Classification of Covid-19 Effected CT Images using a Hybrid Approach Based on Deep Transfer Learning and Machine Learning

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Abstract

Recently, several studies attempt to classify the non-invasive medical images in the case of Covid-19. Among them, many research endeavors started to classify Covid-19 using Computed Tomography (CT) scans. To this end, we have proposed a hybrid method that integrates Deep transfer learning and Machine learning. Five types of pre-trained models are used to extract the hidden features from images and then we applied two supervised machine learning algorithms. In the first step, we have applied pre-processing to resize the image for compliance with pre-trained models. Then, we computed the features through the use of CNN models and, finally fed them into SVM and KNN. For the evaluation, we computed the metrics as accuracy, sensitivity, specificity, precision, Negative Predictive Value (NPV), F1-Score, and Matthew's correlation coefficient (MCC). Our best results stand for both of the classifiers that used the features of ResNet-50 (98.2%, 98.1%, 98.3%, 98.3%, 98.1%, 98.2%, and 96.5%). It has been shown that the performance of our methodology was better than the ones reported in the literature.

Introduction

Coronavirus first appeared in Wuhan at the end of 2019, and it is a new strain of the Coronavirus family. It was called severe acute respiratory syndrome before the World Health Organization (WHO) named it as COVID-19 [1, 2]. Initially a public emergency was declared, and the WHO declared a pandemic for the new virus due to the increasing number of deaths in different countries [3]. Covid-19 transmit from one person to another via coughing, sneezing, or talking to others [4]. Once infected by the virus, various symptoms begin to appear, such as high fever, dry coughing, headache, respiratory symptoms similar as the effect of influenza infection. Moreover, in severe cases, difficulty in breathing with organ failure, which may lead to death [5–7]. Whereas in some people, none of these symptoms appear (asymptomatic) and this causes the spread over worldwide. This led to a large number of deaths and the lack of control over the spread of the virus in many countries, the health system has reached a collapse, forcing governments to carry out a complete closure and asking people to commit to stay at home [8].

The critical step in combating the virus is by checking people infected with the virus for isolation and treatment. At present, the foremost approach utilized so far in detecting the covid-19 virus is real-time reverse transcription poly-merase chain reaction test (rRT-PCR) [9, 10].

The abundance of PCR is its accuracy which is around 90%. However, there are limitations of using the Covid-19 test with PCR such as expense, time of duration, and insufficient number of kits [11, 12]. Due to the limitations, scientists proposed alternative methods based on radiographic chest Images (Computed tomography (CT scan) and X-ray), which can distinguish covid-19 infected from uninfected people without error [13, 14]. Since CT imaging modality is easily achievable at the hospitals, and the use of CT images of the chest has many advantages when compared to traditional methods (PCR) [15].

Because of the rapid growth in positive Covid-19 people, many researchers are working to develop several types of artificial intelligence to detect Covid 19 using CT scan images, but these proposals still need to be tested and improved [7, 16]. For this, deep learning technology is one of the most important systems used

recently, especially in the medical field such as breast, cardiac, abdominal, pulmonary, pneumonia, and chest radiological images [9, 17–19]. The reason behind this success is that the deep learning technology does not depend on personal or manual use, but it depends on algorithms that can be trained by using labelled images. Recently, researchers started to use deep learning for the detection and classification of COVID-19 through the use of CT scans images [20].

In the recent literature, different types of pre-trained deep learning models are formed to be used in the classification of Covid-19 such as (GoogleNet[21], Xception[22], U-Net[23], AlexNet [24], VGG19[25], RestNet50[26], MobileNets[27], DenseNet[28], ResNet18 [26], and SqueezeNet[29]), whereas each one has different mechanics but at the end, the main idea is divided into two parts; to extract the features from the images and then apply the classification. Among these classification studies, Shrivastava et al. used CT and X-Ray images in different types of deep transfer learning (Resnet50, InceptionV4, and EfficientNetB0) to extract features followed by an Ensemble Learning for classification, with an accuracy of 97% [30]. A similar accuracy value was obtained by Halder and Datta [31], where more than 2000 CT images were used in DenseNet201, VGG16, ResNet50V2, and MobileNet for a binary classification problem for Covid-19 and healthy cases. Likewise, Eduardo Soares and et al. [32], proposed a deep learning model called xDNN to classify CT scan images that are infected with Covid-19 and non-infected. In addition to the previous studies, Panwar and colleagues [33], proposed a deep transfer learning model using Grad-CAM techniques which monitor the performance of the network that achieve a 95% accuracy. Furthermore, Arora and et al. [34], used deep transfer learning models such as XceptionNet, MobileNet, Inception V3, DenseNet, ResNet50, and VGG16 to classify CT scans where the dataset consists of two classes of 2481 Covid-19 and Non-Covid-19 images on which super-resolution techniques were applied.

