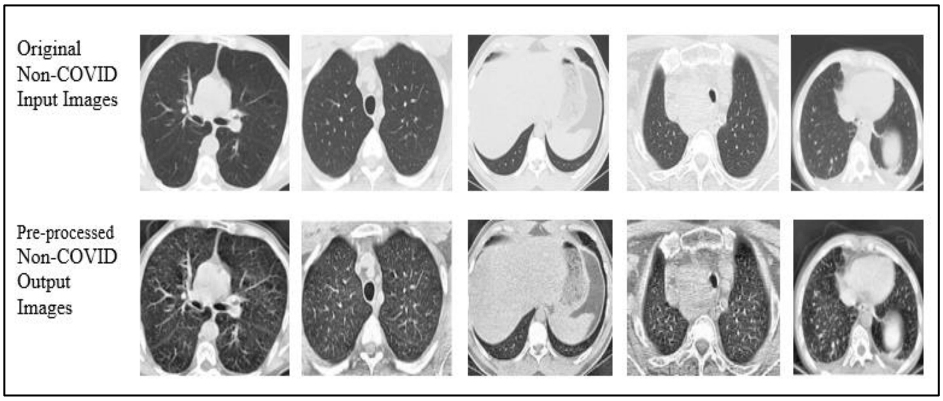

Figure 4. Shows the Original Input Non-COVID-19 and Pre-Processed Output Images

3.3 Data Augmentation

Deep learning models require diverse and representative data sets in order to generalize. However, data, especially those within the health space, such as data concerning COVID-19, are often limited due to privacy concerns and the expense involved in human annotation. Data augmentation methods have been applied in the past in an attempt to expand the data set.

For this purpose, random rotations that range from -10 to 10 degrees, horizontal and vertical translations that range from -5 to 5 pixels, and mild scaling are implemented in this research to simulate changes in patient placement and scanning. This strategy improves the robustness of the classifier by utilizing the capabilities of the classifier to learn rotation and translation-invariant features. According to Shorten and Khoshgoftaar in [31], such transformations lead to significant reductions in overfitting and improvements in model generalization, especially when utilizing small medical datasets.

The aim of the data augmentation technique employed in the study is to counter overfitting, which occurs when the training dataset is small or has low variability, by artificially introducing more variability to the training dataset while maintaining its labels unchanged. The rotation, translation, and scaling operations employed during data augmentation help expose the CNN to variability in orientations as well as image distributions that are essentially common in real-world clinical scenarios in the form of a CT scan.

3.4 Feature Extraction Using ResNet-50

The feature extraction part of the SmartCovNet architecture uses ResNet-50. The global average pooling layer provides a 2048-D feature vector for each input CT scan, indicating relevant information such as texture patterns, diseased areas, and key structural boundaries. All such information plays an essential role in discriminating COVID-19 infection cases from other pulmonary diseases. Since the ResNet-50 network incorporates the concept of transfer learning, it leverages the experiences developed on large databases such as ImageNet to reduce training time and enhance its robustness on an unseen database. Modification of such deeper layers also helps fine-tune their learned filters to adapt to database-specific texture patterns, possibly increasing their sensitivity to COVID infection abnormalities. Previous research has illustrated that ResNet-50-based models using the concept of transfer learning are reliable for the accurate detection of pneumonia and COVID-19 infection cases for chest radiology imaging modalities [32]. The sub-network classifier receives the 2048-D feature vector from ResNet and tries to succinctly represent it by stacking fully connected layers. This indirectly helps filter out superfluous information without resorting to regularization.

By employing the avg_pool layer rather than the flatten layer, the number of constraints becomes significantly smaller, thus averting the chances of overfitting. Recently, some benchmarking analyses indicate that applying global average pooling on ResNet-50 achieves nearly the same level of accuracy as that of flatten-layer-based models, but with much higher efficiency in terms of memory and time complexity [33]. Although the deeper layers may be fine-tuned to perceive the CT-specific texture variability, we decided to fix the feature extractor as ResNet-50 to avoid overfitting on our limited data and to retain consistent feature space.

