Covid-19 Ultrasound image classification using SVM based on kernels deduced from Convolutional neural network

Saif Al-Jumaili
Electrical and computer engineering
Altinbas University
Istanbul, Turkey
saifabdahrhman@gmail.com

Adil Deniz Duru
Neuroscience and Psychology Research in Sports Lab
Marmara University
Istanbul, Turkey
deniz.duru@marmara.edu.tr

Osman Nuri Uçan
Electrical and computer engineering
Altinbas University
Istanbul, Turkey
osman.ucan@altinbas.edu.tr

Abstract— Millions of people are infected daily with Coronavirus to this day, which increases deaths daily, that has made the virus an epidemic. Based on the current crisis, the availability of tool kits for test plays a significant role in fighting against Covid-19. According to less of availability tools and time consume by using traditional medical tools kit, that provide motivation for researchers to use the advantages of artificial intelligence (AI) techniques. Due to the ability of integrated with medical imaging, AI is very useful for precise diagnosis and classification for different types of diseases. However, in this study, we introduce an idea that combines a set of pre-trained deep learning convolutional neural network models with a supervised machine learning classifier, Supporting Vector Machines (SVM). The dataset used in this study was Lung ultrasound (LUS). To extract features from images, we utilized four types of CNN models namely (Resnet18, Resnet50, GoogleNet) and NASNet-Mobile. Depending on the experimental outcomes, our proposed method show outperform compared to the other latest papers published. Our results achieved based on the four types of evaluation metrics which are Accuracy, Precision, Recall, and F1-Score, where all evaluations achieved exceeded of 99%.

Keywords— COVID-19, Convolutional neural network, Feature extraction, SVM, Classification

I. INTRODUCTION

Coronavirus is composed of different types of strains, the new one appeared in Wuhan, China [1]. Since the emergence of the new virus, the speed of its spread around the world and the increase in the number of infected people is increasing daily, which prompted the World Health Organization (WHO) to announce a new virus as an epidemic and called "COVID-19" [2]. The announcement puts a heavy burden on the health system in different countries, which faced a collapse in some of them. The most popular symptoms of Covid-19 are almost identical to influenza which are nausea or vomiting, fatigue, coughing, diarrhea, sore throat, muscle or body aches. Therefore, to diagnose infected people, it needs to be a reliable test, rapid, and accurate. Currently, the most common test is Real-time Reverse Transcription-polymerase Chain Reaction (rRT-PCR) used to check the infected person. Unfortunately, the conventional methods need time-consuming, and the rRT-PCR is one of these methods. On the accuracy side, the rRT-PCR has high false-positive rates [3]. So that, scientists have resorted to develop different methods of machine learning that used medical images which can be fast and in the same way accurate compared with traditional methods [4].

Indeed, radiological images used to diagnose different diseases such as, Lung cancer [5], Chronic Obstructive Pulmonary Disease (COPD) [6], Asthma [7], Tuberculosis (pneumonia) [8], and many other types of diseases cause breathing problems. Due to the Covid-19 highly effect on the pulmonary, scientists used Lung ultrasound (LUS) inasmuch is safe, cheap, non-invasive, and can provide ubiquitous available. Several machine learning algorithms developed to diagnose infected people (Covid-19) by classification of the LUS images, these developed algorithms can help the medical care sector.

Deep learning is considered one of the most important techniques used with the medical images to identify Covid-19 by classification techniques [10]. The significance behind deep learning is that can train algorithm with different types of medical images and the ability to classify multiple images simultaneously [9]. Especially, convolutional neural network (CNN) is very useful with medical images. Normally, the common types of CNN used for classification are two; (first the network that is trained from scratch, and second pre-trained network such as (GoogleNet [11], Xception [12], U-Net [13], AlexNet [14], VGG19 [15], RestNet50 [16], MobileNets [17], DenseNet [18], ResNet18 [16], and SqueezeNet [19]).

According to the recent paper published in the literature, there are many techniques used in machine learning algorithms using X-Ray images and Computed Tomography (CT) scans [20, 21]. But for LUS a few studies published that give us a motivation to use LUS images to classify Covid-19 by proposed a hybrid method that combines the deep learning CNN model and supervised classifiers [22]. The CNN models used were (ResNet18, ResNet50, GoogleNet, and NASNet-Mobile) to deduce the features from the LUS images, and then, adopted as input to the SVM classifier.

