A novel and accurate deep learning based Covid-19 diagnostic model for heart patients only

Ahmed Hassan (ahmedhassancs22@yahoo.com)
Beni-Suef University
Mohamed Elhoseny
Mansoura University
Mohammed Kayed
Beni-Suef University

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Abstract

Using radiographic changes of COVID-19 in the medical images, artificial intelligence techniques such as deep learning are used to extract some graphical features of COVID-19 and present a Covid-19 diagnostic tool. Differently from previous works that focus on using deep learning to analyze CT scans or X-ray images, this paper uses deep learning to scan electro diagram (ECG) images to diagnose Covid-19. Covid-19 patients with heart disease are the most people exposed to violent symptoms of Covid-19 and death. This shows that there is a special, unclear relation (until now) and parameters between covid-19 and heart disease. So, as previous works, using a general diagnostic model to detect covid-19 from all patients, based on the same rules, is not accurate as we prove later in the practical section of our paper because the model faces dispersion in the data during the training process. So, this paper aims to propose a novel model that focuses on diagnosing accurately Covid-19 for heart patients only to increase the accuracy and to reduce the waiting time of a heart patient to perform a covid-19 diagnosis. Also, we handle the only one existed dataset that contains ECGs of Covid-19 patients and produce a new version, with the help of a heart diseases expert, which consists of two classes: ECGs of heart patients with positive Covid-19 and ECGs of heart patients with negative Covid-19 cases. This dataset will help medical experts and data scientists to study the relation between Covid-19 and heart patients. We achieve overall accuracy, sensitivity and specificity 99%, 98.67% and 100%, respectively.

Introduction

Deep learning has made a great development and enhancement in the healthcare sector. As shown in Table 1, deep learning models outperform human medical experts in complex medical tasks not only in the very quick decision, which is very important in healthcare, but also in the high accuracy. Besides, deep learning models are available at any time, not as the human doctors, and also with high accuracy outperforms medical experts ones.

Table 1
outperforming deep learning over medical human experts

Ref.	Object	Deep learning Accuracy	Experts Accuracy
[21]	Classify sporadic Alzheimer	92.4%	80%
[22]	detection of pneumonia	82%	76%
[23]	Diagnosis cancer skin	73%	65.6%
[24]	detect arrhythmic heartbeats	91.6	61.8
[25]	brain tumor detection	90%	74%
[26]	diagnosis retinal disease	99.2%	89.8%

Covid-19 is a health disaster wherein there are 43 million Covid-19 positive cases and 1.2 million people have died as a result. It is necessary to develop an automatic, early and accurate COVID-19 diagnostic mechanism. The disease is typically detected using reverse-transcription polymerase chain reaction (RT-PCR) testing. In spite of this, RT-PCR has been found that the sensitivity of it is not high enough for early detection of COVID-19. Also, the supply of kits of RT-PCR is different from a country to another and many developing countries, that have a big number of cases and deaths, are in short supply of RT-PCR.

Medical images such as CT scans and X-rays for the lungs are used and scanned to diagnose COVID-19. However, these medical images consist of many slices, which requires much time to diagnose. Besides, COVID-19, as a new lung disease, has common symptoms with many types of pneumonia. Therefore, radiologists have to accumulate a big amount of these medical images diagnostic experience to achieve an efficient diagnostic performance, especially in distinguishing similar deceases.

Recently, deep learning technology has achieved a great success in the field of medical imaging due to its high feature extraction capability. Recent research shows that artificial intelligence techniques can surpass the human experts in medical image diagnosis tasks, including also the lung diseases. The AI diagnostic algorithms also have the advantages of high efficiency and easy deployment at large scale. Deep learning techniques have been successfully used in many medical problems such as skin cancer classification [27, 28], lung segmentation [29], brain disease detection [25], pneumonia diagnosis from chest X-ray images, breast cancer detection, and fundus image segmentation. AI techniques is helpful in getting ride of disadvantages such as the unavailability of significant number of RT-PCR test kits, and the much waiting time of check results. Also, there has been many publicly available medical images for healthy cases, also for patients suffering from various pandemics such as Covid-19. So, this enables the researchers to analyze the medical images using AI techniques and identify patterns that may result in automatic diagnosis of Covid-19.

Covid-19 patients with heart disease are the most people that exposed to violent symptoms of Covid-19 and death [30]. This shows that there is a special and unclear relation (until now) and parameters between covid-19 and heart disease. So, as previous works, using a general diagnostic model to diagnosis covid-19 from all patients based on the same rules, whether having heart disease or other chronic disease or not, is not accurate, as we prove later in the practical section of our paper. In all areas of cardiac care, the sooner an accurate diagnosis is made, the likelihood of a full recovery significantly increases .So, this paper aims to propose a model that focuses on diagnosing accurately Covid-19 for heart patients only to increase the accuracy and to reduce the waiting time of a heart patient to perform a covid-19 diagnosis because this diagnostic model is only for heart patient. This has a very important contribution in saving heart patients early from Covid-19-violent symptoms and death.

