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DeepX-Ray: A Comparative Study of Deep Learning-Based Classification and Segmentation Techniques for Automated Detection and Diagnosis of COVID-19 from Chest X-ray Images

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Abstract

The relentless spread of the SARS-CoV-2 virus, causing COVID-19, has underscored the urgent need for efficient early detection and diagnosis methods to mitigate its impact. While traditional techniques like RT-PCR are valuable, they often suffer from time-consuming processes. In this study, DeepX-Ray is presented, a comprehensive investigation into deep learning-based classification and segmentation approaches for the automated detection of COVID-19 from chest X-ray images. Specifically, the authors focus on constructing a custom convolutional neural network (CNN) model to distinguish between COVID-19 and standard X-ray images and benchmark its performance against established models. For segmentation tasks, the effectiveness of various backbone architectures, including ResNet34, ResNet101, DenseNet201, and ResNet50 within the UNet model framework, is explored, with ResNet50 exhibiting superior performance. Furthermore, a novel dataset comprising 7657 images sourced from three publicly available authentic datasets is introduced, and the labelMe tool is employed by the authors to generate ground truth mask datasets for 4137 images to facilitate segmentation of infected lung areas. The authors' custom CNN model achieves an outstanding classification accuracy of 100%, while the segmentation approach attains a mean Intersection over Union (IoU) score of 96.19%. These results underscore the efficacy of the proposed model in enabling early automatic detection and diagnosis of COVID-19, particularly in resource-constrained and remote settings where establishing traditional laboratories may be impractical. This research significantly advances medical imaging techniques for combating the COVID-19 pandemic.

A. Introduction

The emergence of COVID-19, induced by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) in 2019, quickly escalated into a global epidemic, declared as such by the World Health Organization (WHO) in 2020. COVID-19 primarily targets the respiratory system, causing severe damage and posing a significant challenge for timely detection and diagnosis due to the prevalence of nonspecific symptoms. Conventional diagnostic methods, notably reverse transcription-polymerase chain reaction (RT-PCR), computed tomography (CT) scans, and lateral flow assays, have been utilized for rapid detection. However, while widely adopted, RT-PCR suffers from the limitation of false-negative reports. Medical imaging, particularly chest X-rays, has emerged as a promising tool for COVID-19 diagnosis due to its cost-effectiveness, low radiation exposure, and ease of analysis. In the era of the twenty-first century, integrating deep learning into medical imaging has revolutionized early detection and diagnosis processes.

Convolutional Neural Networks (CNNs) have emerged as a preferred choice for segmentation-based classification in medical imaging, leveraging their ability to extract crucial features from X-ray reports, especially for detecting bacterial diseases like pneumonia. Motivated by the imperative need for early and accurate COVID-19 detection, this research aims to bridge gaps in the automated diagnostic process. Despite significant advancements in deep learning-based COVID-19 detection, current approaches primarily focus on binary or multiclass classification, overlooking segmentation-based techniques. The scarcity of publicly available datasets with ground truth masks impedes progress in segmentation-based methodologies. The primary objective of this study is to introduce a simplified yet practical, classification-based segmentation approach for comprehensive medical imaging-based detection, encompassing not only COVID-19 but also other X-ray-based diagnoses. To achieve this objective, the authors have assembled a new dataset from three authentic sources and annotated it using the labelMe tool to create ground truth mask datasets. Furthermore, a custom CNN model is deployed to classify COVID-19 and typical cases, significantly focusing on comparing its performance with established CNN models. Additionally, to enhance accuracy, various pre-trained models are integrated with the UNet model for segmentation purposes [14].

The predominant gap in existing literature lies in the absence of an automated early detection process. While deep learning-based approaches have demonstrated promising results, complexity remains a prevalent issue. Moreover, the scarcity of authentic datasets with ground truth masks hampers segmentation-based methodologies. Furthermore, most studies primarily focus on comparative analyses, overlooking the need for simplified, robust diagnostic solutions. In response to the pressing need for timely and accurate COVID-19 detection, this research aims to contribute to advancing medical imaging-based diagnosis through integrating deep learning techniques. While traditional diagnostic methods such as RT-PCR and CT scans have played crucial roles in identifying COVID-19 cases, their speed, cost, and diagnostic accuracy limitations underscore the importance of exploring alternative approaches. Deep learning, particularly CNNs, has emerged as a powerful tool in medical imaging, offering the potential to automate and enhance the diagnostic process. By leveraging the inherent capabilities of CNNs for feature extraction and classification, researchers have sought to develop more efficient and accurate methods for COVID-19 detection from chest X-ray images. However, despite the promising advancements in deep learning-based COVID-19 detection, several gaps and challenges persist. One critical gap lies in the limited focus on segmentation-based techniques, which have the potential to provide more granular and interpretable diagnostic outputs [15].

Additionally, the scarcity of publicly available datasets with ground truth masks poses a significant barrier to developing and evaluating segmentation-based methodologies. Furthermore, while comparative analyses of different deep learning models have provided valuable insights, there is a need for research to move beyond mere comparisons and focus on the development of simplified yet robust diagnostic solutions. Addressing these gaps will be essential for realizing the full potential of deep learning in medical imaging-based COVID-19 detection [16].

In summary, this research endeavors to bridge gaps in the automated diagnostic process by introducing a simplified and effective classification-based segmentation approach. By assembling a new dataset and deploying a custom CNN model, this study aims to contribute to the development of more accessible and accurate diagnostic tools for COVID-19 and other X-ray-based diagnoses.

B. Related Works

Numerous recent studies have focused on leveraging deep learning models to detect COVID-19 from chest X-ray image datasets. Khan et al. [1] proposed two frameworks, DHL and DBHL, incorporating COVID-RENet 1 & 2, deep learning models designed for feature extraction. While DHL utilized individual COVID-RENet models, DBHL fine-tuned and boosted feature extraction, achieving a superior accuracy of 98.53% compared to other models.

Ajay and Pramod Kumar Mishra [2] introduced a classification approach based on segmentation for detecting COVID-19 and assessing infection severity levels. Employing UNet, DenseUnet, and ResUnet for segmentation, they achieved optimal results with DenseUnet, while MA-DenseNet201 outperformed other CNN models in the classification approach, reaching 96% accuracy.

