Optimizing Deep Convolutional Neural Network With Fine-Tuning and Data Augmentation For Covid-19 Prediction

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Abstract*—Since Corona virus disease 2019 (Covid-19) has been infecting people worldwide, it is important to detect Covid-19 at an earlier phase to fight against the pandemic. Pathogenic and laboratory testing are needed to determine whether someone is infected or not by Covid-19. However, this laboratory test is relatively time consuming and could produce significant false negative rates. This paper presents a study on Covid-19 detection by using deep learning algorithms aiming to predict and detect Covid-19. A set of chest X-ray images are used as the input datasets to prepare and to train the proposed model. In this study, a deep learning architecture (DLA) and optimisation strategies have been proposed and investigated to maintain the automated Covid-19 detection. A platform and a model model based on convolutional neural network (CNN) is introduced to extract the feature of X-ray images for feature learning phase in order to make the model suitable for the problem. Two strategies are applied to improve the performance of proposed model, i.e. Data augmentation and fine-tuning with deep-feature-based. A classifier are employed in order to enhance the performance of model. The experimental investigation was performed between the proposed work with the pre-trained DLAs, such as VGG16 and ResNet50. The results of this study affirm that the proposed model and VGG16 obtain better classification accuracy of 98% and 95% of sensitivity respectively.

***Index Terms*—Deep Learning, Convolutional Neural Network, Fine-Tuning, Data Augmentation, Covid-19, Detection, Prediction**

I. INTRODUCTION

Corona virus disease 2019 or Covid-19 is an extremely contagious epidemic which was first detected in December 2019 at Wuhan, China. Since then it contaminates people and is still spreading rapidly around the world. This disease caused by serious acute respiratory syndrome corona virus 2 [1]. The World Health Organization (WHO) has announced officially that the outbreak of Covid-19 is a global pandemic and becomes a public health emergency of International anxiety.

The common Covid-19 tests are called polymerase chain reaction (PCR) tests which look for the presence of severe acute respiratory syndrome corona virus-2 ribo nucleic acid (SARS-CoV-2 RNA). The diagnosis of Covid-19 depends on criteria as follows: epidemiological history, clinical symptoms, positive computed tomography (CT) scan, and also positive pathogenic testing. The clinical characteristics of Covid-19 include fever, dyspna, cough, pneumonia and respiratory symptoms [2]. However, the pathogenic laboratory testing might yield a significant false negative diagnosis [3].

The medical imaging usage for diagnostic assistance is regarded as a compelling confirmation of appraisal and documentation of many disorder and disease. High quality imaging enhances decision making and might minimize unnecessary medical procedures. For instance, surgical interventions might be evaded if medical imaging technology such as magnetic resonance imaging (MRI) and ultrasound are applicable.

Computer vision has long been used to automatically examine biomedical images. The recent coming of deep learning has succeeded many other machine learning methods, since it avoids the production of hand-engineering features, hence eliminating an analytical error from the process. In addition, the rapid inference speeds of GPU-accelerated fully networks, grants us scale analyses to unprecedented amounts of data.

In this paper, we focus on studying and optimizing of deep learning methods for Covid-19 detection based on medical images, especially chest X-ray (CXR) images. Because Covid-19 has long been enough a deadly disease and has no medicine till this paper is written. Covid-19 can be disastrous if we do not identify it at an earlier phase. In addition, detecting Covid-19 as quickly as possible could potentially save lives.

Inspired by the works [3], and in addition, the best of our knowledge that Indonesia does not have any platform or center research study which handles clinical data such as X-ray images, especially Covid-19 cases. Thus, motivated and inspired by the absence of a platform specifically designed by and for Indonesian, we propose a platform and a deep learning model called Universitas National Covid-19 Indonesia Network (U-CovID-Net) based on a convolutional neural network. The main objective is to provide a platform that can detect Covid-19 from X-ray imaging of patients in Indonesia. All the images will be collected in a centralized dataset for updating our model.

The rest of this paper is organized as follows. We present the related work in Section II and our proposed scheme in Section III. We observe the performance evaluation of our deep learning in Section IV. Finally, Section V concludes and gives some perspectives about future work.

