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RESEARCH ARTICLE

CLASSIFICATION OF COVID-19 OMICRON VARIANT USING HYBRID DEEP TRANSFER LEARNING BASED ON X-RAY CHEST IMAGES

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Abstract
In 2019, the first case of COVID-19 was announced in China in Wuhan Province. Which led to the panic of the world and the declaration of a state of extreme emergency by the World Health Organization. Given that the world was in a state of crisis and closure, the use of deep learning technology provides speed and accuracy in diagnosing disease through chest images. Therefore, in this study, the dental X-Ray images of people infected with the omicron strain of Covid-19 virus were classified in comparison with a group of healthy people. In this study, we used 4 types of pre-trained deep learning algorithms in two ways, the first is using cross-validation and the second is the hybrid method by extracting the features from the models and then applying them to two types of deep learning algorithms (SVM and KNN). Accuracy results were obtained in the first scenario with a percentage of 94%, while in the second scenario, the accuracy results in the SVM classifier are higher than KNN with a difference of 5%, which is 92%. We also compared studies that used X-Ray images to classify COVID-19, as our results showed a clear superiority compared to other studies.

Keywords: Classification, CNN, SVM, KNN, Deep Transfer Learning, Feature Extraction

1. INTRODUCTION

Coronavirus was first detected in Wuhan, China in December 2019. The latest version of virus is a member of the "Coronaviruses family," which includes subgroups such as alpha, beta, gamma, and delta. In February 2020, the World Health Organization (WHO) designated the new version as "Severe Acute Respiratory Syndrome Coronavirus 2" (SARS-CoV-2) COVID-19 (Khan, Shah et al. 2020, Lu, Stratton et al. 2020, Organization 2020, Zhu, Zhang et al. 2020). Covid-19 rapidly prevalence over the world, prompting WHO to declare a Global Pandemic on March 11, 2020, (Gorbalenya, Baker et al. 2020, Wu, Zhao et al. 2020, Zhou, Yang et al. 2020). Covid-19 mainly impacts the upper and lower respiratory tracts, and the virus is potentially lethal in persons with weakened immune systems (Lancet 2020, Razai, Doerholt et al. 2020). The Covid-19 most common contagious routes from person to person include physical contact, breathing, coughing, and sneezing (Al-Jumaili, Al-Azzawi et al. 2021, Al-Jumaili, Duru et al. 2021, Al-jumaili, Duru et al. 2022). Fever, headache, sore throat, and cough are the most prevalent Covid-19 symptoms (Guan, Ni et al. 2020, Huang, Wang et al. 2020, Li, Guan et al. 2020, Singhal 2020).

Deep learning using convolutional neural networks has recently been used to classify medical modality. X-Ray scans is the one of highly utilized forms of image for detecting Covid-19 using deep learning methodologies. These pictures are being utilized to diagnose problems caused by Covid-19 infection prior to therapy (Baltruschat, Nickisch et al. 2019, Zu, Jiang et al. 2020). GoogleNet (Szegedy, Liu et al. 2015), Xception (Chollet 2017), U-Net (Ronneberger, Fischer et al. 2015),AlexNet (Krizhevsky, Sutskever et al. 2012), VGG19 (Simonyan and Zisserman 2014), RestNet50 (He, Zhang et al. 2016), MobileNets (Howard, Zhu et al. 2017), DenseNet (Huang, Liu et al. 2017), and SqueezeNet (Iandola, Han et al. 2016) are examples of pre-trained deep learning models employed in the identification of Covid-19 in the current literature.