Since the accuracy values obtained in the previous studies are fairly acceptable, we tried to increase the accuracy further by modifying the convolutional neural network by incorporating different classifiers after the feature extraction procedure. One of the advantage part of our study is the increased number CT images used in the training set. As a novelty, in the classification part, we implemented K-Nearest Neighbour (KNN) to identify the images. Moreover, we implemented Principle Component Analysis (PCA) on the features deduced from the last Convolutional layer to decrease the dimension of the input to the classifier. Additionally, we adopted SVM to compare the classification performance of the KNN. Thus, we propose to use a hybrid method that companies Deep transfer learning models with SVM and KNN classifiers to identify the binary classes as Covid-19 and Normal.

Methodology

In this study, we used a CT scan image dataset (1252 COVID-19, 1230 Normal) collected from 80 people in a hospital in Sao Paulo in Brazil [32] (Fig. 1).

There are many deep learning algorithms used to classify the COVID-19 dataset, to create a model from scratch needs a huge dataset for training and testing. Due to the size of the dataset is small and the lack of availability of the dataset in public. One can take advantage of using pre-trained models. Transfer learning which is one of the strategies used for classification and it is based on the use of algorithms that

have been trained on a large number of images (millions). And the models configured for use in ad hoc tasks to do it. This technique was used in many types of studies and achieved high results [12, 34–37]. Table 1 illustrates different pre-trained models parameters.

We resized the images appropriately to fit Resnet18 [26], Resnet50 [26], Resnet101 [26], and GoogleNet [38] as 224x224x3, while 227x227x3 size is used for SqueezeNet [29]. Deep features were extracted from the last fully connected layer applied to PCA to reduce the dimensions obtained from these five models.

After that, these features are fed into two supervised machine learning classifications namely SVM and KNN. Figure 2 summarizes the process used in this study that was used to classify the dataset.

Table 1
Number of CNN parameters and the feature vectors used in this study.

Name	Image Input Size	Size	Layers	Parameters (Millions)	Feature Layer	Feature Vector
ResNet-18	224*224*3	44MB	18	11.7	Pool5	512
ResNet-50	224*224*3	96 MB	50	25.6	Avg_pool	2048
SqueezeNet	227*227*3	5.2MB	18	1.24	Pool10	1000
ResNet-101	224*224*3	167MB	101	44.6	Pool5	2048
GoogleNet	224*224*3	27MB	22	7.0	Pool5-7x7_s1	1024

Deep Learning and Feature Extraction

Deep Residual Network (ResNet)

ResNet is one of the most popular CNN algorithms in deep learning due to its speed and efficiency to process the different types of images. The ResNet family consists of several CNN models, where each model has a different architecture and a different number of layers [26]. However, in deep learning the two major problems faced when a train network with increased depth is performance degradation and vanishing gradients [13]. ResNet solved this problem by adding a skip connection which helps not to lose information when it goes deeper. The milestone of ResNet networks is the residual module, which is described in Fig. 3a. The left path is composed of two convolutional layers, where the kernels are 3x3 that keep the spatial dimensions as well as it is an acceleration technique used in Batch normalization and its activation function is ReLU. On the other hand, the right path skips the connection where the input is added directly to the output. Figure 3b illustrates the bottleneck residual module, that also passes from input to the output directly, whereas the left path used two different types of convolution layers whose kernel sizes are 1x1 and 3x3. Additionally, the batch normalization and ReLU are applied and the right path skips connection. This technique was implemented in Resnet-50 and ResNet-101.