Kedia and Rahul Katarya [3] proposed a multilayered ensemble model utilizing VGG-19 and DenseNet121 for COVID-19 detection, achieving an impressive accuracy of 99.71% for two-class classification.

Similarly, Kamil [4] developed a modified VGG-19 model with the highest accuracy of 99% among various CNN models evaluated.

Pathan, Siddalingaswamy, and Tanweer Ali [5] presented a classification model utilizing an ensemble of ResNet50 and ECOC models optimized through automatic processes like the Gray Wolf optimizer and whale optimizer with the BAT algorithm. Their approach yielded the best accuracy in categorizing pneumonia, average, and COVID-19 cases.

Balaha, Balaha, and Ali [6] proposed a hybrid detection framework combining a customized CNN model, genetic algorithm, and weight sum matrix, achieving 99.78% accuracy with VGG16.

Park and Ye [7] employed patch-based CNN architectures for diagnosing five classes, with DenseNet103 used for semantic segmentation, providing interpretable diagnosis via saliency maps.

Bhowal et al. [8] introduced a fine-tuned DCNN approach for categorizing pneumonia, regular, and COVID-19 cases, employing lambda fuzzy measure and coalition game theory for performance evaluation, yielding an accuracy of 95.49%.

Ji et al. [9] proposed fusion-based detection models, combining multiple CNN architectures to achieve optimal accuracy. Model 2, fusing VGG19, Xception, ResNet152, and InceptionResNetV3, demonstrated the highest accuracy of 96.00%.

Shazia et al. [10] compared deep learning models for coronavirus, pneumonia, and standard pneumonia classification, identifying DenseNet as the most accurate model.

In this article [11], the performance of different deep learning models, notably VGG16, VGG19, DenseNet121, and Resnet50, was examined for their ability to distinguish between coronavirus pneumonia and cases of pneumonia.

This paper [12] presents a multi-modal fusion technique for detecting and categorizing COVID-19 using chest X-ray pictures, CT scans, and RT-PCR testing.

In this paper [13], the authors used CNN, activation functions dropout, batch normalization, and Keras parameters to build a model for detecting COVID-19 infection from chest X-ray images. These studies collectively highlight the effectiveness of deep learning models in COVID-19 detection from chest X-ray images and underscore the importance of model selection and optimization techniques in achieving superior accuracy.

C. Methodology

This section contains the results of research and discussion, as well as the implementation of the developed system design. In addition, in this section, the author should interpret the results of his findings and confirm his findings with other existing findings or theories.

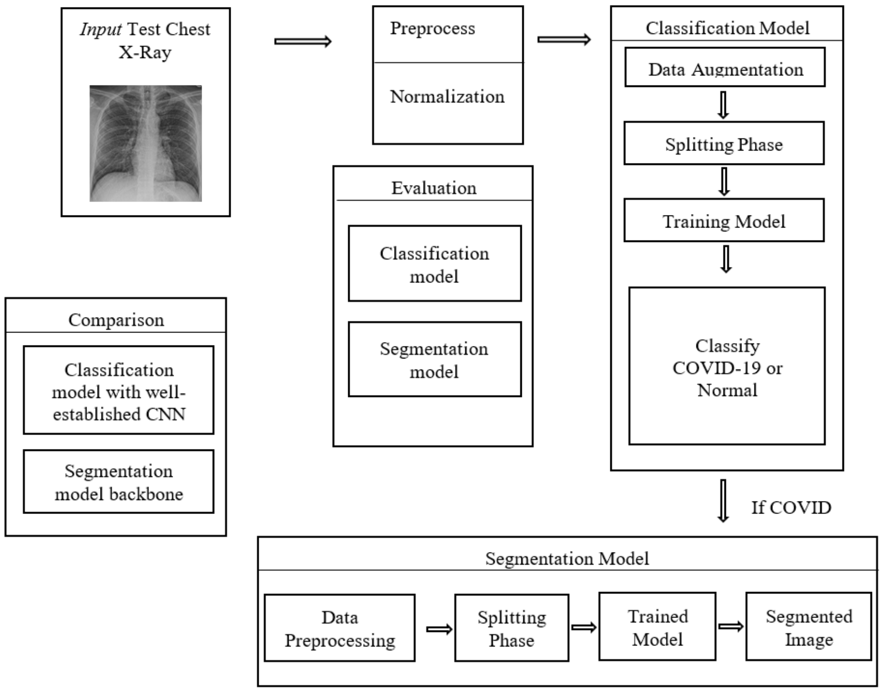


Figure 1. Block Diagram of Proposed Model

The proposed paradigm outlined in Figure 1 encompasses a comprehensive COVID-19 detection and segmentation process. It begins by loading data into the model and normalizing it within a specified range while incorporating augmentation techniques for enhanced classification. Labels are converted to categorical data, and the dataset is shuffled and split for training. Utilizing a custom CNN model, the system undergoes testing to determine COVID-19 presence, triggering segmentation if detected. The segmentation model, trained with a UNet architecture and a pre-trained CNN backbone, is evaluated using the IoU score and loss function. Performance evaluation of the classification model includes metrics such as accuracy, recall, precision, and F-score, with comparisons made against established CNN models [17]. Additionally, the paper discusses comparison results for different backbone architectures employed in the segmentation model, providing a thorough analysis of the proposed methodology's efficacy.

1. Classification Phase

In the Classification Phase, the primary objective is to classify chest X-ray images into COVID-19 positive and COVID-19 negative (standard). This phase involves deploying a custom convolutional neural network (CNN) model trained on a dataset comprising labeled chest X-ray images. The research presents a novel classification architecture centered around a custom CNN model for automatically detecting individuals affected by COVID-19 [18]. Drawing inspiration from the COVID-RENet image classification method, the proposed model is tailored for binary classification, distinguishing between typical and COVID-19 cases.