II. LITERATURE REVIEW

Deep learning shows promise in term of accuracy for use in several diseases. Recently, many scientists have adopted deep learning to detect patients with COVID-19 via radiographs. Based on the recent deep learning techniques used to classify Covid-19, there are many methods proposed that used medical image. Whereas the types of images used...
are CT, X-Ray, and LUS. One of these studies has been done by Wang et al. [23], suggested a CNN network based on X-Ray images. They named a COVID-net and trained with 13,975 X-Ray images. COVID-net achieved accuracy was 93%. On the other hand, Akram et al. [24], used CT scan images to extract the features from them and select the most relevant features and then applied to different classifiers. The highest accuracy obtained by Naïve Bayes was 92%. Furthermore, Albahli [25], used Generative Adversarial Networks (GNN) to solve the problem of data imbalance in the classes, they used X-Ray images to classify seven types of diseases based on the deep neural network. The best result accuracy achieved was 87%.

In addition, Hemdan et al. [26], suggested a new framework called a COVIDX-Net. That is based on the seven types of pre-trained networks namely InceptionV3, Xception, VGG19, MobileNetV2, ResNetV2, DenseNet121, and Inception-ResNet-V2. X-Ray images have been utilized in COVIDX-Net to classify Covid-19, they achieved the highest accuracy value was 91%. Likewise, Pathak [27], used a deep transfer learning technique to classify Covid-19 using CT scan images. They used Loss function that can enhance the results further. The highest accuracy achieved was 93%. Similar to the previous study, Apostolopoulos et al. [28], check the performance of different types of pre-trained models. The authors used X-Ray images as an input to CNN models. They achieved 96% which was highest accuracy result.

By the same token, Born and et al. [22], used an ultrasound images to detect a Covid-19, they used 3 classes namely Pneumonia, Healthy, and Covid-19, the overall number of images was 1103. The authors developed a CNN network called the POCOVID-Net. They achieved accuracy was 89%. In another study done by, Roy and et al. [29], introduce a new deep learning model derived from Spatial Transformer Networks, they used an ultrasound images to classify Covid-19. The images were obtained via segment video into frames and then it used as input into deep learning network for classification. The highest accuracy result achieved was 95%.

### III. DATASET DESCRIPTION

In the study, we used LUS image dataset composed of 3 classes namely Pneumonia, Regular and Covid-19. The total number of images was 2995 (988 Covid-19, 731 Pneumonia, and 1276 Regular). The dataset was gathered from the publicly open-source which is available on Kaggle (Covid19 ultrasound original dataset).

![Fig. 1. Sample of the dataset that used to extract features by applied to CNN models](image)

![Fig. 2. Overview of the methodology we used in this study](image)

### IV. METHODOLOGY

To develop a CNN model from scratch, it needs a huge amount of images in order to train the convolutional neural network and test. Therefore, the pre-trained network used with a few of images due to its already trained with millions images, where these types of networks are composed of the two main parts are features extraction from the images and applied features to the classifier such as (SoftMax, SVM and so on) to classify them. In our study, we used various types of pre-trained models, namely (Resnet18, Resnet50, GoogleNet, and NASNet-Mobile) to extract features and then applied them as input to the SVM classifier. The pre-trained models and SVM classifier are already built-in MATLAB. where each one has different types of parameters and layers, Table 1 shows the parameters of several pre-trained networks. In this study, the hardware we used to achieve results were (workstation (Intel(R) Core (TM) i7-4810MQ CPU @ 2.80GHz, RAM 12 GB, and NVidia Quadro k2100m).

<table>
<thead>
<tr>
<th>Name</th>
<th>Image Input</th>
<th>Size</th>
<th>Layers</th>
<th>Parameters (Millions)</th>
<th>Layer</th>
<th>Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>ResNet-18</td>
<td>224*222</td>
<td>44 M</td>
<td>18</td>
<td>11.7</td>
<td>Pool5</td>
<td>512</td>
</tr>
<tr>
<td>ResNet-50</td>
<td>224*222</td>
<td>96 M</td>
<td>50</td>
<td>25.6</td>
<td>Avg_pool</td>
<td>2048</td>
</tr>
<tr>
<td>NASNet-Mobile</td>
<td>224*222</td>
<td>20 M</td>
<td>*</td>
<td>5.3</td>
<td>global_average_pool</td>
<td>1056</td>
</tr>
<tr>
<td>GoogleNet</td>
<td>224*222</td>
<td>27 M</td>
<td>22</td>
<td>7.0</td>
<td>Pool5</td>
<td>1024</td>
</tr>
</tbody>
</table>