II. RELATED WORK

Since the epidemic of corona virus in December 2019, many researchers have been working on this field, not only

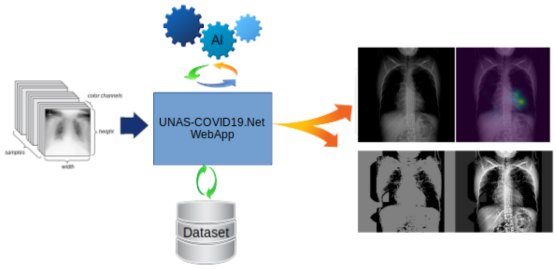


Fig. 1: The proposed platform

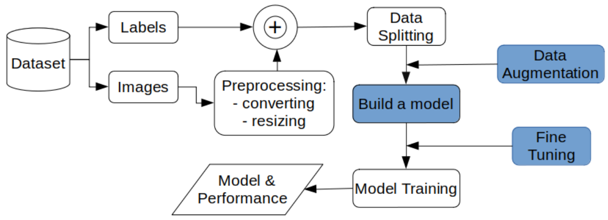


Fig. 2: The Flowchart of Proposed Transfer Learning

researchers from department of medicine, clinical, radiology, oncology but also from bio-informatics and computer science.

Artificial Intelligence (AI) can be as precise as humans, can save radiologists' time [4], and execute a diagnosis faster if we compare to the standard ones. Both Computed Tomography (CT) and X-rays scans can be used in this technology. The work in [5] has introduced a framework using built-in smartphone sensors such as cameras, microphone, humidity-sensor, temperature sensor, inertial sensors, colour-sensor, proximity, and wireless sensors for Covid-19 detection. However, their framework is still far from optimal results since the smartphone sensor factors might vary and have a low level of accuracy.

Some efforts are undertaken in this view. Forced by the need for faster examination and determination of radiography images, a number of AI based on machine learning have been introduced [6]–[10] and results have shown fairly promising in terms of accuracy in detecting Covid-19 by CT and CXR imaging. Additionally, [11] has been developed as an open source network designs to detect Covid-19 from X-ray images. It has about 13,000 images of patient cases, including Covid-19 and Non Covid-19 cases. However, the authors have stated that this Covid-Net is by no means a production-ready solution, thus in particular it needs an improvement.

A deep convolutional neural network based on Xception [12] architecture pre-trained model, called CoroNet [13], has been proposed to detect Covid-19 from X-ray images. Their model is a multi-class model which differentiate into 4 classes; Normal, Covid-19, Pneumonia-viral and Pneumonia-bacterial. The Authors in [14] proposed a model based on DarkNet [15] to detect and classify Covid-19 cases from X-ray images. Their proposed model achieved binary and 3-class classification accuracy of 98.08% and 87.02%, respectively on a dataset containing of 125 Covid-19, 500 normal and 500 Pneumonia chest X-ray images. More initiatives published recently some deep learning architectue (DLA) in order to diagnose Covid-19 from a set of CT or/and X-ray images, although they are still under peer-review.

III. Proposed Work

In this section we will provide our proposed work along with the architecture design, methodology, the network architecture, dataset preparation, and implementation. Figure 1 depicts the proposed deep learning platform for Covid-19 detection from X-ray images of patients in Indonesia which collected in a centralized dataset.

As can be seen in Figure 2, the proposed work includes the main deep learning processes, like preprocessing, data splitting, training, validation and testing. These phases will be explained in the next subsections.

A. Dataset and Model

A machine learning requires a training dataset which is used to train the model. Before delivering the dataset for training the model, thus the early step is collecting the specific data. We collect a dataset containing 349 chest X-ray images of Covid-19 and 397 of Non Covid-19. These images are collected from [16]. We admit that the dataset is limited due to the lack of benchmark datasets of Covid-19 especially in chest X-rays images. We also collected another images from the other repositories [11]. Hence, we have now a dataset which contain 513 chest X-rays of Covid-19 and 619 of Non Covid-19. Although, this number of dataset is inadequate to validate the model. This frequently happens to have a limited data to resolve a problem. Gathering a big dataset could be prohibitively timely and costly, especially X-rays images. As a consequence, there is often no choice but to work with a limited dataset, and trying to achieve as accurate predictions as possible. We initiate naively training a small network, without any regularization, on the X-rays images as training samples in order to set a preliminary study. While this scheme produces a classification accuracy of overfitting, then we applied data augmentation method for mitigating this issue in order to improve the network and reach a better accuracy. In addition, as can be seen in Figure 2, we also applied fine-tuning to our pretrained network to get an optimal accuracy. These strategies are designed in order to tackle the problem of performing image classification on a small dataset on samples of images used in this study.