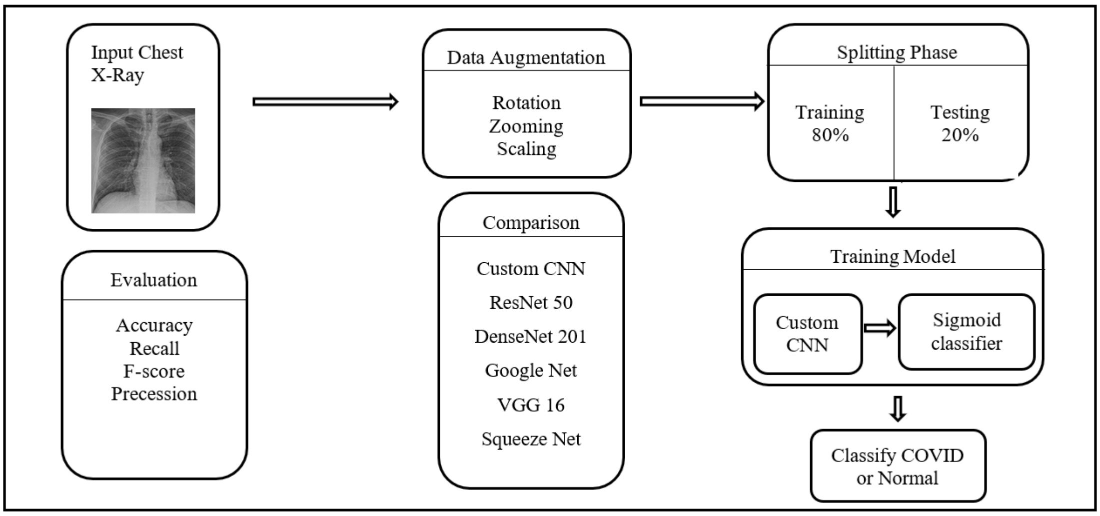


Figure 2. Block Diagram of Proposed Classification Model

The workflow begins with data loading, followed by preprocessing steps such as resizing, scaling, zooming, and shifting to enhance the dataset's diversity and quality. The data is then split into training and validation sets, with 80% allocated for training and 20% for validation. The custom CNN model comprises four convolutional layers and four max-pooling layers, serving as the backbone for the classification task. Each convolutional layer utilizes a 3-by-3 matrix, while each max-pooling layer employs a 2-by-2 matrix. The output channels for the convolutional layers are progressively increased, with 32, 64, 128, and 256 channels for the first, second, third, and fourth layers, respectively. The convolutional process extracts relevant information from the input chest X-ray images [19]. Subsequently, the max-pooling layers reduce the size of the filtered images by retaining the highest values. After the flattening procedure, the feature matrix is passed to a fully connected layer, where the sigmoid function is applied to classify the input as either COVID-19 or normal. The model's output provides the final classification results. In summary, the proposed custom CNN model offers a practical framework for binary classification, leveraging convolutional and pooling layers to extract and classify relevant features from chest X-ray images. This architecture demonstrates promising potential for automating the detection of COVID-19 cases with high accuracy and efficiency.

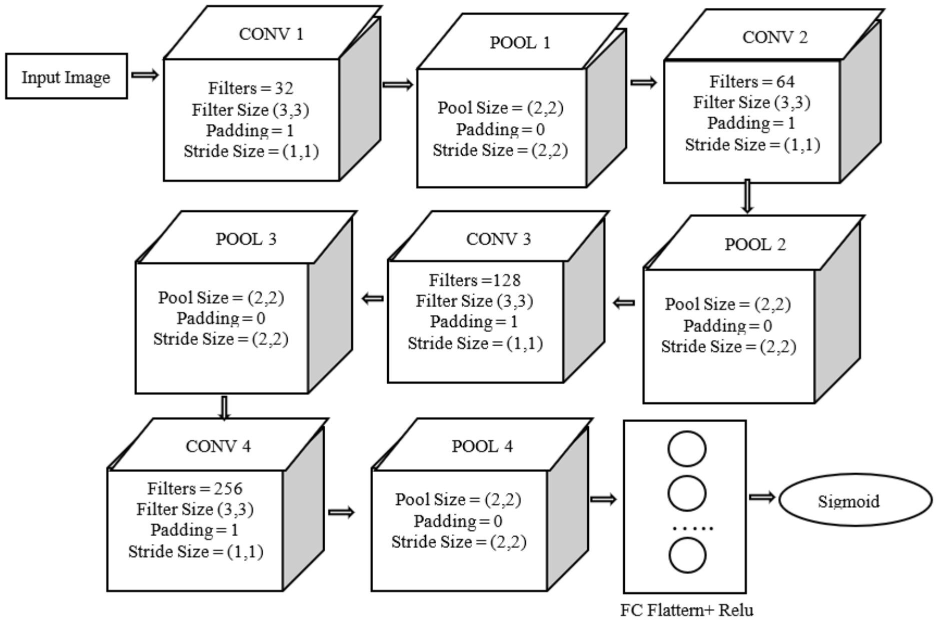


Figure 3. Block Diagram of Custom CNN Model

During the training process, the backpropagation approach is employed to optimize the parameters of the custom CNN model. The training is conducted with a batch size of 16 over 100 epochs, utilizing the Adam optimizer. The accuracy for both the training and validation datasets is monitored and recorded throughout the training iterations. This iterative optimization process ensures that the model learns to effectively classify chest X-ray images into COVID-19 and standard categories, with the recorded accuracies serving as metrics for evaluating the model's performance and convergence [20].

2. Segmentation Phase

In the Segmentation Phase, the focus shifts to identifying and delineating the regions of the chest X-ray images that indicate COVID-19 infection. This phase involves utilizing a segmentation-based approach, explicitly employing the UNet architecture, a popular choice for medical image segmentation tasks. Image segmentation plays a crucial role in artificial vision, particularly in medical imaging, where it aids in identifying potentially harmful features within visual data [21]. Unlike classification, which categorizes entire images, segmentation provides detailed information by dividing the image into segments. In medical science, various deep learning approaches are employed for image segmentation tasks, with UNet being widely recognized for its effectiveness. This study used a deep learning-based semantic segmentation technique to develop a modified UNet model. The UNet architecture is characterized by encoder-decoder structures, with the encoder acting as a bottleneck and the decoder reconstructing the segmented image. This architecture allows for direct concatenation of feature maps extracted by the encoder and decoder, facilitating skip connection integration and effective solutions for medical imaging tasks [22]. The segmentation model in our proposed framework complements the classification model by focusing on segments identified as COVID-19-positive by the classification model. The ultimate objective is to assist radiologists in swiftly diagnosing COVID-19 cases. The accompanying figure illustrates the complete architecture of the proposed segmentation model, showcasing its components and the flow of information through the network.