To diagnose various illnesses, several deep learning approaches are presented utilizing radiography and computed tomography datasets. In the (Liu, Cao et al. 2017)study created an improved CNN model that detects tuberculosis detection (TB) using an image dataset. Moreover, random sampling was utilized in the model to solve the problem of an imbalanced dataset, with the greatest accuracy being 85.68%. In (Dong, Pan et al. 2017), utilized an Xray dataset with various kinds of pre-trained models, involving ResNet, AlexNet, and VGG16. They used a pre-trained model with over 16000 photos as input for models. The binary classification achieved the highest precision of 82%, while the others had an accuracy of more than 90%. In (Chouhan, Singh et al. 2020),reported a 96% accuracy for pneumonia identification from X-Ray pictures after implementing an ensemble of AlexNet, DenseNet121, GoogLeNet, and ResNet18 with deep transfer learning. In (Hemdan, Shouman et al. 2020), created a novel CNN model called the COVIDX-Net and compared seven different pre-trained deep learning models: VGG19, DenseNet121, InceptionV3, ResNetV2, Inception-ResNet-V2, Xception, and MobileNetV2. In (Khan, Shah et al. 2020), introduced a new CNN model called CoroNe, that uses the Xception architecture. The CoroNet was trained using an X-Ray image collection acquired from several publicly available sites for both Covid-19 and pneumonia. In (Wang, Lin et al. 2020), created COVID-Net, a novel CNN model that be able to identify the Covid-19 virus using publicly accessible X-Ray imaging datasets. In (Mahmud, Rahman et al. 2020), CovXNets was develop a new CNN model to implement several forms of classification for detecting COVID/normal/Viral/Bacterial pneumonia cases.

The purpose of this study is to explore the classification accuracy of Covid-19 impacted Chast X-Ray images for two types Covid-19 with Omicron variant and healthy. For this problem, four types of pre-trained CNN models used in order to classify these two classes. As a novelty, in the classification section, we applied two scenarios, first is by implement Cross-Validation. And second, features deduced from the last Convolutional layer to decrease the dimension of the input to two types of classifiers K-Nearest Neighbour (KNN) and Support Vectors Machine (SVM). Additionally, we adopted SVM to compare the classification performance of the KNN.

2. DATASET

Since Covid-19 is a novel condition, and the datasets are not immediately available and appropriate to be used for deep learning. As a result, we sought to identify a dataset that could be made freely available. We gathered Chest X-Ray images from Kaggle. At the moment of this present study, the database comprised of the positive case is 111, while negative is 230 and the number of the images is 230, the total images number of the images are 341 X-Ray with a size of 512×512px JPG. Figure 1 illustrates the sample of the image for both classes.

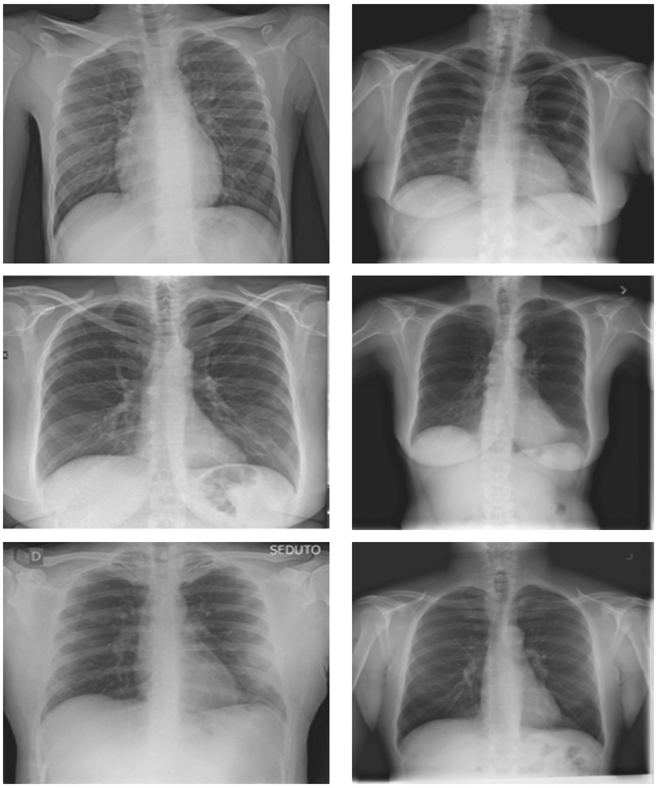


Figure 1. Sample images that were used in the study

3. METHODOLOGY

We choose many kinds of pre-trained models, which are namely ((GoogleNet, AlexNet, VGG16, MobileNet-V2, ResNet50, DenseNet201, ResNet18, Xception). We conducted out all by using MATLAB (R2021a) and workstations (GPU NVIDIA GeForce GTX 3080 8GB, Intel CPU i7-11800 @2.30HZ, RAM 32 GB). The last completely layer has been replaced with a new one in order to classify only binary classes. The InitialLearnRate set at 0.00001, the Validationfrequency to 30, MiniBatchSize to 20, and the MaxEpochs to 40 for-all pre-trained models. We have applied a Stochastic Gradient Descent with Momentum (SGDM) optimizer. Order to prevent over-fitting, we utilized a 5-fold cross-validation approach. The dataset was divided among training and testing with ratio is 70:30 ratio. For each of the five portions. The average outcomes from five graded folds of testing results utilized to establish to check the final performances of each model.