Prior to the study, our proposed model was trained by using the public Covid-19 image dataset [16], [17] which consist of labelled images, Covid-19 and Non Covid-19. Nevertheless, we have been collecting of 168 X-rays images from National Brain Center Hospital and UKI Hospital, Jakarta since October 2020. All X-ray images are defined as Covid-19 positive cases by the doctors from two hospitals. Therefore, we used those images for validation dataset.

As we have already know that images, in general, usually have three dimensions: width, height, and color depth. Before being fed into the neural network, since in this case the data is images with different formats, thus the data should be formatted into a properly format, because the original data is not formatted properly for the neural network. Therefore we require a data preprocessing phase. For getting it into the neural network, we perform some procedures as follows; firstly, scan the images files and then interpret them into RGB grids of pixels; secondly, transform them into floating-point and finally, rescale the pixel values into [0,1] interval, this is due to neural networks handle with small input values.

In data preparation phase such as pixel scaling and image resizing steps; it must be employed constantly to all datasets which cooperate with the model. We performed this pre-processing strategy in order to eliminate the variance and bias in data. Because models with big variance and small bias commonly overfit the data, whilst models with small variance and big bias underfit the data.

The next operation is reshaping image which preprocessing the digits data before providing it into the neuron network. Reshaping images represents reorganize its rows and columns to match a target format. Naturally, the reshaped image admits the same total number of coefficients as the initial one. Regardless of reshaping phase will be very pragmatic for the next phases in deep learning procedure such as transfer learning and fine-tuning processes which we will explain later.

Basically, there are some lung syndromes which refers to many disorder affecting the lungs. However, since we focus on Covid-19 detection, then in this study, we classify lung diseases into 2 classifications; Covid-19 positive and Covid-19 Negative (Non Covid-19). The X-ray images dataset (X, Y) where X refers to set of N input data, each image has l length $\times$ w width and Y has two classes, Y = $\{y/y \ \epsilon \{$Covid-19; Non Covid-19$\}\}$. However, the classification of images has been done and confirmed by experts. The dataset then divided into train and test, as can be seen in Table I.

TABLE I: Classification Number of Images from Covid-19 Dataset

Dataset	Covid-19	Non Covid-19	Total
Train	466	542	1008
Test	210	262	472
Total	676	804	1480

In order to eliminate bias data, dataset splitting is a necessity for deep learning process. The dataset classified into train and test, where 80% of dataset is for training set and the remaining 20% of dataset for testing set. The selection of this percentages has been demonstrated its efficient in many works.

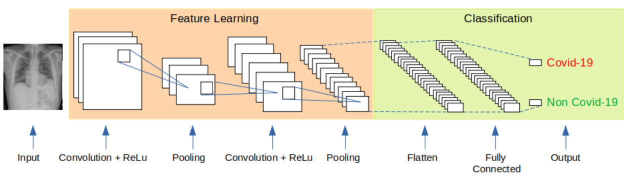


Fig. 3: Structure of proposed DLA CNN-based

In our case, we are attacking a binary-classification problem, then the model network should end with a single unit where this unit will encode the probability which the network is recognize at one class (Covid-19) or the other (Non Covid-19). As depicted in Figure 3, the general design of a convolutional neuron network (CNN) model has a feature extractor in the first phase and then a classification phase. Our deep learning architecture is designed based on CNN scheme which consists of 4 transposed convolutional layers, 3 rectified linear unit (ReLU) layers, 3 pooling layers, and softmax layer, as shown in Figure 4. An image will convolved with filters, then applied max pooling and at the end of this process will obtained the recognizable features.