3.5 Novel Neural Network Architecture

The output feature vector extracted from the ResNet-50 avg_pooling layer is directly fed into a customized neural network classifier. Without the need for human feature engineering, our proposed SmartCovNet ensures that the rich high-level features that ResNet-50 has learnt are effectively used for classification. Although the proposed neural classifier is lightweight, it is intended to work on high-level and discriminative features obtained from the ResNet-50 architecture. Thus, the strategy mitigates any possible depth in the architecture and prevents overfitting on the smaller CT datasets, as the complex patterns in the imaging modality can be learned by the network employing deep fully connected layers with normalization and nonlinear activation.

The customized neural network model comprises a feature input layer, followed by two fully connected layers trailed by batch normalization and a ReLU activation function. The utilization of such layers improves the learning rate as it enhances the flow of gradients. Additionally, a dropout layer is employed to counter the problem of overfitting, followed by a bottleneck layer to make the feature representation smaller while capturing the essential information. Finally, a fully connected output layer with a SoftMax activation function is employed to produce the final class labels of either COVID-19 or Non-COVID-19. This model ensures a blend of both performance and generalization capability to effectively classify even small datasets. To optimize the training process, the classifier is trained using the Adam optimizer, which adaptively adjusts learning rates for faster convergence. Training was conducted over 100 epochs with a mini-batch size of 32, and the dataset was randomly shuffled at every epoch to improve generalization. The categorical cross-entropy loss function was chosen since it can help in binary classification and a 30 percent validation split was adopted to measure performance during training.

Table 2. Layer-Wise Information of the Customized Neural Network

Layer No.	Layer Type	Description
1	Input Layer	Feature input layer 2048 (from ResNet-50 avg_pool)
2	Fully Connected Layer	128 neurons
3	Batch Normalization	Normalizes activations to accelerate training
4	ReLU Activation	Applies ReLU non-linearity
5	Fully Connected Layer	64 neurons
6	Batch Normalization	Normalizes activations
7	ReLU Activation	Applies ReLU non-linearity
8	Dropout Layer	Dropout rate = 0.5 to reduce overfitting
9	Fully Connected Layer	32 neurons

10	Batch Normalization	Normalizes activations
11	ReLU Activation	Applies ReLU non-linearity
12	Fully Connected Layer	Output layer with neurons = numel(categories (YTrain))
13	SoftMax Layer	Converts scores into class probabilities
14	Classification Layer	Predicts final class label

Table 3. Training Options for the SmartCovNet

Parameter	Value
Input Image Size	224 × 224 × 3
Optimizer	Adam
Loss Function	Categorical Cross-Entropy
Epochs	100
Mini-Batch Size	32
Validation Split	30%
Learning Rate	Default (Adaptive)
Data Augmentation	Rotation ±10°, X/Y translation ±5 pixels