GoogleNet

The Google model is a deep learning algorithm as it consists of 22 (27 layers including pooling layers)) layers. The model is developed by the team at Google and named as GoogleNet [21]. GoogleNet is used in many fields such as face recognition, classification, object detection, and adversarial training. However, increasing the number of layers means increasing the vanishing gradient problem. To overcome vanishing gradient problem, GoogleNet used a gradient injection. GoogleNet architecture idea use multiple filter sizes to operate at the same level synchronously, which makes the network wider rather than deeper. Although there are many layers in GoogleNet, it was able to solve the problem by using 9 blocks of the Inception module stacked linearly in total. The end of the inception blocks all of them connected with the global average pooling layer. The main idea of the Inception module is to reduce the number of the parameters by using several small convolutions layers.

SqueezeNet

The building block of SqueezeNet is called as fire module, and it contains two layers: a Squeeze layer has (1x1 convolution filter) and an expanded layer (two convolution filters 1x1 and 3x3) [29]. SqueezeNet stacks a bunch of firing modules and a few pooling layers. The Squeeze layer and expand layer keep the feature map the same size, while the first layer reduces the depth to a smaller number and increases it later. Squeeze (bottleneck layer) and expansion behavior are very popular in neural structures [39]. Another popular pattern is increasing the depth while decreasing the feature map size for a higher-level abstraction. One of the advantages of this model is that the model relies on a 1x1 filter, which means reducing the depth increases of the speed of execution.

Classification of the features

K-nearest Neighbors (KNN)

KNN is a classifier that was developed in 1951 [40], where the technique of classifying data depends on measuring the distance to a specific point. The KNN classifier names the point with a specific name indicating the group to which it belongs. The distance between the points is measured during the training phase and all the points are checked after that the algorithm divides the data based on the shortest distance.

Svm

SVM is one of the most widely used classifiers in machine learning with high performance in many practical problems. The basic idea of the SVM algorithm is to dividing the data into classes by creating a line or hyperplane that separates the data into classes. The basic idea in a hyperplane is to find the best distance that can be used for the separation as well as the best margin distance between the point and the data set. There are many cores used in the SVM algorithm, the most common being sigmoid, polynomial, Radial Basis Function (RBF), Gaussian kernel, and Linear [41, 42].

Evaluation Metrics

In this study, we used accuracy, sensitivity, specificity, precision, negative predictive value (NPV), F1-Score, and Matthew's correlation coefficient (MCC) values. Table 2 shows the equations used to calculate the scales for each metric.

Table 2
Evaluation metrics used to check the performance of classifiers

$\boldsymbol{Accuracy = \frac{TP+TN}{TP+FP+TN+FN}}$
$Sensitivity = \frac{TP}{TP+FN}$
$Specificity = \frac{TN}{TN+FN}$
$precision(PPV) = \frac{TP}{TP+Fp}$
$\text{negativepredictivevalue}(NPV) = \frac{TN}{TN+FN}$
$F1 - score = \frac{2*TP}{2*TP+FP+FN}$
$MCC = \frac{(TP*TN)-(FP*FN)}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}$

Results

We applied 5-fold cross-validation to avoid overfitting which can be observed during the training of the algorithms used in this study. Confusion matrices are computed to mimic the performance of the classifiers as shown in Table 3. Depending on the results obtained from the confusion matrix, it is clear that the best one was obtained by using the Resnet50 algorithm as it achieved the best results compared to the others.

Table 3
Confusion matrix results in terms of number of images are summarized as a result of classifiers when the CNN extracted features are used.

CNN Name	Classes Name		SVM		KNN	
			Predicted Class		Predicted Class	
GoogleNet	Actual Class	Covid-19	1198	54	1206	46
		NON	27	1202	70	1159
ResNet18	Actual Class	Covid-19	1218	34	1233	19
		NON	42	1187	50	1179
ResNet50	Actual Class	Covid-19	1229	23	1230	22
		NON	20	1209	39	1190
ResNet101	Actual Class	Covid-19	1227	25	1221	31
		NON	27	1202	44	1185
SqueezeNet	Actual Class	Covid-19	1220	32	1218	33
		NON	41	1188	84	1145

In our study, the first scenario was the classification with SVM. It showed superiority using deep features that are extracted from ResNet50 in all metrics namely accuracy, sensitivity, specificity, precision, NPV, and MCC having the results of 98.2%, 98.1%, 98.3%, 98.3%, 98.1%, 98.2%, and 96.5%, respectively. While the lowest result obtained by the use of the features extracted from the deep learning transfer model GoogleNet for all evaluation metrics, the average scores regarding to accuracy, sensitivity, and all other metrics are fairly acceptable.