Here, we can list the contributions of our proposed model as shown below:

1. As a novel approach in Covid-19 diagnosis, we are the first to present an accurate diagnostic model for Heart patients only, compared to previous works that present a general diagnostic model to any one that cause a dispersion in the training process and affects the performance of the model, as we prove practically in the practical section.
2. Differently from previous works that focus on using X-ray or CT-scan dataset for their Covid-19 diagnostic models, we use ECGs images which are recently proved that ECGs show some specific features caused by Covid-19 [32]. To the best of our knowledge there is only one dataset, that contains ECGs of Covid-19 patients, which was published recently [31].
3. We handle this dataset [31] to be suitable to our model with the help of a heart diseases expert. We produce a new version of the dataset that consists of two classes: ECGs of heart patients with positive Covid-19 cases and ECGs of heart patients with negative Covid-19 cases.

This paper is organized as follow: “Related Works” section discusses the existing literature in the field of COVID-19; proposed classification model is discussed in the “the proposed model” section; performance analyses are discussed in the “Experimental evaluation” section; the “Conclusion” section concludes the paper.

Related Works

In this section, we firstly collect and summarize the active research tracks and open challenges of applying deep learning techniques to face Covid-19 pandemic, as shown in Table 2. Also in this section, we illustrate and compare the most high cited previous works that presented deep learning based Covid-19 diagnostic model, as shown in Table 3. We compare these works based on four basic dimensions: 1) the dataset 2) the preprocessing techniques to handle the dataset to increase the performance 3) the key points of the paper 4) the results. Covid-19 is a new pandemic, so the dataset of this pandemic stills limited and requires some pre-processing techniques to present the required performance. We compare these pre-processing techniques based on the average accuracy achieved by the most 10 high cited papers that use this technique to handle the dataset, as shown in Fig. 1.

Table 2
summarization of the research tracks and open challenges of using deep learning in Covid19

Target	Research tracks	Research challenges
Diagnosis	-CT scan based diagnostic models [4]. -X rays based diagnostic models [1, 2].	- Unavailability of large datasets with also efficient-quality images for training. -Most DL models are trained for 2D images, however CT images are usually 3D. -Covid-19 stills unclear, so the same Covid19 case may be disagreed on it among medical experts. So, the labels of the dataset are not very accurate. -AI applications basically depend on big amounts of labeled data and less interaction with human experts. The basic challenge is how to decrease the labeling cost when time and human resources are limited.
Covid-19 drugs	-Drugs repurposing [12, 13] -Drugs discovery [11]	-Most works focus on drug-disease associations, but the relationships between drug–drug interactions must be considered in the model. -Most works depend in their predictions on general symptoms like fever, cough that may occur to any one due to climate change. This makes the predictions inaccurate.
Prevention measures	-Facial mask detection based DL [15]. -Social-distancing alarm based DL [14].	Most these DL based models utilize image processing techniques, however in real crowded places or vehicles, where we want to apply these prevention measures, the faces of some people are hidden partially or completely behind the crowd. So, these applications do not achieve the required results in an efficient manner.
Handling Covid19 side-effects	fraud transactions during the pandemic based deep learning [16] Predicting the most suitable educational system for the country during Covid-19. [17] Because of Covid-19, fuel demand decreases and the price of oil future becomes negative. So, in [18], a deep learning based model is proposed that uses information such as travel activities and fuel usage to develop a model to predict the US gasoline demand in the medium-term and the effect of government interventions. -predicting the people at a high risk of later chronic health disorders because of the big distress during the pandemic [19]. -Fake healthy information or news detection based deep learning during Covid-19 [20].	Hard implementation and time consuming challenge due to the difference among language and accents in applications such as misinformation or fake news detections during Covid-19 based deep learning. - Applications such as predicting the suitable education system must include forecasting for the pandemic status at the coming period. Because the model may forecast based on the current status, but these status may change soon.