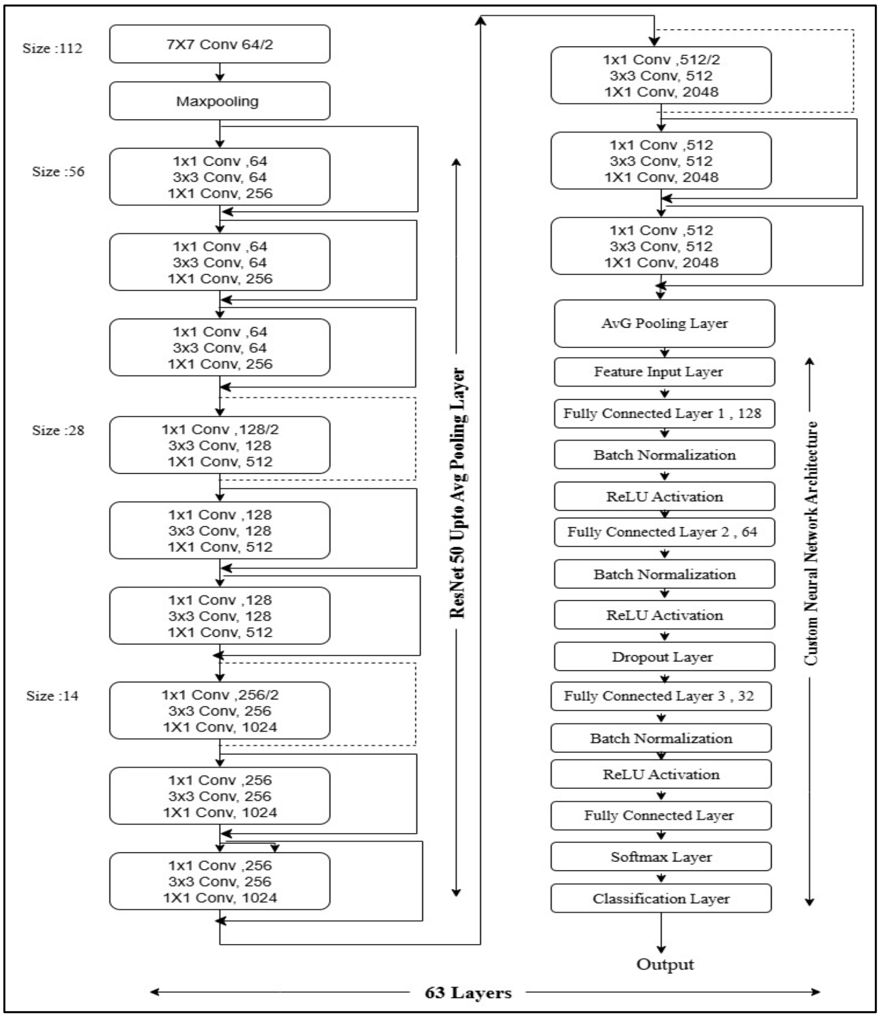

Figure 5. Proposed SmartCovNet Architecture

In the SmartCovNet, the use of region of interest (ROI) visualization helps analyze the impact of the areas within the lungs on classification result. However, since the proposed model is focused on the classiification and not segmentation, the ROI areas are determined based on the activation response of the final convolutional layers within the ResNet-50 architecture. The regions with high activation responses relevant to the appropriate class are highlighted and overlaid on the original CT scan. The highlighted regions signify the areas of highest influence within the decision-making phase, including opacified areas within the lungs.

3.6 Classification and Evaluation Metrics

To assess the performance of SmartCovNet, we engaged a complete set of evaluation metrics commonly used in medical image classification. Accuracy was used as the primary metric, measuring the overall proportion of correctly classified CT scans. However, accuracy alone may not fully capture model reliability, particularly in imbalanced datasets. Therefore, additional metrics such as sensitivity, specificity, F1-score and precision were included to provide a more detailed performance analysis.

- **Sensitivity (Recall):** Defines how well the model identifies COVID-19 instances which is essential for lowering the false negative rate during clinical screening.
- **Specificity:** The ability to accurately identify non-COVID scans, preventing the occurrence of false alarms.
- **Precision:** Demonstrates the effectiveness of COVID-detections by measuring the percentage of real positives relative to all positive forecasts.
- **F1-Score:** Provides a moderate representation of performance where the effects of false positives and false negatives are noticeable, as it gives the harmonic mean of precision and recall.
- **Classification Error:** Represents the proportion of incorrectly classified samples.

To view the results of classification, a confusion matrix is produced. To further demonstrate the interpretation of the CT scans by the model and the detection of abnormalities associated with COVID-19 labeled regions of interest (ROI) are shown. A combination of these measures and visualizations demonstrates the strength and clinical significance of the proposed framework SmartCovNet. The metrics are computed using the following formulas:

$$\text{Accuracy} = \frac{No.of\ images\ correctly\ classified}{Total\ no\ of\ images} \quad (1)$$

$$\text{Precision} = \frac{sum\ of all\ true\ positives\ (Tp)}{Sum\ of\ all\ True\ Positives(TP)+All\ False\ Positives\ (FP)} \quad (2)$$

$$\text{Recall} = \frac{sumofall\ true\ positives\ (Tp)}{sumofall\ true\ positives(Tp)+\ AllFalse\ Negatives\ (FN)} \quad (3)$$

$$\text{F1 Score} = \frac{2*Precision*Recall}{Precision+Recall} \quad (4)$$

$$\text{Classification Error} = \frac{total\ number\ of\ misclassified\ images}{Total\ no\ of\ images} \quad (5)$$

4. Investigational Outcomes

To evaluate the performance of the proposed SmartCovNet technique, extensive experiments were conducted on the SAS-Cov-2 CT scan dataset. This aimed to assess the model's potential to correctly segregate the COVID-19 and Non-COVID classes while simultaneously guaranteeing the model's strength against different test samples. The evaluation included quantitative and qualitative analysis, along with standard classification measures, the confusion matrix, and sample prediction outputs with ROI marking. In this section, we introduce the model's diagnostic performance and how its benefits surpass those of state-of-the-art approaches.