In the second scenario, we applied the KNN classifier and we obtained the highest performance using the ResNet50 model same as in the first scenario. The accuracy, sensitivity, specificity, precision, NPV, and MCC values were 97.5, 98.2, 96.8, 96.9, 98.1, 97.5, and 95.0, respectively. In contrast to ResNet50, the lowest results were obtained as a result of GoogleNet that showed fairly acceptable results. The classification results are summarized in Table 4.

The evaluation metrics which are computed using our proposed methodology are summarized in Table 5. It can be clearly seen that, all of the metrics computed overcomed the ones that were reported by the other studies in literature.

Table 4
The classification performance results of two classifiers.

Classifier Types	Feature Extraction	Evaluation Metrics						
		Accuracy	Sensitivity	Specificity	Precision	NPV	F1-Score	MCC
SVM	GoogleNet	95.7	95.6	95.8	95.9	95.6	95.8	91.5
	ResNet101	97.9	98.0	97.8	97.8	97.9	97.9	95.8
	SqueezeNet	97.0	97.4	96.7	96.8	97.3	97.1	94.1
	ResNet50	**98.2**	**98.1**	**98.3**	**98.3**	**98.1**	**98.2**	**96.5**
	ResNet18	96.9	97.2	96.5	96.6	97.2	96.9	93.8
KNN	GoogleNet	95.3	96.3	94.3	94.5	96.1	95.4	90.6
	ResNet101	96.9	97.5	96.4	96.5	97.4	97.0	93.9
	SqueezeNet	95.2	97.3	93.1	93.5	97.1	95.4	90.6
	ResNet50	**97.5**	**98.2**	**96.8**	**96.9**	**98.1**	**97.5**	**95.0**
	ResNet18	97.2	98.4	95.9	96.1	98.4	97.2	94.4

Table 5
Comparison of the sensitivity (Se)/specificity (Sp)/ accuracy (Acc) values as a result of our proposed method with the ones that were obtained by the other studies used the were applied on the same dataset.

Authors	Data types	Data source	Se	SP	Acc
Panwar et al. [33]	SARS-COV-2 CT	https://www.kaggle.com/plamenedua rdo/sarscov2-ctsca n-dataset/notebooks	94.04	95.84	95.00
Jaiswal et al. [37]			96.29	96.21	96.25
Singh et al. [43]			90.5	90.5	93.0
Angelov et al.[32]			95.53	NA	97.38
Y. Pathak et al. [44]			91.45	94.77	93.1
Umut Özkaya et al. [45]			96.09	92.19	94.03
Arpita Halder et al. [31]			98.0	95.0	97.0
VinayArora et al. [34]			96.11	NA	94.12
Shrivastava et al. [30]			98.18	96.6	97.47
Proposed Approach			**98.1**	**98.3**	**98.2**
			98.2	**96.8**	**97.5**

Conclusion

In this study, we presented a hybrid methodology that consists of deep learning transfer models, and machine learning, to extract features and then perform classification of CT images into two classes. For the former issue, the dataset that we used is publicly available formed by two classes of CT images. The first class was the images of the people infected with the Covid-19 virus and the second class were people who were not infected with the virus Covid19.

There are several types of classification used where in this study, we performed a supervised learning technique. While, on the other hand, Deep learning is a subset of machine learning, it is also used for images due it has the ability to classify, but in deep learning the mechanism of classification is different. In deep learning, the backbone is neural network. There are different types of neural networks and the most widely used categories in deep learning are Convolutional neural networks (CNN) [46, 47], and Recurrent Neural Networks (RNN) [48]. Thus the use of deep learning has advantages for the classification

of Covid-19 images. We utilized CNN model, whereas the essential advantage of the CNN model is that it has an automatic feature extraction. Based on this principle, we used the CNN method to deduce features from the last pooling layer to provide a function that has progressively reduce the spatial size of the features [49]. Then we applied Principal Component Analysis (PCA) to resultant extracted features, which also reduces the dimensionality of large features obtained from CNN models [50, 51]. Finally, obtained features are fed to different classifiers.