4. EVALUATION METRICS

Using the confusion matrix results from the validation tests, we employed several sorts of performance assessment criteria to examine every model independently. The confusion matrix data were utilized as input to validate measures such as Accuracy, Sensitivity, Specificity, Precision, Negative Predictive Value (NPV), F1-Score, and Matthew's correlation coefficient (MCC), as well as the receiver operating characteristic curve. As demonstrated in Eq. 1, accuracy is determined as the number of true predictions from the entire dataset. The sensitivity is computed by subtracting the number of true positive (TP) predictions from the overall of positive predictions Eq. 2. The true negative (TN) prediction produced from all over the negatives in the dataset so-called true negative rate (TNR) Eq. 3.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{2}$$

$$Specificity = \frac{TN}{TN + FN} \tag{3}$$

Eq. 4 illustrates the precision (Positive Predictive Value (PPV)) as a proportion of true positive predictions to the overall number of positive predictions. While the negative predictive value (NPV) is provided in Eq. 5, The harmonic mean, often called the F1-score, will be calculated based on accuracy and sensitivity, as stated in the Eq. 6. In the end, the correction coefficient is calculated through the Matthew's correlation coefficient range (MCC) from Eq. 7.

$$precision(PPV) = \frac{TP}{TP + Fp} \tag{4}$$

$$\text{negative predictive value } (NPV) = \frac{TN}{TN + FN} \tag{5}$$

$$F1 - score = \frac{2 * TP}{2 * TP + FP + FN} \tag{6}$$

$$MCC = \frac{(TP * TN) - (FP * FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{7}$$

5. RESULTS

In this section, we used four diverse types of CNN models to classify Omicron virus. We also used, two scenarios of classifiers: the first on using SoftMax classifiers which is the standard one used in the architecture of these models, second is a hybrid technique based on extract the features from CNN models and applying them to the supervised machine learning classifiers, namely (support vector machine (SVM) and K-nearest neighbors algorithm (KNN)).

For the first scenario, as shown in the Figure 2, the result that we achieved from the confusion matrix used to calculate the result and check the performance of each model with different scenarios is shown. It is clear that the ResNet50 obtained the highest results for all evaluation matrices, while the ResNet18 also showed good results compared with two other types of CNN models. All the results shown in the Table 1, which illustrate the performance of all models that applied in this study.

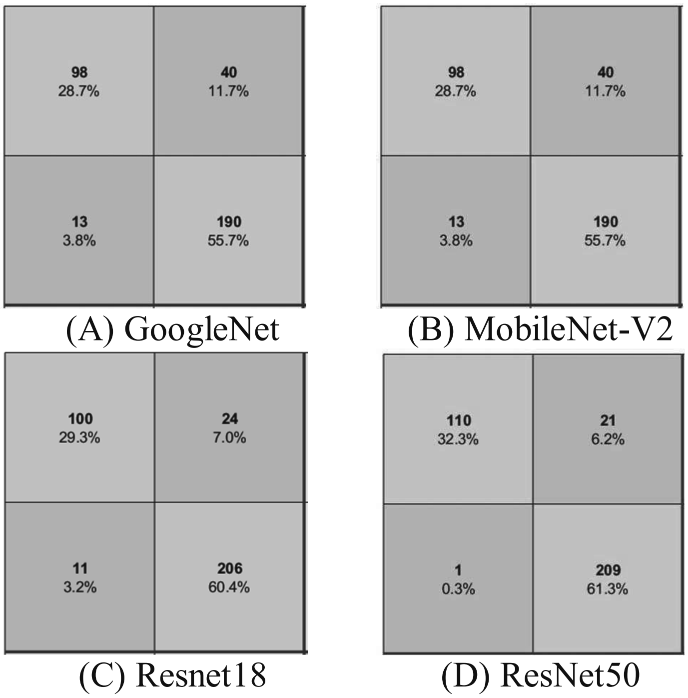


Figure 2. Result of confusion matrix by using SoftMax classifier

Table 1. performance of CNN models using SoftMax Classifier

Classifier Types	Dataset	Model	Evaluation Metrics						
			Accuracy	Sensitivity	Specificity	Precision	NPV	F1-Score	MCC
SoftMax	X-Ray	GoogleNet	0.84	0.71	0.93	0.88	0.82	0.78	0.67
		MobileNet-V2	0.71	0.56	0.79	0.57	0.78	0.56	0.35
		ResNet50	**0.94**	**0.84**	**1.00**	**0.99**	**0.91**	**0.91**	**0.87**
		ResNet18	0.90	0.81	0.95	0.90	0.90	0.85	0.78