Table 3: a comprehensive comparison among the most ten top cited papers of using deep learning in Covid-19 diagnosis

Ref.	Dataset							Pre-processing				Key points
	type	Total	Covid-19 samples	bacterial pneumonia samples	normal	Format	Dataset publicly available	Samples exclusions	augmentation	Samples segmenta--tion	Re-sized	
[1]	X-ray images	1125	125	500	500	PNG	✓	✓	_	_	_	It develops a model using already pre-trained models such as Darknet-19.
[2]	X-ray images	1428	224	700	504	various	✓	_	_	_	✓	The technique called Transfer Learning was applied. So, the detection of diverse abnormalities in small datasets is applicable.
[3]	X-ray images	13962	358	5538	8,066	various	✓	_	_	_	_	According to the authors' knowledge, this model is one of the first open source CNNs for the diagnosis of COVID-19 from CXR images.
[4]	CT scans	4352	1292	1735	1325	N/A	-	✓		✓		For example, given a 3D CT scan, the paper first extract the lung region as the region of interest using a Unet (17) based segmentation technique. After that, this region of interest image is then transferred to COVNet for the classification.
[5]	X-ray images	1251	284	657	310	various	✓				✓	The model used the pre-trained Xception CNN which was also trained later on a dataset consists of COVID-19 and other chest pneumonia X-rays.
[6]	CT scan	274	15	259	-		✓			✓		The architecture contains three basic processes: (1) preprocessing of the input

										images (selecting region of interest (ROI) from CT scan image) (2) training using ROIs and (3) classification and prediction of binary classifiers.
[7]	CT scan	2006	1020	86		-			✓	Ten popular CNNs were used to classify the cases of COVID-19 anc non-COVID-1 groups.
[8]	CT	-	-	-	-	-	-			A convolutional neural network (CNN) is utilized to detect COVID-19. Also, the initial parameters o the CNN are tuned by multi-objective differential evolution (MODE).
[9]	X-ray	5310	76	4290	1583	✓		✓		The network archicture is tuned for the COVID-19 detection wit Bayesian optimization additive. Fine-tuned hyper parameters and also augmented dataset (to overcome the unbalance problem) make the proposed model achieves high efficiency.
[10]	CT	618	219	224	175	-			✓	First, it uses a 3D deep learning model to segment the regions of interest out from the CT image. The segmented images were then categorized into COVID-1 or not.

Discussion

CT images is often considered as the main detector for COVID-19. This creates so much load on the departments of radio diagnosis. Also, some hospitals focused on using CT scanners for only scanning suspected COVID-19 patients. This also makes the researchers focuses on using CT-scan as datasets for their deep learning models. In spite of all of this, we found that, as shown in Table 3, most papers that used X-ray images, as dataset for their models, achieved larger accuracy from the papers that used CT-scan images, as dataset for their models. So, the researchers were able to achieve efficient results, if they focused on using X-ray datasets. Because X-ray datasets can achieve more accuracy (X-ray datasets have a higher ability to detect Covid-19 cases), as shown in Table 3, and also X-ray datasets are largely available than CT-scans datasets, as shown in Table 3 that all X-ray datasets, that are used in the reviewed papers, are publicly available (5 datasets), while there is only one CT-dataset publicly available from 5 CT-datasets. So, there is many publicly available X-ray datasets that can be feed to deep learning models and achieve more efficient results.

Deep learning based Covid-19 diagnostic models suffer from a common dangerous challenge that is the small number of Covid-19 samples existed in the public datasets, because Covid-19 is a novel pandemic. This may lead to poor results. Model [9] achieves the highest sensitivity and specificity compared to other models, in spite of it has very low Covid-19 samples in its corresponding dataset. It handles this challenge by using efficient technique which is data augmentation. Data Augmentation is a technique used to increase the size of specific class's samples in an efficient manner. This solve the unbalance problem between covid-19's samples and other class's samples. We can also note that the papers such as [1, 2] that use efficient transfer learning have achieved very efficient results, wherein transfer learning is suitable to the training of small dataset such as Covid-19 datasets. So, the researchers have to focus on the techniques that handle the problem of Covid-19 small datasets such as efficient transfer learning and augmentation.

Methodology

In this section, information will be presented about the used COVID-19 dataset in details, the architectures used for classification which is based on combining transfer learning and ensemble learning. The steps of our proposed model are given in Fig. 4.

3.1. Dataset generation

The target of our paper is to develop a deep learning based Covid-19 diagnostic model for specifically heart patients instead of the previous works that develop general Covid-19 diagnostic model to anyone. This increases the accuracy and the care for the heart patients that have the most dangerous cases during the pandemic. Whereas our model focuses on heart patients, we choose the ECG image as samples for the dataset that trains our model because the ECG images record the electrical signals in the heart. Also, it's a popular test used to quickly detect heart problems and monitor your heart's health. Besides this, a team of researchers from New York University "Langone Medical Center", USA, has found that the clinical severity of patients with COVID-19 disease can be predicted by analyzing the value of troponin elevation and electrocardiographic (ECG) abnormalities [32]. So, our model, based on an ECG dataset, predicts whether a heart patient is positive or negative Covid-19 case. This study [31] includes the dataset of ECG images of Cardiac and COVID-19 patients. This dataset consists of around 250 ECG images of confirmed COVID-19 patients, 77 ECG images of Myocardial Infarction Patient, 203 patients of Previous History of Myocardial Infarction positive patients and total and 504 patients of abnormal heartbeats and finally 859 Normal Person ECG Images. The dataset which we use must contain only heart patients (our model diagnosis Covid-19 specifically for heart patients). So, the dataset must have two basic classes: ECG images of heart patient with positive Covid-19 case and ECG images of heart patient with negative Covid case. So, we updated the dataset, in this study [31], by reviewing the class of ECGs of Covid-19 cases with a cardiac diseases expert, and then dividing this class into two categories: heart patient with positive Covid-19 case and not-heart patient with positive Covid-19 case. Finally, we excluded the category of not-heart patient with positive Covid-19 case.