The Resnet-50 model with SVM classifier and KNN was used respectively. In the former one, we achieved 98% and in the latter one accuracy was 97%. To conclude, it was shown that the performance of our proposed methodology was superior than the others reported in the literature (Table 5). This methodology can be further applied to other types of medical images regarding different diseases.

Declarations

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Competing Interests

All of the authors declare that they have no financial interests. The authors declare that they have no conflicts of interest. All authors have seen and agree with the contents of the manuscript

Author Contributions

All authors contributed to the study conception and design. The first draft of the manuscript was written by Saif Al-jumaili and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Ethical approval

Since the dataset used in this study was obtained from an open source repository, ethical approval was not supplied.

This article does not contain any studies with human participants performed by any of the authors.

Data Availability

In this study, we used a CT scan image dataset (1252 COVID-19, 1230 Normal) collected from 80 people in a hospital in Sao Paulo in Brazil [32].

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Figures

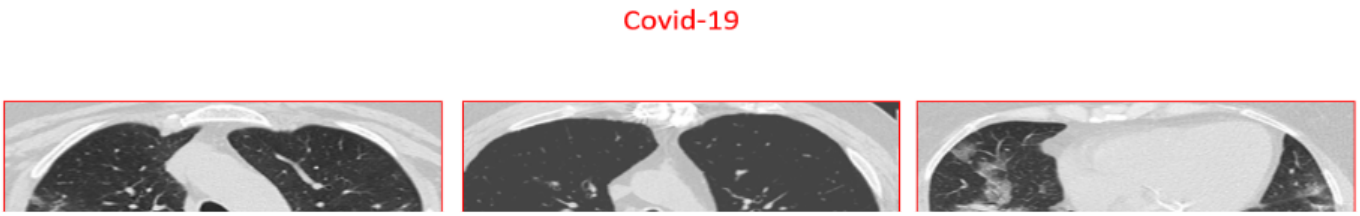

Figure 1

CT scans images for Covid-19 and Normal people.