Generally, the transposed convolutional and ReLU layers are the feature learning stage. These layers also called as freeze layers. The few last layers, the unfreeze layers, are the classifier, also called fine-tuning stage. The ReLu activation function converts the value results of a neuron, by $y = max(0, x)$, and prevents any negative values to 0, and positive values remain unaffected. The result of this transformation is applied as the output of the continuing layer, and as input to the next layer. Additionally, all the convolutional layers apply the same size of 224 $\times$ 224 pixel with 64 filters for each layer.

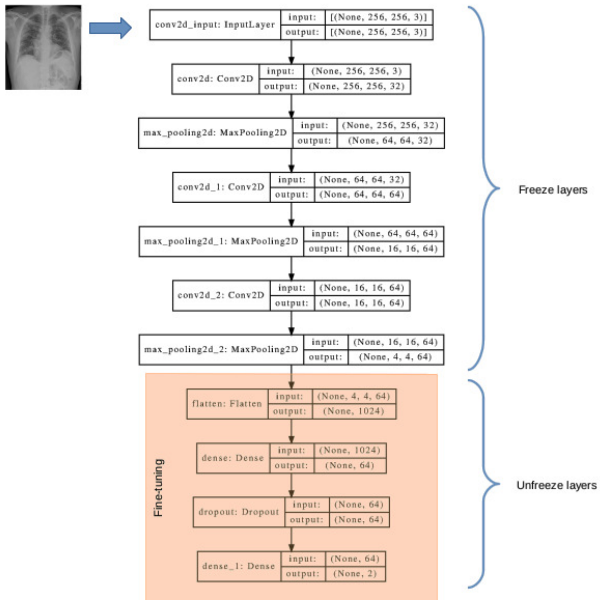


Fig. 4: The structure of layers for the proposed model

Feature extraction phase improves the accuracy of a model by extracting features from the images data. This phase decreases the dimensionality of image data by eliminating the redundant data. As consequence, it increases the training speed and attains new generated features by performing the consolidations and/or transformations of the original feature set. The feature extraction in our model is executed automatically since CNN is a deep learning model which implement certain feature extraction from its input data.

The model training appears within a training loop, which works as follows; first, designate a batch of training samples x and corresponding targets y; second, introduce the network model on x in order to achieve predictions y_pred; third, calculate the loss of the network on the batch, a measure of the mismatch between y_pred and y; fourth, renew all weights of the network.

This process will eventually end up with a network model which admit a very small loss on the training data: a small inaccuracy between predictions y_pred and expected targets y.

B. Deep Transfer Learning

The common problem of image classification is regularly presented as follows:

- There are N potential image classes. A set $\{0, 1, ..., N-1\}$ determines the labels of the diverse classes. In our case, for example: 1 for Covid-19 class and 0 for Non Covid-19 class.
- We have a set of K input images: $\{Xi\}$ i ϵ $\{1, ..., K\}$.
- The classes of K images are well-known in advance: every image Xi is labeled by $yi\ \epsilon \{0, 1, ..., N-1\}$.
- The purpose is to properly classify a new image, whose class we do not recognize: we need to identify the right label.

From a deep learning perspective, transfer learning mechanism can resolve the image classification issue. Literally, some state-of-the-art results in image classification [18], [19], [20] are based on transfer learning methods.

There are two different approaches in transfer learning; develop model approach and pre-trained model approach. However, in our case, we used the develop model approach. Therefore, we select a related predictive modeling problem where present some relations between input data, output data and/or image learned under the mapping process from input data to output data. Then, we establish a source model for the prior phase to assure that some feature learning has been realized. Later, we reuse the model which means that the source model can be recycled as the basis for a model on the next assignment of interest. Next action is fine-tuning our model, due to the model requires to be regulated on the input and output data.

C. Data Augmentation and Fine-Tuning

Having a large dataset is essential for a deep learning process, particularly for its performance. Training a deep learning model on a large dataset could produce an optimal model, and the data augmentation method might create image variations which allow an improvement on the ability of the fit model to generalize what model has learned to new images that never seen before. In our proposed scheme, we employed image data augmentation only to the training dataset, and not to the validation or test dataset. Additionally, data augmentation method can increase the dataset images larger than the original one. we could augment image data by flipping the images, either horizontally or vertically. We use some of common data augmentation techniques, such as rotation, zoom, horizontal flip and color variations. We rotate the image of 15 degrees, zoom in by 10% maximum, and fill in the missing pixels with the nearest filled value.