Indeed, the dataset undergone to the preprocessing in order to achieve higher results, the dimensions should be 224*224*3 to be fit with pre-trained networks. So, the images resized to get compatible with models. Figure 1 illustrates the images that are utilized as input to the several deep learning models and the methodology we used in this study.
A. Deep Residual Network (ResNet)

ResNet considers the utmost important CNN model due to it can classify different types of images with efficacy and fast [16]. There are different types of ResNet models, where each one relies on the number of layers that are built. In this study, we used the two most common types namely ResNet-18 and ResNet-50. The main idea behind the ResNet family is to solve the problem that happened after the increased depth of the network by using the skipped connections that can avoid losing information when network be deep [30]. Whereas the ResNet-18 composes of 18 layers, While Resnet-50 Composes of 50 layers. Figure 2 illustrates the residual module which is the backbone of ResNet family. These two models were used to extract the features from the LUS images.

![Deep residual network block used in Resnet family](image)

B. GoogleNet

GoogleNet was developed by the Google team, it is a type of convolutional neural network based on the Inception architecture. GoogleNet is used in various fields like recognition, classification, object detection, and adversarial training. GoogleNet is trained with ImageNet that can classify 1000 classes. Since GoogleNet composes of 22 layers that cause a problem called vanishing gradient, GoogleNet avoids this problem by using gradient injection.

C. NasNet-Mobile

NAS stands for Neural Architecture Search and is a technique developed by Google Brain, it was trained on two types of datasets: "CIFAR10 and ImageNet". The NASNet research is one of the best convolutional neural networks that optimize CNNs for different sizes. There are two types of this model where the smaller model is called "NASNet-Mobile", which we used in this study.

D. Support Vector Machine (SVM)

SVM is an extremely popular classifier in machine learning compared to the other supervised classifiers. SVM used within two types of problems are a classification or regression. It provides a golden solution and high performance with these types of problems. The main idea behind SVM is a hyperplane that is used to classify the features into classes, by check the distance between the margin and the point. Several types of the core are utilized in SVM such as polynomial, Gaussian kernel, Radial Basis Function (RBF), Sigmoid, and Linear each one has its own mechanism to classify the data.

E. Statistical measures of classification performance

Four types of the most popular measurement used to evaluate SVM classification are Accuracy, Precision, Recall, and F1 Score. Let recall (Or sensitivity), it means the percentage of people number who have correctly identified that having Covid-19 infection and expressed as:

\[
\text{Recall or Sensitivity} = \frac{TP}{TP + FN}
\]

The number obtained from a true positive (TP) is the number of people identified as having Covid-19, while the false negative (FN), denoting the number of people that are misclassified they have no infection with Covid-19. True negative (TN) is the number of people who have correctly identified they have no infection with Covid-19. False-positive (FP) is the number of people how misclassified as having the infection.

Where the total accuracy (ACC) for classification is calculated for all classes as shown below

\[
\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}
\]

Precision is the rate of the correct number that can predicted as positive to the total number of positives predicted expressed as

\[
\text{Precision} (PPV) = \frac{TP}{TP + FP}
\]

Whereas the F1-Score is the scales of between the precision and the recall by (TP divided by TP and FP)

\[
F1 - \text{score} = \frac{2 \times TP}{2 \times TP + FP + FN}
\]

V. RESULT

This part shows the results obtained from the SVM classifier by performing four types of LUS features obtained by using CNN models namely Resnet18, Resnet50, GoogleNet, and NasnetMobile. In order to check the performance of the trained classifier, the dataset divided in to 80% for training and 20% for testing with randomly separate. To avoid overfitting, the cross-validation technique was used with k=5. The results of each CNN model made using SVM are shown separately in Tables II, III, IV, and V.