4.1 Quantitative Results and Performance Analysis

SmartCovNet was the proposed technique that was intensively tested on a dataset of 1,251 COVID-positive and 1,229 Non-COVID chest CT scan images. The evaluation of the method was conducted according to conventional measures such as accuracy, recall, precision, F1-score, and specificity. As Table 4 below indicates, our proposed SmartCovNet achieved a total accuracy of 99.53%, demonstrating its effectiveness in distinguishing between COVID-19 and normal chest CT scans. The proposed method correctly identified 1,245 of the 1,251 COVID-19 samples (True Positives, TP) and 1,223 of the 1,229 Non-COVID samples (True Negatives, TN). There were only a few misclassifications, with 6 false positives (FP) and 6 false negatives (FN). The accuracy of 99.52% indicates that nearly all predictions made for COVID-positive cases were correct, while the recall (sensitivity) of 99.52% suggests that nearly all actual COVID cases were correctly identified by the model. The specificity of 99.51% indicates a strong ability to correctly identify Non-COVID scans, and the F1-score of 99.52% reflects high stability between precision and recall. The overall classification error of SmartCovNet is 0.47%, corresponding to only 12 misclassified samples (6 FP and 6 FN) out of 2,480 CT images, confirming its strong generalization capability. The six false positives mainly arose from Non-COVID CT images that exhibited patchy opacities or blurred lung regions resembling early COVID-like ground-glass patterns, leading the classifier to misinterpret them as infections. The six false negatives occurred in cases where COVID lesions were very faint, extremely localized, or masked by low contrast, making their global feature presence too weak for the classifier to capture. These patterns appear in the confusion matrix as symmetric misclassification errors, reflecting that visually ambiguous cases in both classes contribute equally to prediction mistakes.

When the size of the COVID lesion becomes very small, involving only certain regions, the classifier could potentially perform inadequately because the features gleaned from the entire section of the CT scan could be considered weak. This is because the classifier uses high-level features, some of which could possibly be missed in the very small lesion regions without the specific focus of the ROI processing.

Figure 6 depicts the confusion matrix of the proposed SmartCovNet. The high accuracy of the proposed approach is a clear demonstration of the power of a combination of ResNet-50 with a particular neural network classifier, which ensures high discriminative power and the capability of generalization in spite of variations in CT samples. This particular harmony is a balance of the approach in reducing type I errors (a non-COVID case is treated as a COVID case) and type II errors (a real COVID case is treated as a false alarm), which is an exceptionally critical task in the screening procedure, as both false alarms and false negatives can have a high clinical impact. This stability is ensured because of the extracting capabilities of ResNet-50, which recognizes complex textures as well as organizational changes in the lungs. These are high-level features that, upon processing by the custom neural network classifier, increase the discriminative capability of the model. Figure 7 shows the ROI visualization of the COVID-detected images.

Furthermore, the preprocessing process (CLAHE + bilateral filtering + sharpening) is designed so that subtle lesions, as well as ground-glass opacities, are not masked by noise or low-contrast areas, thereby further improving the accuracy of the detection as a whole. This indicates that the model is optimistically trained on the invisible clinical datasets without any compromise on performance.

Table 4. Class-wise Performance Evaluation of SmartCovNet for COVID-19 Detection

Class	TP	FP	FN	TN	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)
COVID	1245	6	6	1223	99.53	99.52	99.52	99.51	99.52
Non-COVID	1223	6	6	1245	99.53	99.52	99.51	99.51	99.52