Fine-tuning is a technique widely used for model reuse and as complementary to feature extraction. This method resides of unfreezing some of the top or head layers of a frozen $basemodel$ for future extraction and mutually training both the freshly added layer of the network, in order to make the network more relevant for the problem. The purpose of fine-tuning will be as follows: Firstly, we will provide the neural network the training data, $train\_images$ and $train\_labels$. The neural network will then find out to correlate images and labels. Finally, we will ask the neural network to generate predictions for $test\_images$, and we will validate whether these predictions fit in the labels from $test\_labels$.

The proposed model applied the softmax activation function which is used to define the probability distribution of a set of numbers within an input vector. The output of softmax activation function is a vector in which its set of values shows the probability of an instance of a class. In addition, we also applied optimizer scheme, the Adam [21] with momentum value of 0.9 is used in our approach. This optimizer updates weights parameters at training iteration and fine-tuning phase. We employ dropout layer in order to decide the best training steps. At training step, the proposed scheme produces a batch of images called the training batch. The Model is trained with learning rate of 0.0001. Nonetheless, the learning rate is a hyperparameter which conducts how much to adjust the model in response to the predicted error each time the model weights are renewed.

D. Detection and Prediction

The major issue for Covid-19 prediction based on X-ray image is that the number of objects in the foreground might differ across images. The CNN model shown in Figure 4 performs a solution to the classification issues for our specified object detection problem. Thereafter using CNN layers to extract feature maps and the region proposal network generates many windows which are prone to enclose an object. The model then recovers the feature maps within each window, resizes them into defined or fixed sizes, named as region of interest (RoI) pooling, and then predicts the class probability.

Every pixel resides to a appropriate class, either background or RoI, which are defined by the same color. The proposed scheme uses a simple semantic segmentation with a threshold value where the pixel values will be contrasting for the objects and the background if there's a sharp contrast among them. The pixel values lowering inferior or superior the threshold value can be labelled as an object or a background respectively.

As a proof-of-concept, a web application is developed by using Flask platform based on Python, hoping that it would be helpful for researchers, doctors or paramedics. The purpose of this web application is to find out whatever our proposed model could classify, detect and predict an X-ray image that never seen before. In other words, it was implemented to demonstrate the detection and prediction functions of Covid-19, as can be seen in Figure 5.

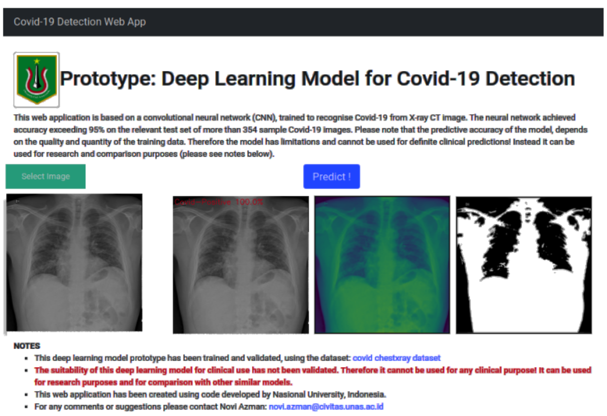


Fig. 5: Prototype Web Application

IV. Performance Evaluation and Comparison

This section provides our investigation and comparison between our proposed scheme, called U-CovID-Net, with other models such as VGG16 [18] and ResNet50 [19].

The proposed model is designed by using Keras, Tensorflow in Python environment. We conducted all simulation on a computer server equipped by an Intel socket 16 core hyperthreads, 64 GB of RAM, and a graphics processing units. We measured and compared the classification performance of models by using some metrics as follows:

- *Accuracy*. This is a metric for evaluating classification models, calculated as the fraction of number of correct prediction on total number of predictions.
- *Sensitivity* (*Recall*). This metric measures the rate of negatives which are correctly detected.
- *Specificity*. This indicator is defined as the proportion of actual negatives, which obtained predicted as the negative or in other words true negative rate.
- *F-score*. F-score is a measure of a model's accuracy on a dataset and is used to assess binary classification schemes, which analyze images into 'Covid-19' or 'Non Covid-19'. F-score combines the recall and precision of the model, and determines the harmonic mean of the model's recall and precision.
- *Area Under Curve (AUC)*. This indicator evaluates the performance of the classifier. AUC represents the degree of separability. It defines how much the model is efficient of distinguishing between classes. Higher the AUC means the better the model at distinguishing images between 'Covid-19' and 'Non Covid-19.'
- *Confusion Matrix*. It provides a recap of prediction results on a classification issue, and demonstrates the approaches in which the classification model is confused during the predictions. The number of true and false predictions are outlined with count values and broken down by respectively class.