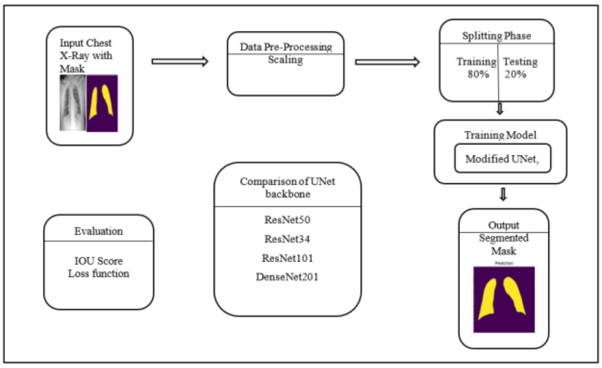


Figure 4. Block Diagram of Proposed Segmentation Model

In the study, UNet was employed for segmentation purposes, leveraging its effectiveness in semantically segmenting medical images. UNet, an enhanced version of Fully Convolutional Networks (FCN), is particularly well-suited for this task due to its unique architecture, which includes a single convolutional layer as its core component [23]. To enhance the segmentation performance, various pre-trained CNN models that were previously trained on the ImageNet dataset were integrated by the authors. By leveraging transfer learning properties from these models, the authors aimed to improve the model's ability to extract relevant features from the input medical images. The proposed network architecture consists of both an encoder and a decoder part. The encoder section replaces traditional 3*3 convolutional blocks with residual or dense blocks to enhance feature extraction capabilities.

Additionally, the authors eliminated the final fully connected layer, commonly called the backbone of the CNN model, from the encoder part to streamline the feature extraction process [24]. On the other hand, the decoder part of the network comprises five blocks, which are responsible for reconstructing the segmented image based on the features extracted by the encoder. This encoder-decoder architecture, combined with the integration of pre-trained CNN models, enables the authors' proposed network to effectively segment medical images and identify regions indicative of COVID-19 infection.

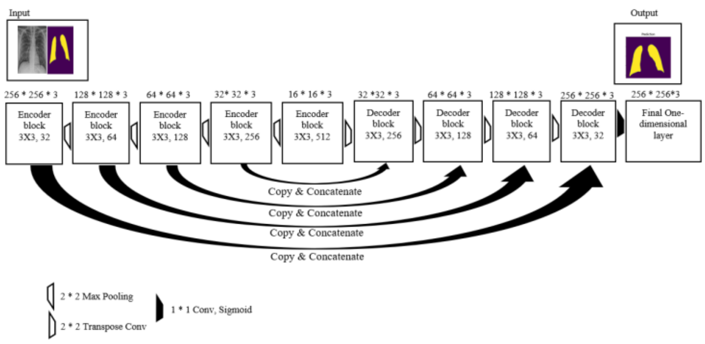
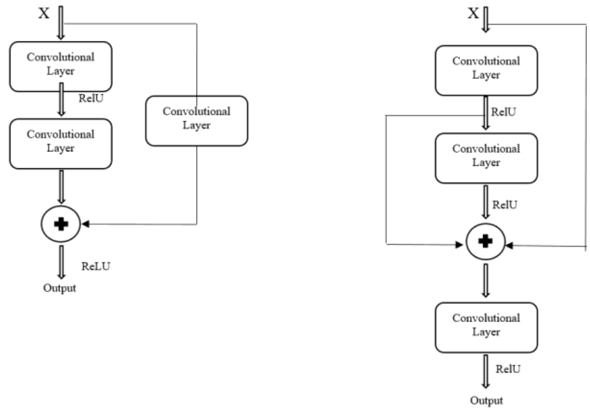


Figure 5. Modified UNet Model

Within each Block, two operations are repeated: a convolutional layer followed by batch normalization and ReLU activation, culminating in a 2*2 upsampling layer. The first four blocks share identical configurations in the encoder section, and their outputs are concatenated. The segmented mask is derived from the concatenated features by applying a 1*1 convolutional layer with sigmoid activation. This step produces the final segmentation output, delineating the regions of interest within the input image.



(a) (b)

Figure 6. (a) Residual Block (b) Dense Block

Below are examples of image data accompanied by their corresponding ground truth masks:

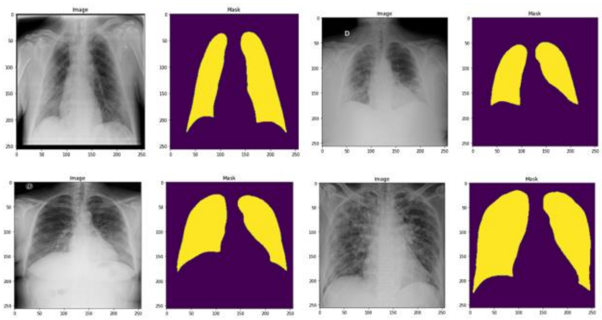


Figure 7. Input image data with manually labeled data

Once training is completed, a prediction type is required to initiate the segmentation stage obtained from the classification model. The classification model identifies the label of the test image, facilitating the segmentation process [25]. For segmentation purposes, the chest X-ray images were manually labeled using the LabelMe tool to generate ground truth masks. These masks served as the reference for segmentation. Subsequently, the image data and corresponding masks were loaded, with the masks serving as ground truth labels. The dataset was then preprocessed like the classification model, splitting the data into training and testing sets in an 80/20 ratio. A modified UNet architecture was utilized to train the segmentation model, with ResNet50 as the backbone for the encoder and decoder sections. Below are some randomly selected results of the predicted masks :