<table>
<thead>
<tr>
<th>Classifier Types</th>
<th>Feature Extraction</th>
<th>Evaluation Metrics</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>GoogleNet</td>
<td>Accuracy</td>
</tr>
<tr>
<td>Pneumonia</td>
<td>99.19</td>
<td>97</td>
</tr>
<tr>
<td>Regular</td>
<td>99.16</td>
<td>99</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Classifier Types</th>
<th>Feature Extraction</th>
<th>Evaluation Metrics</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>NasNet-Mobile</td>
<td>Accuracy</td>
</tr>
<tr>
<td>Pneumonia</td>
<td>99.26</td>
<td>98</td>
</tr>
<tr>
<td>Regular</td>
<td>99.12</td>
<td>99</td>
</tr>
</tbody>
</table>
As shown aforementioned in Table 4, the highest result achieved by using ResNet50 which was 99.19% for the accuracy, while the lowest value by using NasNet-Mobile, was 98.79% accuracy for all classes. Our results were compared with other studies, it is clear that we achieved higher results compared to the previous studies in all statistical measures. Table 6 shows the results obtained in comparison with other studies.

VI. DISCUSSION

In this study, we introduce a method that combines CNN and SVM to classify three types of pneumonia diseases. We used point-of-care ultrasound (POCUS) dataset which is collected by [22], while this dataset is publicly available and it is one of the earliest datasets that collected data for global uses. It consisting of three types of categories namely pneumonia, healthy and COVID-19 patients. To extract features from this dataset, we use kernel of four types of CNN models to deduce the feature from the LUS images. And then adopt these as input to the SVM for classification features.

The highest result achieved by using SVM classifier based on the features deduced form ResNet50, was 99% of accuracy. While the other CNNs models (GoogleNet, NasNetMobile, and ResNet18) achieve accuracy of around 98%. As well as we compared our results with recent papers published in the literature that they used different methods to classify Covid-19 using the LUS dataset, it is obvious our results were higher compared to the previous studies.

REFERENCES


TABLE IV: CLASSIFICATION RESULTS USING RESNET50 WITH SVM

<table>
<thead>
<tr>
<th>Classifier Types</th>
<th>Feature Extraction</th>
<th>Evaluation Metrics</th>
<th>Class</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>F1-Score</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>SVM</td>
<td>Pneumonia</td>
<td>99.66</td>
<td>99</td>
<td>100</td>
<td>99</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SVM</td>
<td>Regular</td>
<td>99.29</td>
<td>99</td>
<td>99</td>
<td>99</td>
</tr>
</tbody>
</table>

TABLE V: CLASSIFICATION RESULTS USING RESNET18 WITH SVM

<table>
<thead>
<tr>
<th>Classifier Types</th>
<th>Feature Extraction</th>
<th>Evaluation Metrics</th>
<th>Class</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Recall</th>
<th>F1-Score</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ResNet18</td>
<td>SVM</td>
<td>Covid-19</td>
<td>99.46</td>
<td>100</td>
<td>98</td>
<td>99</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SVM</td>
<td>Pneumonia</td>
<td>99.33</td>
<td>98</td>
<td>100</td>
<td>99</td>
</tr>
<tr>
<td></td>
<td></td>
<td>SVM</td>
<td>Regular</td>
<td>99.06</td>
<td>99</td>
<td>99</td>
<td>99</td>
</tr>
</tbody>
</table>

TABLE VI: COMPARED RESULTS WITH RECENT PAPER PUBLISHED USING LUS IMAGES

<table>
<thead>
<tr>
<th>Authors</th>
<th>Data sources</th>
<th>AC</th>
<th>Se</th>
<th>Sp</th>
</tr>
</thead>
<tbody>
<tr>
<td>Che et al.</td>
<td><a href="https://github.com/bvanberl/covid-us-ml">https://github.com/bvanberl/covid-us-ml</a></td>
<td>95</td>
<td>95</td>
<td>N/A</td>
</tr>
<tr>
<td>Amrifyeed et al.</td>
<td><a href="https://github.com/jannishorn/covid19_ultrasound">https://github.com/jannishorn/covid19_ultrasound</a></td>
<td>96</td>
<td>88</td>
<td>92</td>
</tr>
<tr>
<td>Gholam et al.</td>
<td><a href="https://covid19.disi.unin.it/icloud/login">https://covid19.disi.unin.it/icloud/login</a></td>
<td>91</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Carrier et al.</td>
<td><a href="https://www.kaggle.com/bachabos/covid19-ultrasound-original-dataset">https://www.kaggle.com/bachabos/covid19-ultrasound-original-dataset</a></td>
<td>94</td>
<td>N/A</td>
<td>N/A</td>
</tr>
</tbody>
</table>
segmentation,” in International Conference on Medical image computing and computer-assisted intervention, 2015, pp. 234-241: Springer.