TABLE II: Comparison Results of models training on the dataset

Model	Accuracy	Sensitivity	Specificity	F-Score	AUC
U-CovID-Net	0.98	0.95	1.00	0.98	0.89
ResNet50	0.85	0.67	0.97	0.92	0.25
VGG16	0.98	0.95	1.00	0.98	0.99

The performance comparison results of models are described in Table 2. In terms of *accuracy*, the proposed scheme, U-CovID-Net, achieved 98% which is equal to VGG16, and ResNet50 obtained 85%. It means that the proposed model has 98% accuracy classifying X-ray images as Covid-19 or Non Covid-19.

We analyzed the *sensitivity* (recall) of the trained models, we notice that the enhancement in *sensitivity* as a result of utilization of data augmentation and fine-tuning approaches, and is consistently along with *specificity*. The proposed model achieved 95% of *sensitivity* and 100% of *specificity* in a way that the proposed scheme is good at predicting Covid-19 or Non Covid-19. However, *sensitivity* of ResNet50 is the lowest which means that Covid-19 cannot be detected by the model even when Non Covid-19 can be detected correctly. As consequence, it can lead to a higher false negative rate, where patients with Covid-19 (positive) predicted as Non Covid-19 (negative).

In terms of *F-score*, U-CovID-Net obtained an F-score of 98% which corresponded to VGG16 model. Therefore, we can claim that U-CovID-Net and VGG16 have a great precision and sensitivity. However, in this study, ResNet50 achieved only 67% of F-score meaning that it has lower precision and sensitivity.

In terms of validation on training *loss* and *accuracy*, as seen in Figure 6, in general, U-CovID-Net does not underfit as much as ResNet50. At the basic level, the loss curve demonstrates how good or bad a given model is at classifying. As can be seen that U-CovID-Net has lesser *loss* which is almost identical to VGG16 model. It means that both U-CovID-Net and VGG16 have a good classifier. In addition, from the epoch of 0 till around 60, validation loss of U-CovID-Net is lower than the training loss. A quick observation, this phenomenon is due to regularization applied during the training phase, but not during the validation or testing phase. In addition, the training loss is measured at the time of any epoch while validation loss is measured after each epoch. Apparently, it is feasible to enhance the model by increasing the number of epochs and batch size. However, ResNet50 suffers from the start of training, as depicted in Figure 6(b).

In terms of the *area under the curve* (AUC), the comparison results obtained of the models are given in Figure 7. We found that VGG16 has AUC near to 1, and so do U-CovID-Net. This means that both of them have best measure in distinguishing between Covid-19 and Non Covid-19 classes. In contrast, ResNet50 is likely to be a poor model since it has AUC near to the 0 which means that ResNet50 has bad measure of classification, or in other words it has no class separation efficiency.

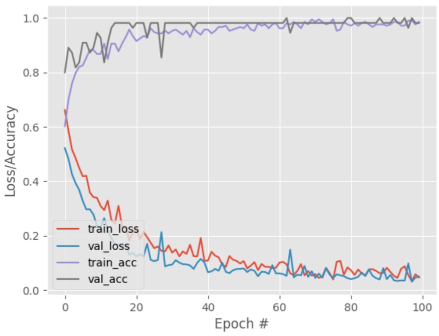
Table III demonstrates the comparison of *confusion matrix* between the proposed model (U-CovID-Net), ResNet50 and VGG16. We found that U-CovID-Net outperforms ResNet50 and attains the same results as VGG16. U-CovID-Net admits *true positive* (TP) of 20, which means that 20 positive Covid-19 images were accurately classified and 1 image were falsely classified as belonging to the positive class. These results are corresponding to VGG16. Moreover, U-CovID-Net admits *true negative* (TN) of 34, which means that 34 negative Covid-19 images were accurately classified. Despite, ResNet50 admits 14 positive Covid-19 images were correctly and 7 images were falsely classified. Even though, ResNet50 can detect correctly of 33 of 34 negative Covid-19 images.