Based on our update and the original dataset, we generate an updated dataset consists of 240 ECGs of heart patient with positive Covid-19 cases, as shown in Fig. 2, and 777 ECGs of heart patient with negative Covid-19 cases,, as shown in Fig. 3.

4.1. Dataset pre-processing

Whereas the size of the samples (ECGs) in the data set is not the same and the sizes of ECG images are different. So, we have changed the size of all the ECG images into the same size of 1000 x 1000 pixels. For this, RGB reordering has been achieved and the input to the proposed model is presented as 1000 × 1000 × 3 image.

Large dataset is a very important requirement to classify efficiently by deep learning models. However, large datasets are not always available as Covid-19 case, because it is a novel pandemic. So, the data augmentation techniques should be applied to increase the classification efficiency. As we proved before in Fig. 1, data augmentation technique has achieved the best results for covid19-diagnostic models compared to other pre-processing techniques. In this paper, changing the image brightness and zooming-in (randomly zooming the image by a certain

range) augmentation techniques are used to increase the ECG images of Covid-19 patients. So, data augmentation presents data diversity and high accuracy for classification models.

Changing the image brightness and zooming-in augmentation techniques have been applied to ECGs which belong to the COVID-19 class, which has a limited number of samples. After applying the data augmentation process, the number of COVID-19 class images are raised, and the number of new COVID-19 class samples has become 480. The brightness of ECG images of the Covid-19 class are changed in a value from 0 to 5.0 according to a random generated number.

4.2. The proposed Model

As shown in Fig. 1, after data augmentation technique which we used above to balance the classes of the dataset, the transfer learning technique achieved the largest average accuracy for deep learning based diagnostic models. Whereas the transfer learning technique helps the model by using CNNs that were trained before based on a huge dataset, and so these CNNs have an efficient experience in classifying and processing images. Also, ensemble learning has a great impact on improving the accuracy of the deep learning model by combining the advantages of more than one CNNs in one model to improve the accuracy. So, in our proposed model, we combine the transfer learning and the ensemble learning techniques to improve the accuracy and the performance of the model.

In this paper, 3 common pre-trained CNNs were utilized to classify COVID-19 cases from non-COVID-19 cases: 1) VGG-19, 2) AlexNet, 3) ResNet-101. For VGG19, we utilized VGG-19 network with pre-trained weights of imagenet. VGG19 is a 24- layer network which consists of 5 convolutional blocks, 3 max pool layers, and 3 fully connected layers, but we made a fine-tuning by utilizing pre-trained weights for the convolutional blocks, getting rid of the last two fully connected layers and finally adding 2 fully connected layer with 4096 neurons. Compared to VGG-16 model, VGG-19 is a deeper CNN architecture. AlexNet is a feedforward CNN with 8-layer depth. It consists of 5 convolution layers and 3 connected layers. AlexNet was trained on 1000000 images to classify images into 1000 different classes. ResNet-101 is a version of “Resnet” CNN. It is 101 layers depth with 33 residual blocks.

There are two approaches to apply the ensemble technique: bagging and boosting approaches. We choose the bagging technique because it achieves more stability and accuracy. Bagging approach decreases the overfitting issues, compared to Boosting approach, because, in each stage of the Boosting technique, the samples that are not classified correctly in the previous phase are only utilized as training data to the next CNN. In this paper, the Bagging technique trains all the 3 pre-trained models independently based on the same training set. Let n models numbered as 1, 2,…, n are used for classification of m classes, and the prediction probability values are denoted by P. The prediction probabilities for an image from model i can be described as a matrix as in Eq. 5.

$P_1^{(i)} = P_1^{(i)} P_2^{(i)} \cdots\cdots P_n^{(i)}$

Experimental Evaluation

5.1. Confusion matrix

Confusion matrix consists of four factors: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN), as shown in Table 4. In the confusion matrix, the rows contain the ‘Real class values’, and the columns are the ‘Predicted class values’. This evaluates the efficiency of our model. Based on the confusion matrix on the validation data set, our proposed model has achieved the sensitivity of 97.6% and specificity of 100%. Whereas Sensitivity points to the quantity of True Positives (TP) or the number of cases in which the model predicts they are Covid-19 patients and they actually Covid-19 patients. So, out of the 125 Covid-19 patients in the test data set we were accurately predicted COVID- 19 in 122 of them presenting 97.6% probability. This shows that we can diagnosis COVID-19 in the patients, with only 2.4% error. Specificity point to the quantity of True Negatives (TN) or the number of cases in which the model predicts they are not Covid-19 patients and they actually not Covid-19 patients. So, out of the 126 patients that are actually not infected by Covid-19, in the used validation data set, we accurately predict that these 126 persons are not infected by COVID-19 providing 100.00% probability. By calculating the accuracy of our model based on the confusion matrix we have achieved an overall accuracy of 99%.