In the second scenario, we applied the hybrid method by extracting features from a fully connected layer and using them as inputs to SVM and KNN. Figure 3 shows the results obtained from the confusion matrix using the CEPSIB algorithm, and Figure 4 shows the results of the confusion matrix obtained using KNN.

As shown in these two types, the results obtained using the SVM algorithms were also good and close to the results in the first scenario, where the advantages that were obtained using the ResNet18 algorithm had the highest results compared to the other advantages that were applied to the same algorithm which illustrate in the Table 2.

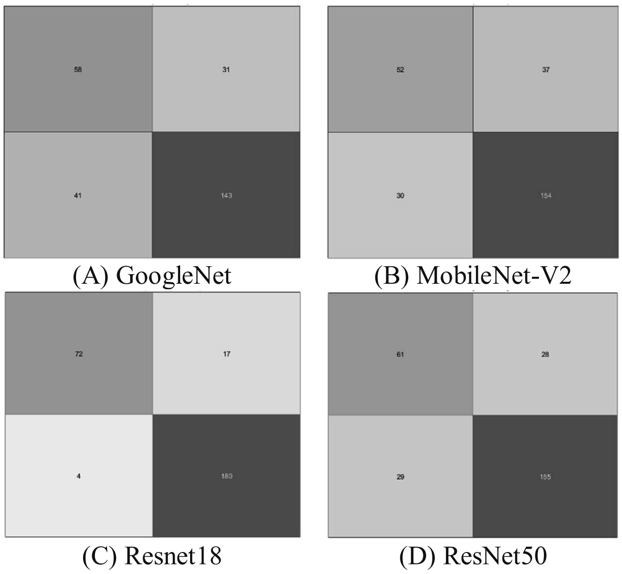
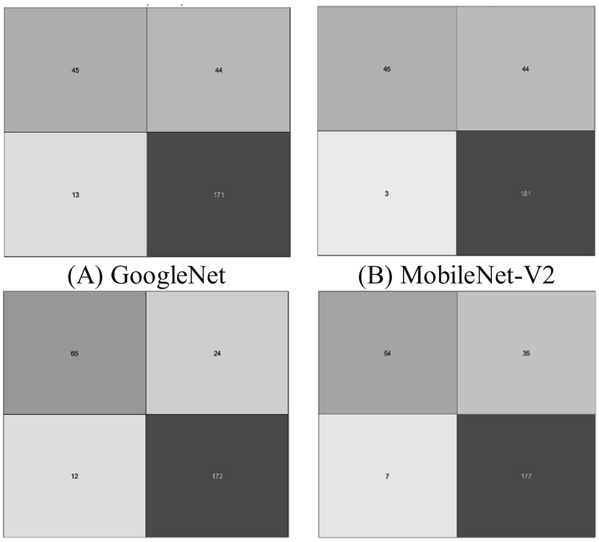


Figure 3. Result of confusion matrix by using feature extracted form CNN models and applied to SVM classifier

Table 2. Performance of CNN models using SVM Classifier

Classifier Types	Dataset	Model	Evaluation Metrics						
			Accuracy	Sensitivity	Specificity	Precision	NPV	F1-Score	MCC
SVM	X-Ray	GoogleNet	0.74	0.65	0.78	0.59	0.82	0.62	0.42
		MobileNet-V2	0.75	0.58	0.84	0.63	0.81	0.61	0.43
		ResNet50	0.79	0.69	0.84	0.68	0.85	0.68	0.53
		ResNet18	**0.92**	**0.81**	**0.98**	**0.95**	**0.91**	**0.87**	**0.82**

Table 3 shows the results obtained by using the KNN algorithm, which shows that again the highest result was obtained using the features obtained by Resent 18, although the results are less than the previous algorithm (SVM), but it is clear that the classification of the virus Omicron is possible using the two methods that have been suggested using chest X-Ray.