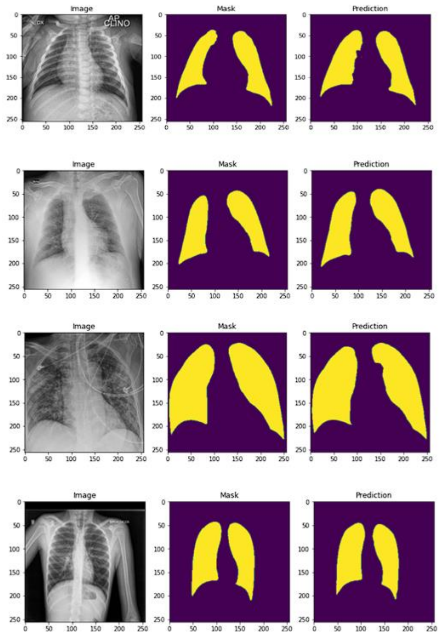


Figure 8. Final Prediction of the Segmented Images

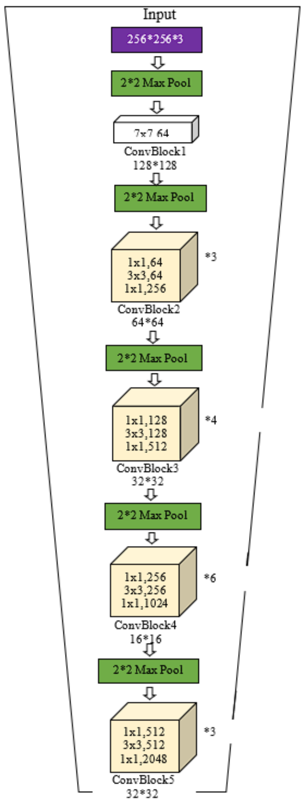


Figure 9. ResNet50 as Encoder of Unet

Figure 9 illustrates the integration of ResNet50 as the encoder component of the UNet model. ResNet50 utilizes a bottleneck structure comprising three convolutional layers to mitigate temporal complexity. As the depth of the CNN increases, the gradient value during backpropagation to initial layers diminishes, necessitating the use of such structures [26]. In addition to ResNet50, other backbone architectures, including ResNet34, ResNet101, DenseNet201, VGG16, and InceptionV3, were also considered. ResNet34, with its 34 weighted layers, employs equal kernel sizes for input and output, with the strategy of doubling filter size while halving feature map kernel to reduce temporal complexity. ResNet101, in contrast, incorporates more convolutional layers in each Block than ResNet50 yet maintains lower complexity than VGG-16 or VGG-19 architectures. The Dense-UNet architecture, based on the U-Net structure, employs dense concatenation to facilitate feature reuse and enhance network depth, featuring four expansion modules with four downsampling layers each for effective feature extraction. VGG was used to reduce the parameters of convolutional layers and expedite training [27]. The choice of kernel size in image analysis poses challenges due to varying feature sizes, prompting the utilization of different-sized kernels. Inception architecture addresses this by employing layers more broadly rather than deeper, incorporating kernels of different sizes within the same layer. Among these architectures, ResNet50 demonstrated superior performance and was thus selected as the backbone for the UNet model in segmenting the affected areas. The training utilized the Adam optimizer, softmax function, a batch size of 8, a learning rate 0.0001, and spanned 100 epochs. The entire classification and segmentation process was implemented using Python 3.9 [28].

D. Results And Discussion

The dataset utilized in this study primarily originated from two sources: Kaggle and GitHub, both renowned open repositories regularly updated and accessible to researchers and developers. The dataset comprises chest X-ray images depicting individuals diagnosed with COVID-19 and those deemed healthy. Each image underwent validation by radiologists to ensure accuracy and reliability. The dataset comprises 7657 images, with 4137 depicting COVID-19 patients and 3520 portraying standard cases.
Below are examples showcasing some of the image data included in the dataset:

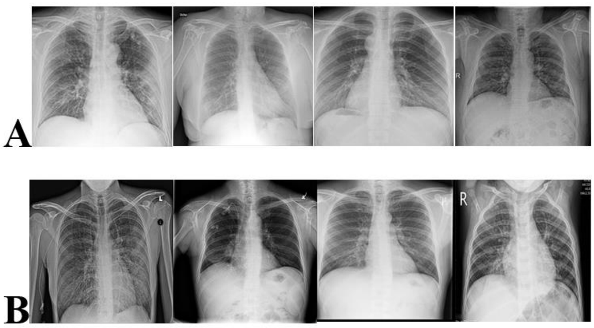


Figure 10. Panel A shows COVID-19-affected Chest X-ray Images, and Panel B shows Normal Chest X-ray Images

The chest X-ray image dataset is sourced from three distinct repositories, with the newly introduced batch referred to as the JA dataset. The dataset undergoes random shuffling to ensure unbiased training of the classification and segmentation models. Below, examples of the ground truth masks generated using the LabelMe tool are presented:

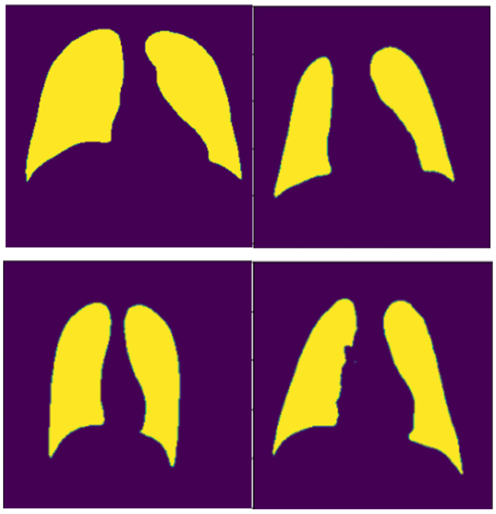


Figure 11. Ground Truth Mask

Table 1: List of Image Data

Reference	Dataset	COVID-19	Normal
[13]	COVID-19 Radiography Database from Kaggle	2593	1520
[11]	Actualmed-COVID-chest X-Ray-dataset from GitHub	1000	1035
[12]	Covid-chest X-ray dataset from GitHub	544	1250
Total	**7657**	**4137**	**3520**

The evaluation of the proposed classification model's performance will involve the utilization of standard classification performance metrics, including recall, accuracy, and F-score, as outlined by:

Accuracy=(TN+TP)/(TN+TP+FN+FP)*100

Precision=TP/(TP+FP)*100

Recall=TP/(TP+FN)*100

F-score=2 X (Precesion X Recall)/(Precesion+ Recall)*100

In this context, recall represents the proportion of correctly predicted COVID-19 samples, while accuracy indicates the percentage of correctly predicted samples overall. Precision, conversely, signifies the ratio of projected samples that align with the actual class. The F-score, incorporating precision and recall, is a metric for assessing the model's overall accuracy [29].