Table 4: the confusion matrix of our proposed model

		Predicted class	
		Covid	Other
Actual Class	Covid	*TP*=123	*FN*=2
	Other	*FP*=0	*TN*=126

5.2. Various Evaluation metrics

We have trained our proposed model for 10 epochs and the learning rate has been 0.0001. The validation accuracy, as shown in Fig. 5, lies around 98.91–100%. The obtained results show that the validation accuracy could reach up to 100% which could be considered as one of the best Covid-19 diagnostic measures. As shown in Table 4, our approach practically outperforms [1, 2, 3, 4] models, which are the most high models until now, in accuracy, sensitivity and specificity.

5.3. Area under the curve (AUC)

AUC is an indicator for a classifier’s capability of distinguishing between different classes. The higher AUC value the classifier has, the more efficient in distinguishing between classes. Whereas an AUC close to 0.50 shows that the classifier makes guesses and has no separation amplitude. A low value in AUC shows that the model is predicting classes in opposite. We have got AUC of 97.4% which considered as a strong indicator for the efficiency of our model.

5.4. A novel comparison among the general Covid-19 diagnostic approach and our proposed approach

Compared to previous works that present general Covid-19 diagnostic models for any one regardless its health conditions, we present a Covid-19 diagnostic model for heart patients only. We compare the two approaches based on “validation-loss” metric as shown in Fig. 6. We have found that the validation loss metric in the case of general Covid-19 diagnostic model is unstable (transfers from up to down and vice versa). This indicates that there is dispersion in the data, so the learning process in not well. However, the validation- loss metric in our proposed approach (diagnostic model for only heart patients not any one) decreases in a continuous manner and reaches a very small value (0.0008) almost equal to zero. This indicates that our proposed model achieve better performance and learning.

Table 4
Practical comparison among general diagnostic models and our approach

Ref.	Accuracy	Sensitivity	Specificity
[1]	98.08%	95.13%	95.30%
[2]	96.78%	98.66%	96.46%
[3]	93.3%	91%	94%
[4]	93%	90%	96%
Proposed Model	99%	98.67%	100%

Conclusion

We have proved practically that using a general diagnostic model for Covid-19 is not efficient because in this case there is dispersion in the data which affects the performance. So, in this paper, we have proposed a deep learning based Covid-19 diagnostic model for heart patients only. Our proposed model has achieved very efficient results. We handle the only one available dataset which contains ECGs for Covid-19 patients to be suitable to our model with the help of a heart diseases expert. We produce a new version of this dataset that consists of two classes: ECGs of heart patients with positive Covid-19 cases and ECGs of heart patients with negative Covid-19 cases.