TABLE III: Confusion Matrix

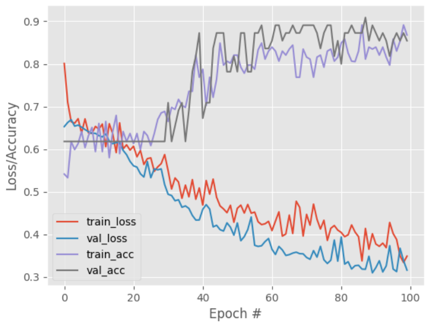
	U-CovID-Net		ResNet50		VGG16	
	True	False	True	False	True	False
Positive	20	1	14	7	20	1
Negative	34	0	33	1	34	0

V. Conclusions

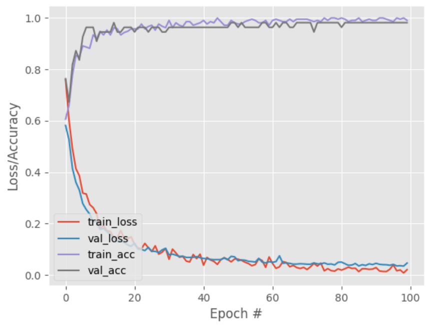
As Covid-19 cases are still rising day-to-day, many researchers around the world are trying to find a way to cope with this health problems. We proposed a deep learning architecture based on convolutional neural network which



(a) U-CovID-Net

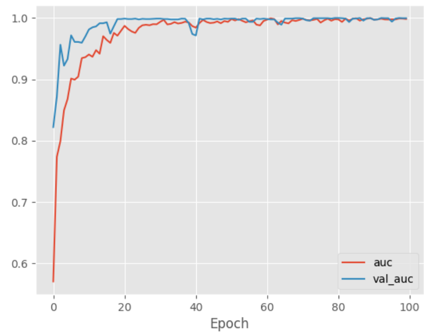


(b) ResNet50

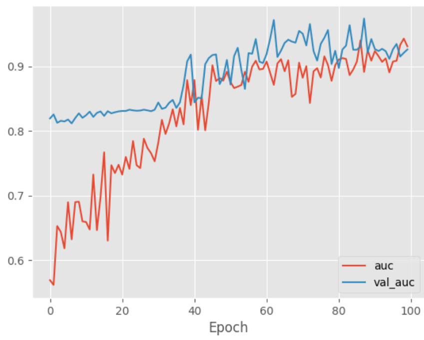


(c) VGG16

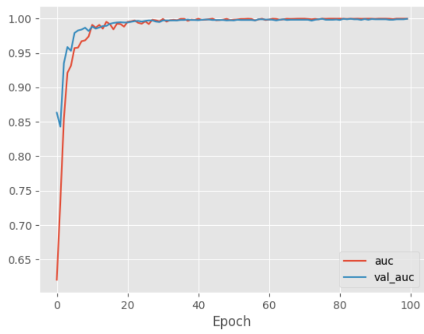
Fig. 6: Training Loss and Accuracy Comparison



(a) U-CovID-Net



(b) ResNet50



(c) VGG16

Fig. 7: AUC Comparison

designed to detect or identity Covid-19 using chest X-ray images. The proposed model, U-CovID-Net, has been trained, tested and compared with some other pre-trained models, such as VGG16 and ResNet50. We also defined the fine-tuning and data augmentation strategies to reuse the pre-trained model in order to enhance the performance of model. Moreover, we developed a web based application in order to find out the performance of our proposed model on new images that never seen during the training phase. The simulation performance has shown that our proposed work has a comparable result with VGG16 but outperforms ResNet50, especially in terms of accuracy and sensitivity. However, this work is certainly not designed for clinical purpose. We hope that this study will continue in order to improve the model. Some future works that might be undertaken are adding more chest X-ray images into the dataset and continuing to enhance sensitivity as well as improve the proposed work for predicting and detecting not only Covid-19, but also other lung infections or diseases.

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