Table 2: Performance evaluation with existing well-established CNN models

Models	Accuracy	Precision	Recall	F1 score
Proposed Model	100%	100%	100%	100%
ResNet 50	97.57%	97%	97%	97%
DenseNet 201	96.13%	97%	97%	97%
GoogleNet	96.36%	96%	96%	96%
VGG16	95.81%	96%	96%	96%
SqueezeNet	94.05%	94%	94%	94%

Table 2 illustrates that the suggested model surpasses another prominent CNN model in accuracy. Additionally, the training and validation accuracy and loss of the proposed classification model over 100 epochs are depicted in the following figure.

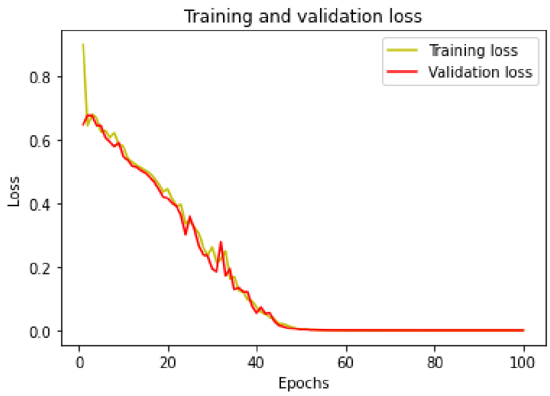


Figure 12. Training and Validation Accuracy of the Proposed Classification Model

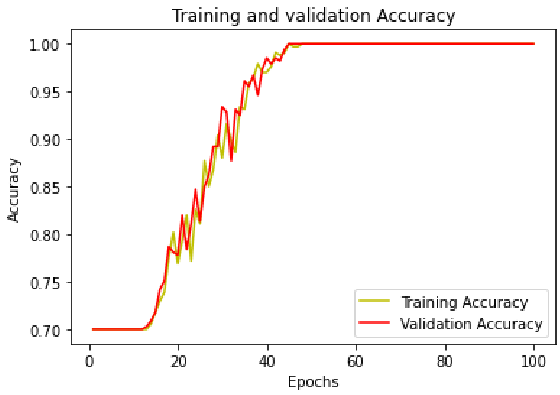


Figure 13. Training and Validation Loss of the Proposed Classification Model

a. Performance Evaluation of Segmentation Model

IoU, short for Intersection over Union, is a widely used matrix in semantic segmentation tasks. It quantifies the agreement between the ground truth mask ($P_{\text{Grand-truth}}$) and the predicted segmentation area ($P_{\text{Predicted-Segmentation}}$) by measuring the overlapping region relative to their combined area. This ratio effectively assesses the accuracy of segmentation predictions, offering a valuable metric for evaluating model performance [30].

$$\mathrm{IoU}\left(P_{Grand-truth}, P_{Predicted-Segmentation}\right) = \frac{P_{Grand-truth} \cap P_{Predicted-Segmentation}}{P_{Grand-truth} \cup P_{Predicted-Segmentation}}$$

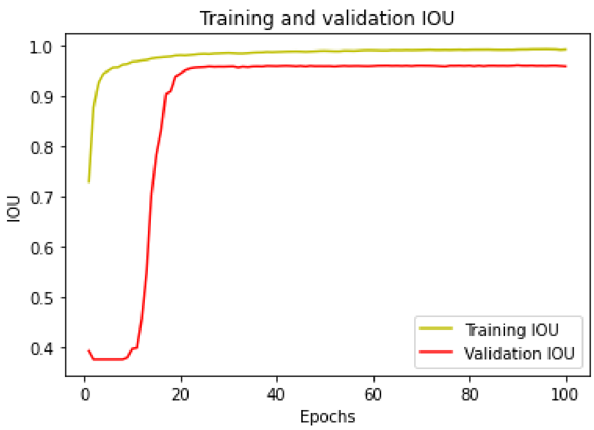
In this study, the IoU score serves as our accuracy metric, being region-based and widely recognized as the primary evaluation measure for image segmentation tasks. Table 3 presents the performance of various pre-defined models when integrated with the UNet architecture, offering insight into the effectiveness of different backbone functions.

Table 3: A comparison of various preconfigured CNN models as the core of the UNet model

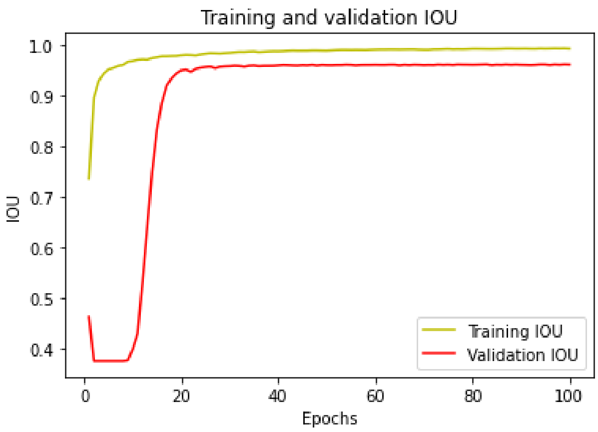
Model Name	IoU score(Training Data)	Mean IoU(Testing Data)
ResNet 50	99.34%	96.19%
ResNet34	99.27%	96.18%
ResNet101	99.34%	96.12%
DenseNet201	99.30%	37.69%
Vgg16	97.49%	81.16%
Inceptiionv3	99.13%	95.12%

According to the experiment results, the ResNet50-UNet semantic segmentation model achieves an IoU score of 0.9934, with each epoch lasting 12 seconds, as indicated in Table 3. In comparison, ResNet34 achieves an IoU score of 0.9927, with epochs lasting around 8 seconds. ResNet101, despite sharing the same IoU score as ResNet50 at 0.9934, takes approximately 16 seconds per epoch. DenseNet201 requires about 15 seconds per epoch and achieves an IoU score of 0.9933. VGG16 completes each epoch in under 13 seconds with an IoU score of 0.9949, while InceptionV3 takes 16 seconds per epoch and achieves an IoU score of 0.9913 [31].