References

1. Ozturk, T., Talo, M., Yildirim, E. A., Baloglu, U. B., Yildirim, O., & Acharya, U. R. (2020). Automated detection of COVID-19 cases using deep neural networks with X-ray images. *Computers in biology and medicine*, *121*, 103792.
2. Apostolopoulos, I. D., & Mpesiana, T. A. (2020). Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks. *Physical and Engineering Sciences in Medicine*, *43*(2), 635–640.
3. Wang, L., Lin, Z. Q., & Wong, A. (2020). Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images. *Scientific Reports*, *10*(1), 1–12.
4. Li, L., Qin, L., Xu, Z., Yin, Y., Wang, X., Kong, B., … Xia, J. (2020). Using artificial intelligence to detect COVID-19 and community-acquired pneumonia based on pulmonary CT: evaluation of the diagnostic accuracy. *Radiology*, *296*(2), E65-E71.
5. Khan, A. I., Shah, J. L., & Bhat, M. M. (2020). CoroNet: A deep neural network for detection and diagnosis of COVID-19 from chest x-ray images. *Computer Methods and Programs in Biomedicine*, *196*, 105581.
6. Wang, S., Kang, B., Ma, J., Zeng, X., Xiao, M., Guo, J., … Xu, B. (2021). A deep learning algorithm using CT images to screen for Corona Virus Disease (COVID-19). *European radiology*, 1–9.
7. Ardakani, A. A., Kanafi, A. R., Acharya, U. R., Khadem, N., & Mohammadi, A. (2020). Application of deep learning technique to manage COVID-19 in routine clinical practice using CT images: Results of 10 convolutional neural networks. *Computers in biology and medicine*, *121*, 103795.
8. Singh, D., Kumar, V., & Kaur, M. (2020). Classification of COVID-19 patients from chest CT images using multi-objective differential evolution–based convolutional neural networks. *European Journal of Clinical Microbiology* & *Infectious Diseases*, *39*(7), 1379–1389.
9. Ucar, F., & Korkmaz, D. (2020). COVIDiagnosis-Net: Deep Bayes-SqueezeNet based diagnosis of the coronavirus disease 2019 (COVID-19) from X-ray images. *Medical hypotheses*, *140*, 109761.
10. Xu, X., Jiang, X., Ma, C., Du, P., Li, X., Lv, S., … Li, L. (2020). A deep learning system to screen novel coronavirus disease 2019 pneumonia. *Engineering*, *6*(10), 1122–1129.
11. Jha, N., Prashar, D., Rashid, M., Shafiq, M., Khan, R., Pruncu, C. I., … Saravana Kumar, M. (2021). Deep learning approach for discovery of in silico drugs for combating COVID-19. *Journal of Healthcare Engineering*, *2021*.
12. Hooshmand, S. A., Zarei Ghobadi, M., Hooshmand, S. E., Azimzadeh Jamalkandi, S., Alavi, S. M., & Masoudi-Nejad, A. (2021). A multimodal deep learning-based drug repurposing approach for treatment of COVID-19. *Molecular diversity*, *25*(3), 1717–1730.
13. Mohanty, S., Rashid, M. H. A., Mridul, M., Mohanty, C., & Swayamsiddha, S. (2020). Application of Artificial Intelligence in COVID-19 drug repurposing. *Diabetes* & *Metabolic Syndrome: Clinical Research* & *Reviews.*
14. Ahmed, I., Ahmad, M., Rodrigues, J. J., Jeon, G., & Din, S. (2021). A deep learning-based social distance monitoring framework for COVID-19. *Sustainable Cities and Society*, *65*, 102571.
15. Rahman, M. M., Manik, M. M. H., Islam, M. M., Mahmud, S., & Kim, J. H. (2020, September). An automated system to limit COVID-19 using facial mask detection in smart city network. In *2020 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS)* (pp. 1–5). IEEE.
16. Bandyopadhyay, S. K., & Dutta, S. (2020). Detection of Fraud Transactions Using Recurrent Neural Network during COVID-19: Fraud Transaction During COVID-19. *Journal of Advanced Research in Medical Science* & *Technology (ISSN: 2394–6539)*, *7*(3), 16–21.