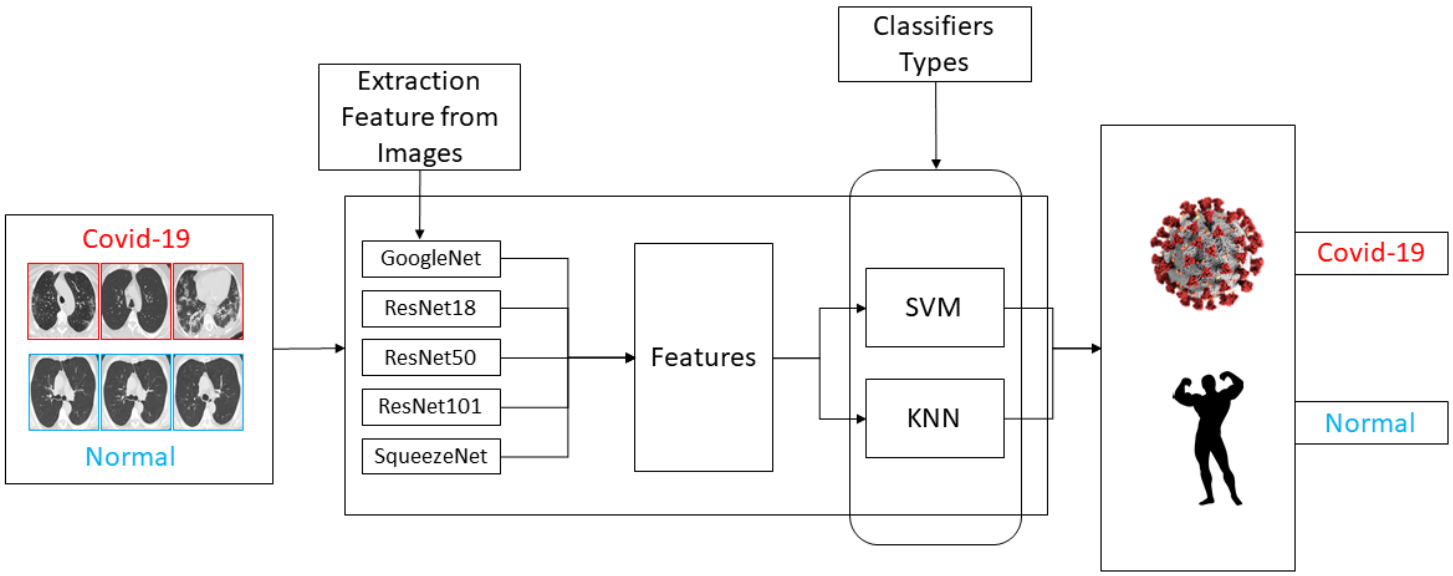

Figure 2

Flowchart of the proposed method. Combination of Deep transfer learning and machine learning classifiers.

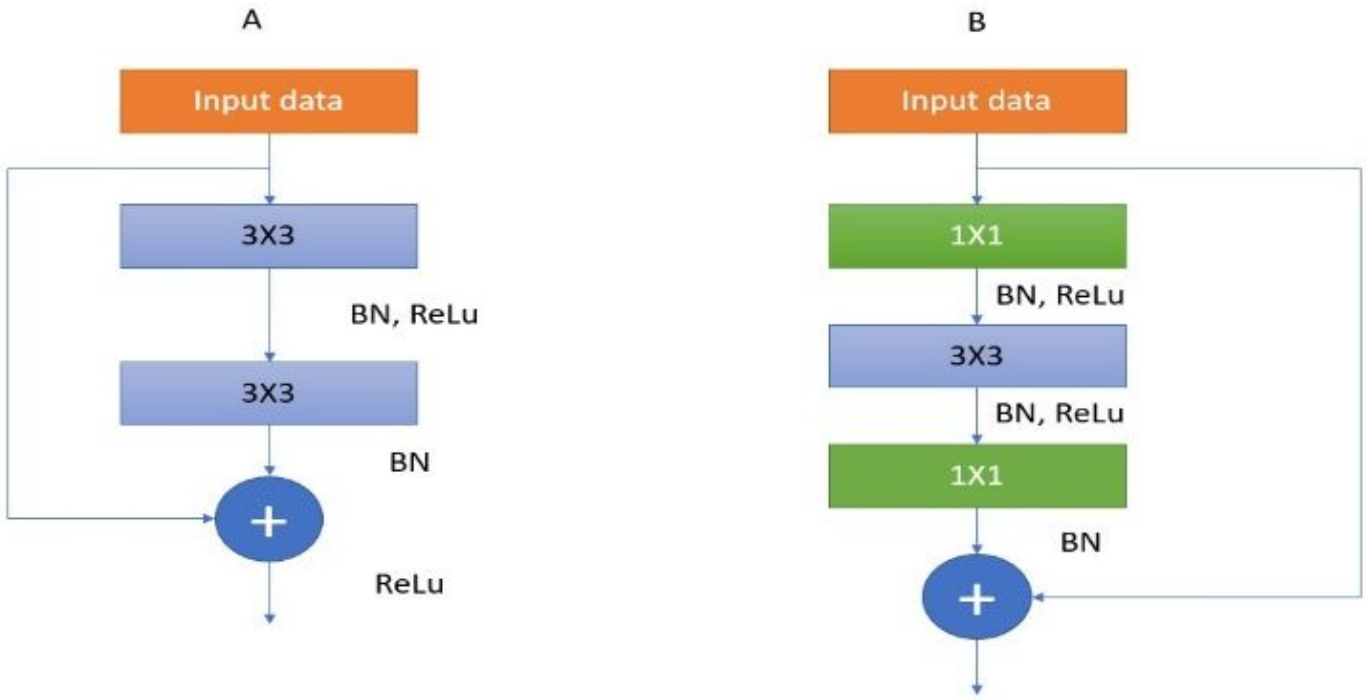

Figure 3

The residual module implemented in ResNet18(A), where the bottleneck residual module is used in ResNet50 and ResNet101(b)