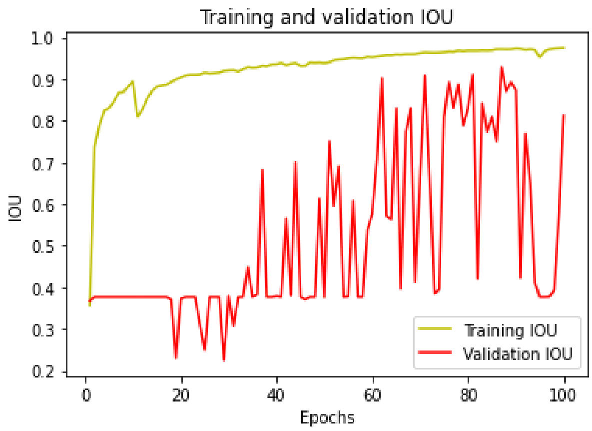
Based on these findings, the ResNet50-UNet model is chosen for its high IoU score and relatively quick convergence. ResNet architectures, characterized by residual blocks and skip connections, leverage the simplicity of skip connections inspired by the VGG neural network's 3x3 filters [32]. These skip connections allow ResNet models to address the vanishing gradient problem, ensuring adequate training across various depths. While deeper layers typically enhance model accuracy, excessively adding layers can lead to diminishing returns and slower training. ResNet50, with its 50 convolutional layers, balances depth with performance, making it a superior choice as a backbone for semantic segmentation compared to other CNN architectures [33].