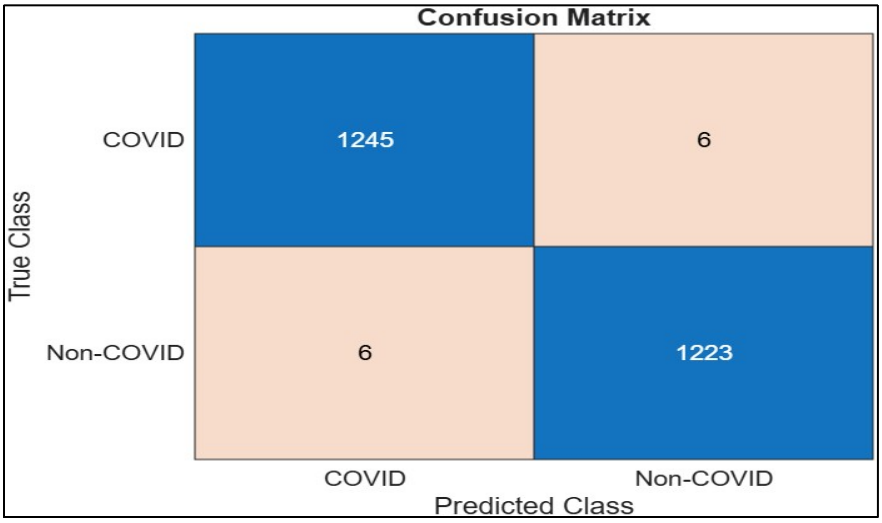

Figure 6. Shows the Confusion Matrix of the Proposed SmartCovNet

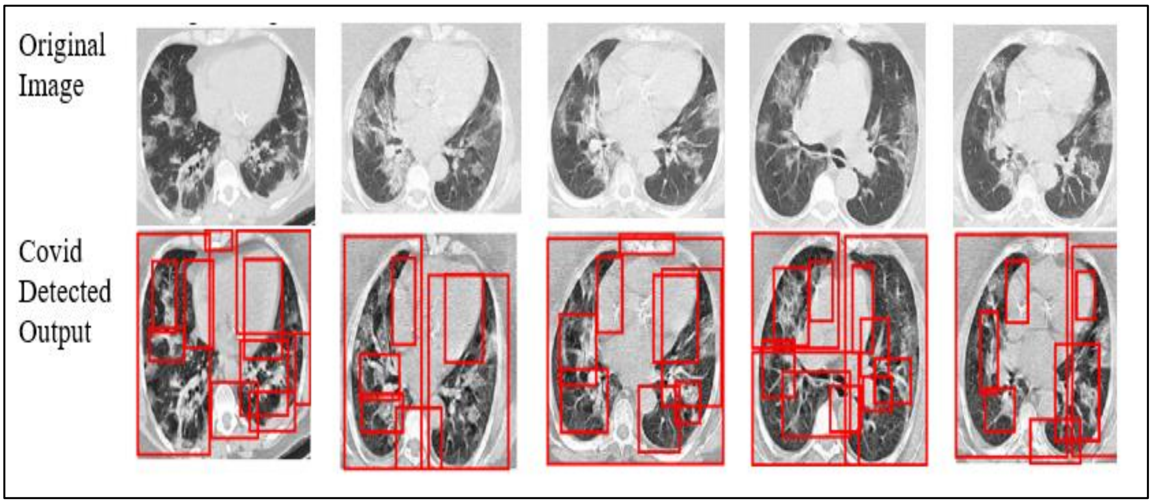

Figure 7. Shows the ROI Visualization of the COVID Detected Images

4.2 Evaluation Outcomes

4.2.1 Accuracy

The comparison of recent deep learning models is presented in Table 5 for the automatic detection of COVID-19 from chest images obtained from a CT scan. The U-Net-based FCN model had a moderate level of accuracy of 96%, while a slight enhancement was observed in techniques like pre-trained DenseNet and InceptionV4, with an accuracy rate of nearly 92%. Techniques based on transfer learning using ResNet had an accuracy rate of 95%.

Recent models involving the integration of pre-trained models of ResNet-18, DenseNet, and Inception were able to reach an accuracy of 99%. Ensemble methods like Covid-19Net, which involve the integration of diverse convolutional neural networks, further enhanced accuracy to about 98.8%. Methods involving the use of pre-trained models exclusive to CT scans also achieved levels of accuracy close to 98.94%. Fine-tuned efficient models produced some of the best results, reaching an accuracy of 99.26%.