17. Chen, T., Peng, L., Yin, X., Rong, J., Yang, J., & Cong, G. (2020, September). Analysis of user satisfaction with online education platforms in China during the COVID-19 pandemic. In *Healthcare* (Vol. 8, No. 3, p. 200). Multidisciplinary Digital Publishing Institute.
18. Ou, S., He, X., Ji, W., Chen, W., Sui, L., Gan, Y., … Bouchard, J. (2020). Machine learning model to project the impact of COVID-19 on US motor gasoline demand. *Nature Energy*, *5*(9), 666–673.
19. Ćosić, K., Popović, S., Šarlija, M., Kesedžić, I., & Jovanovic, T. (2020). Artificial intelligence in prediction of mental health disorders induced by the COVID-19 pandemic among health care workers. *Croatian medical journal*, *61*(3), 279.
20. Choudrie, J., Banerjee, S., Kotecha, K., Walambe, R., Karende, H., & Ameta, J. (2021). Machine learning techniques and older adults processing of online information and misinformation: a covid 19 study. *Computers in Human Behavior*, *119*, 106716.
21. Tsang, G., Xie, X., & Zhou, S. M. (2019). Harnessing the power of machine learning in dementia informatics research: Issues, opportunities, and challenges. *IEEE reviews in biomedical engineering*, *13*, 113–129.
22. Patel, B. N., Rosenberg, L., Willcox, G., Baltaxe, D., Lyons, M., Irvin, J., … Lungren,M. P. (2019). Human–machine partnership with artificial intelligence for chest radiograph diagnosis. *NPJ digital medicine*, *2*(1), 1–10.
23. Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *nature*, *542*(7639), 115–118.
24. Hannun, A. Y., Rajpurkar, P., Haghpanahi, M., Tison, G. H., Bourn, C., Turakhia, M. P., & Ng, A. Y. (2019). Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. *Nature medicine*, *25*(1), 65–69.
25. Akil, M., Saouli, R., & Kachouri, R. (2020). Fully automatic brain tumor segmentation with deep learning-based selective attention using overlapping patches and multi-class weighted cross-entropy. *Medical image analysis*, *63*, 101692.
26. De Fauw, J., Ledsam, J. R., Romera-Paredes, B., Nikolov, S., Tomasev, N., Blackwell,S., … Ronneberger, O. (2018). Clinically applicable deep learning for diagnosis and referral in retinal disease. *Nature medicine*, *24*(9), 1342–1350.
27. Nahata, H., & Singh, S. P. (2020). Deep learning solutions for skin cancer detection and diagnosis. In *Machine Learning with Health Care Perspective* (pp. 159–182). Springer, Cham.
28. Jinnai, S., Yamazaki, N., Hirano, Y., Sugawara, Y., Ohe, Y., & Hamamoto, R. (2020). The development of a skin cancer classification system for pigmented skin lesions using deep learning. *Biomolecules*, *10*(8), 1123.
29. Gordienko, Y., Gang, P., Hui, J., Zeng, W., Kochura, Y., Alienin, O., … Stirenko,S. (2018, January). Deep learning with lung segmentation and bone shadow exclusion techniques for chest X-ray analysis of lung cancer. In *International Conference on Computer Science, Engineering and Education Applications* (pp. 638–647). Springer, Cham.
30. Bader, F., Manla, Y., Atallah, B., & Starling, R. C. (2021). Heart failure and COVID-19. *Heart failure reviews*, *26*(1), 1–10.
31. Khan, A. H., Hussain, M., & Malik, M. K. (2021). ECG Images dataset of Cardiac and COVID-19 Patients. *Data in Brief*, *34*, 106762.
32. Bergamaschi, L., D'Angelo, E. C., Paolisso, P., Toniolo, S., Fabrizio, M., Angeli,F., … Galié, N. (2021). The value of ECG changes in risk stratification of COVID-19 patients. *Annals of Noninvasive Electrocardiology*, *26*(3), e12815.