(A) GoogleNet (B) MobileNet-V2

(C) Resnet18 (D) ResNet50

Figure 4. Result of confusion matrix by using feature extracted form CNN models and applied to KNN classifier

Table 3. performance of CNN models using KNN Classifier

Classifier Types	Dataset	Model	Evaluation Metrics						
			Accuracy	Sensitivity	Specificity	Precision	NPV	F1-Score	MCC
KNN	X-Ray	GoogleNet	0.79	0.51	0.93	0.78	0.80	0.61	0.50
		MobileNet-V2	0.83	0.51	0.98	0.94	0.80	0.66	0.60
		ResNet50	0.85	0.61	0.96	0.89	0.83	0.72	0.64
		ResNet18	**0.87**	**0.73**	**0.93**	**0.84**	**0.88**	**0.78**	**0.69**

Finally, we compared our findings with other pioneering work on COVID-19 classification of X-ray datasets recently published in the literature. As shown in Table 5, our results clearly outperformed the studies in which different techniques were used for classification, as the best accuracy results obtained are shown in bold.

Table 4. Comparison of state-of-the-art deep learning model results with our proposed methods

Ref.	Dataset	Image Types	DL Model	Layers Num.	Classifier	Accuracy %
(Hemdan, Shouman et al. 2020)	Cohens GitHub	X-Ray	COVIDX-Net	Standard	SoftMax	90
(Khan, Shah et al. 2020)	Different Datasets	X-Ray	Coronet	Modified	SoftMax	89.5
(Basu, Mitra et al. 2020)	Different Datasets	X-Ray	CNN	12	Grad-CAM	90.1
(Khobahi, Agarwal et al. 2020)	COVIDx	X-Ray	Coronet	2 separates (FPAE) + ResNet18	SoftMax	93.50
(El Asnaoui and Chawki 2020)	Different Datasets	X-Ray, CT-scan	Inception-ResNetV2	Standard	MLP Classifier	92.18
(Hall, Paul et al. 2020)	Different Datasets	X-Ray	Resnet50, VGG16	Modified	Snapshot Ensembles	91.24
(Rahimzadeh and Attar 2020)	Different Datasets	X-Ray	Xception, ResNet50V2	Modified	SoftMax	91.04
(Goodwin, Jaskolski et al. 2020)	Different Datasets	X-Ray	mobilenetv2, Densenet121, Resnet (18,50,101,152), Densenet (169,201), Resnext50, wideresnet (50,101) Rresnext101	Modified	SoftMax	89.4
(Khalifa, Smarandache et al. 2021)	Different Datasets	X-Ray	GoogleNet	Standard	SoftMax	73.12
(Moutounet-Cartan 2020)	Different Datasets	X-Ray	VGG16	Modified	SoftMax	84.1
present	**Kaggle**	**X-Ray**	**ResNet50**	**Modified**	**SoftMax**	**94**

6. CONCLUSION

The classification of diseases is one of the most important pioneering topics in the current era because of its direct impact on the speed of diagnosis and the high accuracy in determining the type of disease. The deep learning algorithm has been used in many diseases for classification, and this indicates the positivity offered by deep learning techniques and the high impact on classification.

In this study, the Omicron virus, which is the new strain of Corona virus, was classified. In view of what has happened in the last few years and the damage done to human society by the previous Delta dynasty, which killed many countries and led to the collapse of their health sectors and the death of many people. Therefore, in this study, we used chest X-Ray images of people infected with the Omicron Covid virus with healthy people. We used pre-trained models to classify the images. We also used to work on a hybrid method between deep learning and machine learning algorithms, by extracting features from images and using them as inputs to the machine learning algorithm.

In the first scenario, where the highest results obtained using the Resent 50 was 94% of accuracy, while in the second scenario (hybrid) the highest accuracy was obtained using the characteristics extracted by the Resent 18 model in the two algorithms (SVM and KNN), which is 92 % and 87 %. In order to verify the validity of the results obtained, we compared our results with the results of other recently published studies that also use X-Ray images. It is very clear that the results obtained by the proposed method significantly outperformed the other studies.

We can conclude that the use of these dental images with deep learning techniques has obtained higher results than the hybrid method, and that is why deep learning methods provide the possibility of analyzing the images with extreme accuracy. Since in the future we can develop an algorithm that can provide higher results than the results of the pre-trained model.

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