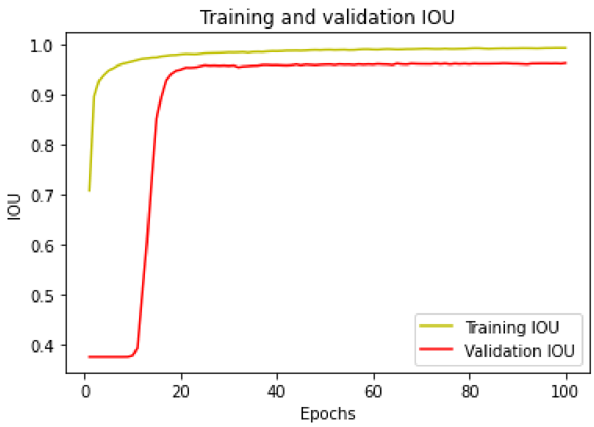
(a) ResNet50



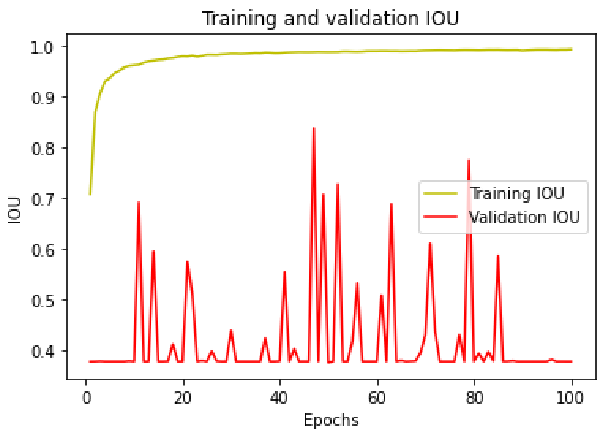
(b) ResNet101



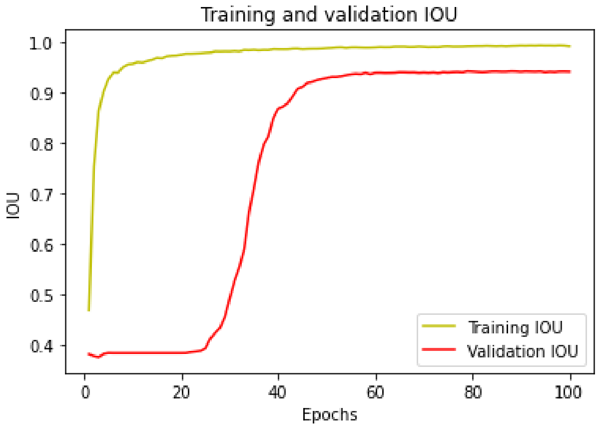
(c) VGG16



(d) ResNet34

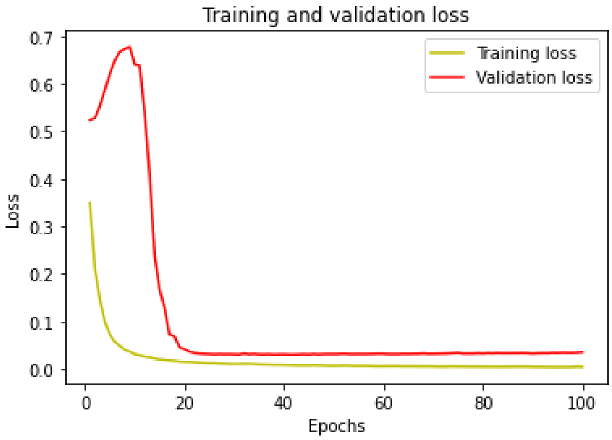


(e) denseNet201

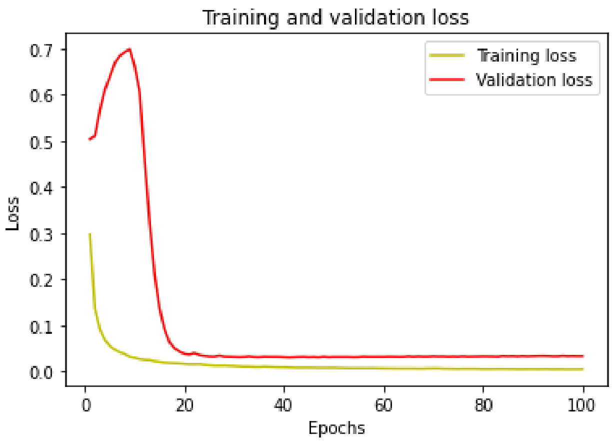


(f) InceptionV3

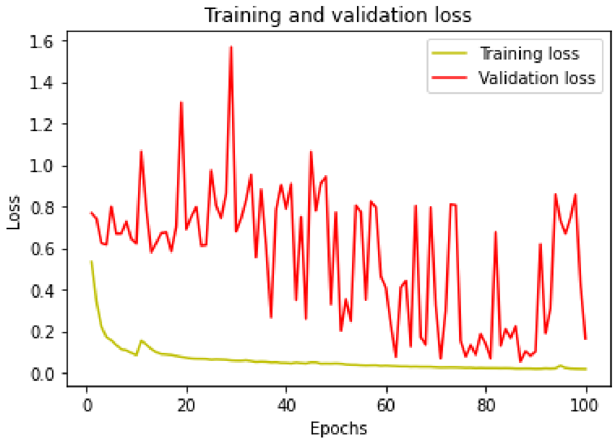
Figure 14(a,b,c,d,e,f). IoU Score for the Proposed Segmentation Model's Training and Validation



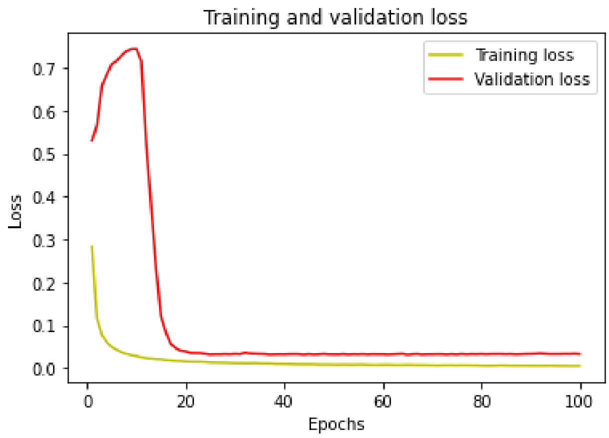
(a) ResNet50



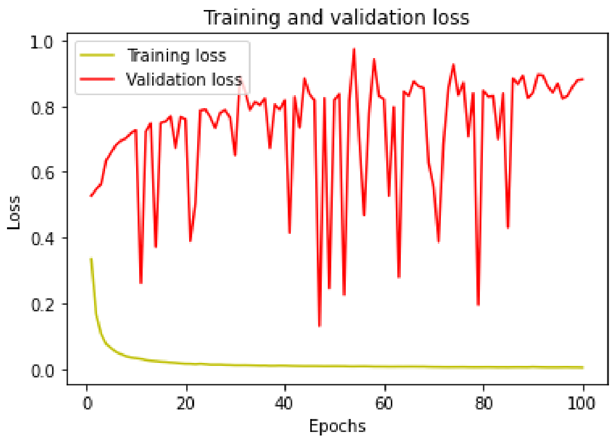
(b) ResNet101



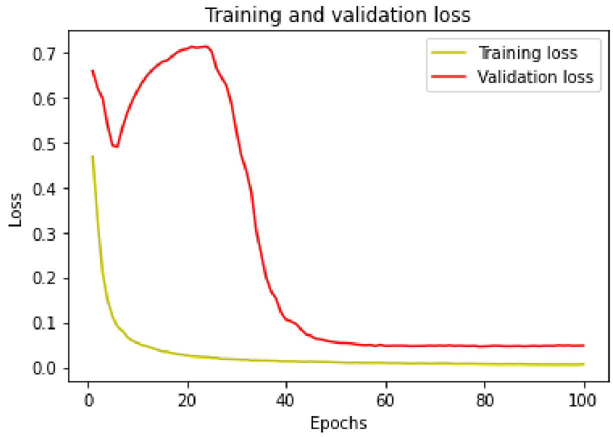
(c) VGG16



(d) ResNet34



(e) denseNet201



(f) InceptionV3

Figure 15 (a, b, c, d, e, f). The Suggested Segmentation Model's Training and Validation Loss

Figure 14 displays the training and validation IoU score evaluation across training epochs for the suggested segmented networks. Upon examining Figure 15, it becomes evident that DenseNet201 and VGG16 exhibit more scattered results for validation data than the other pre-trained CNN models. However, the remaining pre-trained CNN models perform similarly in the modified UNet architecture. In the final segment of the discussion, existing works are compared with the proposed model to highlight its strengths and contributions to the field [34].

E. Conclusion

The proposed system categorizes chest X-ray images into COVID-19 and standard categories, aiming to simplify the diagnostic process by leveraging readily available X-ray equipment. The primary goal of the method is to swiftly segment the COVID-19-affected region using a semantic approach, thereby reducing the time burden on radiologists [35]. To ensure accurate classification during categorization, authors developed a customized CNN model comprising four convolution blocks tailored to influence the input of the segmentation model. The input data for the classification and segmentation models were sourced from diverse and reliable datasets, meticulously labeled for accuracy. The segmentation model achieves a maximum mean IoU score of 96.19%, while the classification model attains a perfect accuracy of 100%. The variable infection pattern of COVID-19 poses challenges in diagnosis compared to other vi-rus-related disorders, necessitating a careful approach in utilizing chest X-ray images. While chest X-rays are considered more straightforward and cost-effective than computed tomography, manual determination of the afflicted lung section remains a limitation [36]. Future endeavors will focus on expanding the dataset with a wider variety of chest X-ray images and developing an automated radiology assistant and an API for segmentation and classification methods.

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