Figures

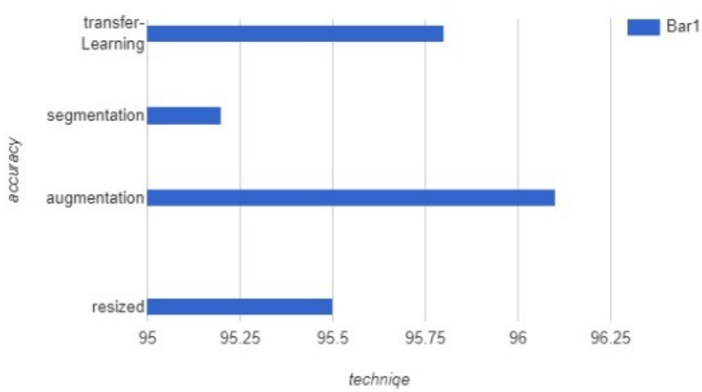

Figure 1

novel practical comparison among pre-processing techniques for Covid-19 datasets

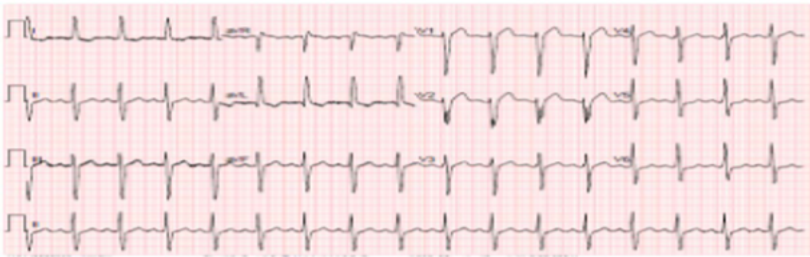

Figure 2

ECG of heart patient with positive Covid-19 case

Figure 3

ECG of heart patient with negative Covid-19 case

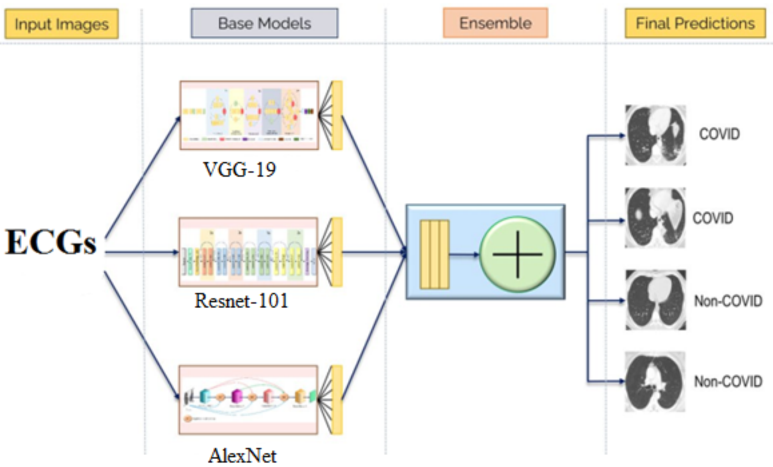

Figure 4

the steps of our proposed model

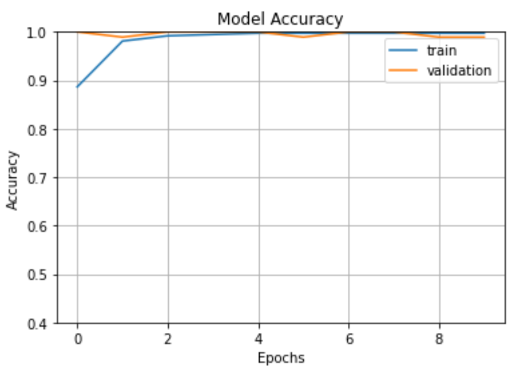

Figure 5

the training and validation accuracy of our proposed model

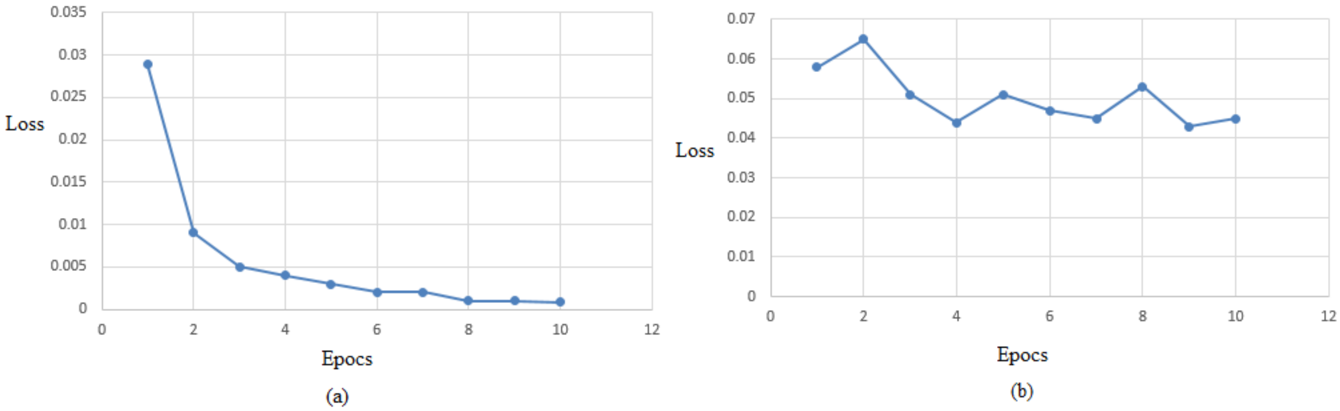

Figure 6

(a) validation-loss of our proposed model vs (b) validation-loss of general Covid-19 diagnostic model.

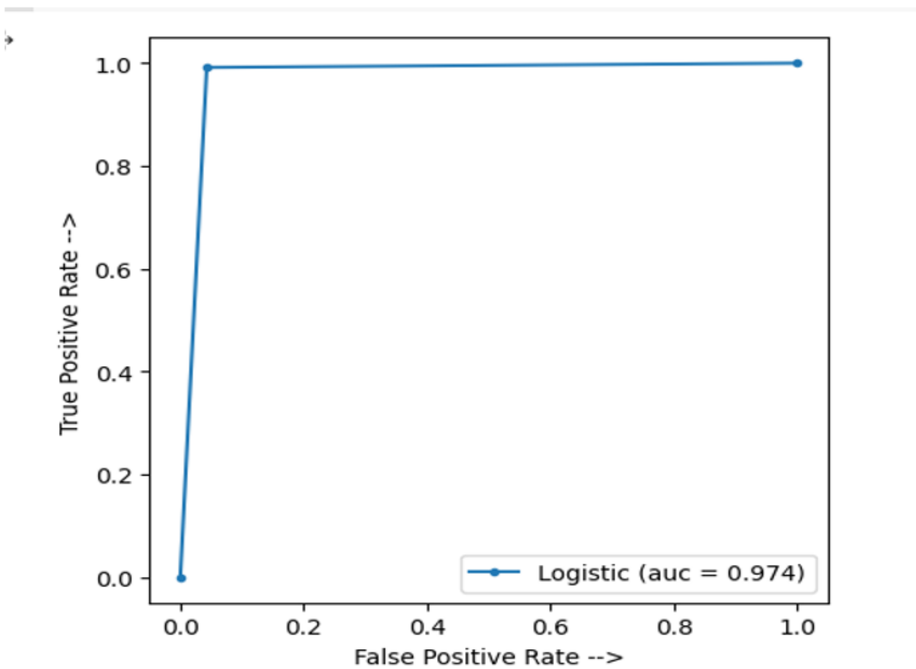

Figure 7

AUC of our proposed model