Table 5. Comparison of Accuracy with State-Art-Methods

Model / Study	Accuracy (%)
U-Net-based FCN [7]	96
Pre-trained DenseNet, InceptionV4[9]	92
Transfer Learning - ResNet variants [15]	95
Pre-trained ResNet-18, DenseNet, Inception [20]	99
Covid-19Net: Ensemble of ConvNet-24 + custom pre-trained models [24]	98.8
Several pre-trained models on CT image [25]	98.94
Fine-tuned EfficientNet [26]	99.26
Proposed SmartCovNet	99.53

Comparison to it indicates that SmartCovNet performed better than these state-of-the-art approaches, thus qualifying for an accuracy level of 99.53%. This result clearly reveals the effectiveness of the combination and implementation of state-of-the-art image analysis capabilities and ResNet-50-based feature extraction, as well as a specially designed neural classifier that demonstrated the highest discriminant capabilities and generalization in COVID-19 CT images for this work. The graphical representation of the classification accuracy of the proposed SmartCovNet and other approaches introduced in this work, in relation to Table 5, is shown in Fig. 8.

The running time of the proposed SmartCovNet framework is dominated by three steps: image preprocessing, the computation of handcrafted feature extraction using the pre-existing ResNet-50 model, and the lightweight CNN model. Considering a general computer setup capable of supporting a GPU, the average running time of the proposed system on each CT image is in the range of a few hundred milliseconds, making this a near-real-time system, which is very adequate in a medical environment, especially when working with a CT image instead of a video.

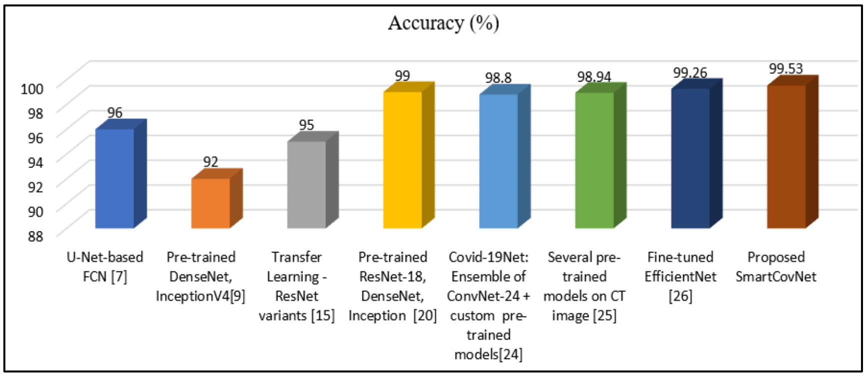

Figure 8. Comparative Accuracy of Proposed SmartCovNet and Existing Methods for COVID-19 Detection

5. Conclusion and Future Scope

In this paper, the design of SmartCovNet should include the following: the intelligent system consists of the ResNet-50 module, which will extract the features, and the Novel Neural Network module, which will perform the classification of the detection of either COVID-19 or Non-COVID. The proposed tool has achieved an accuracy level of 99.53%, along with a high level of precision, recall, specificity, and F1 measures for COVID and Non-COVID detection after conducting rigorous testing on samples of COVID and Non-COVID totaling 1,251 and 1,229, respectively. The performance is competent and capable enough to outperform diverse models that were claimed to be the state-of-the-art at that particular time, and this clearly testifies to the effectiveness and usefulness of the architecture that can identify COVID and Non-COVID with a minimum amount of confusion. In summary, the effectiveness and competency of SmartCovNet should clearly demonstrate the massive potential the proposed project carries towards being an effective tool for radiologists involved in the precise and speedy detection of COVID-19. This will definitely alleviate the load on medical staff while, at the same time, accelerating the speed at which detection takes place, making the separation or treatment process easier, especially in the case of a massive spread. The improvement of the algorithm regarding potential future applications would therefore be carried out via the application of U-Net algorithms. The generalizability of the algorithm would be enhanced by the inclusion of additional variations of the CT scan images among the variations of the population and equipment involved. Perhaps the use of multimodal variations, specifically the symptoms or tests performed on the patient, would become applicable with the intention of ensuring the overall accuracy and completeness of the predictions. The overall application value of the proposed system could be enhanced by the use of explainable AI models and techniques capable of being executed on resource-poor platforms.

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