International Journal of Nanotechnology

ISSN online: 1741-8151 - ISSN print: 1475-7435
https://www.inderscience.com/ijnt

Deep learning-based feature extraction coupled with multi class SVM for COVID-19 detection in the IoT era

Mubarak Auwalu Saleh, Sertan Serte, Fadi Al-Turjman, R.A. Abdulkadir, Zubaida Sa'id Ameen, Mehmet Ozsoz

Article History:
Received:
Accepted:
Published online: 31 May 2023

Deep learning-based feature extraction coupled with multi class SVM for COVID-19 detection in the IoT era

Mubarak Auwalu Saleh* and Sertan Serte

Department of Electrical and Electronics Engineering,
Near East University,
Nicosia, Mersin 10, Turkey
Email: auwalusaleh.mubarak@neu.edu.tr
Email: sertan.serte@neu.edu.tr
*Corresponding author

Fadi Al-Turjman

Department of Artificial Intelligence Engineering,
Research Center for AI and IoT,
Near East University, Nicosia, Mersin 10, Turkey
Email: fadi.alturjman@neu.edu.tr

R.A. Abdulkadir

Department of Electrical Engineering,
Kano University of Science and Technology,
Wudil, 713271, Nigeria
Email: rabiualiyu.abdulkadir@neu.edu.tr

Zubaida Sa'id Ameen and Mehmet Ozsoz

Department of Biomedical Engineering,
Near East University,
Nicosia, Mersin 10, Turkey
Email: mehmet.ozsoz@neu.edu.tr
Email: zubaida.saidameen@neu.edu.tr

Abstract: The deadly coronavirus virus (COVID-19) was confirmed as a pandemic by the World Health Organisation (WHO) in December 2019. Prompt and early identification of suspected patients is necessary to monitor the transmission of the disease, increase the effectiveness of medical treatment and as a result, decrease the mortality rate. The adopted method to identify COVID-19 is the Reverse-Transcription Polymerase Chain Reaction (RT-PCR), the method is affected by the shortage of RT-PCR kits and complexity. Medical imaging using deep learning has proved to be one of the most efficient methods of detecting respiratory diseases, but efficient deep learning architecture and low data are affecting the performance of the deep learning models. To detect COVID-19 efficiently, a deep learning model based feature extraction coupled with support vector machine (SVM) was employed in this study, Seven pre-trained models were employed as feature extractors and the extracted features are classified by multi-class SVM classifier to classify

COVID-19, common pneumonia and healthy individuals' CT scan images, to improve the performance of the models and prevent overfitting, training was also carried out on augmented images. To generalise the model's performance and robustness, three datasets were merged in the study. The model with the best performance is the VGG19 which was trained with augmented images, the VGG19 achieved an accuracy of 96%, sensitivity of 0.936, specificity of 0.967, F1 score of 0.935, precision of 0.934, Yonden Index of 0.903 and AUC of 0.952. The best model shows that COVID-19 can be detected efficiently on CT scan images.

Keywords: artificial intelligence; COVID-19; SVM; support vector machine; feature extraction.

Reference to this paper should be made as follows: Saleh, M.A., Serte, S., Al-Turjman, F., Abdulkadir, R.A., Ameen, Z.S. and Ozsoz, M. (2023) 'Deep learning-based feature extraction coupled with multi class SVM for COVID-19 detection in the IoT era', *Int. J. Nanotechnol.*, Vol. 20, Nos. 1/2/3/4, pp.7–24.

Biographical notes: Mubarak Auwalu Saleh received his BTech Electrical Engineering with a Specialisation in Electronics and Control from Cape Breton University, Canada in 2012. He obtained his MTech Electrical and Electronics Engineering with specialisation in Instrumentation and control from Sharda University. India in 2015. He is a Lecturer at Kano University of Science and Technology, Kano, Nigeria. He is a PhD Student in Electrical Engineering at Near East University. His research interest is on artificial intelligence and control systems.

Sertan Serte is an Associate Professor in the Department of Electrical and Electronic Engineering at Near East University. His research focus is on computer vision and machine learning.

Fadi Al-Turjman received his PhD in Computer Science from Queen's University, Kingston, Ontario, Canada in 2011. He is a full-time professor and research centre director at Near East University, Nicosia, Mersin 10, Turkey. He is a leading authority in the areas of smart/cognitive, wireless, and mobile networks' architectures, protocols, deployments, and performance evaluation. His publication history spans over 250 publications in journals, conferences, patents, books, and book chapters.

R.A. Abdulkadir received his Bachelor's degree in Electrical Engineering from the Kano University of Science and Technology, Wudil, Nigeria, and the Master's degree in Instrumentation and Control from Sharda University, India. He is currently a Lecturer with the Department of Electrical Engineering, Kano University of Science and Technology. His research interests include control systems design, robotics, computer vision, image processing, and artificial intelligence.

Zubaida Sa'id Ameen received her BSc in Biochemistry from Bayero University Kano in 2010. She obtained her MSc in Bioengineering from Cyprus International University in 2016. Currently, she is an Academic staff in Biochemistry Department, Yusuf Maitama Sule University, Kano. Now, she is a PhD student in Biomedical Engineering at Near East University. Her research mainly focuses on deep learning and CRISPR technology.

Mehmet Ozsoz is a Professor in the Biomedical Engineering Department, Faculty of Engineering, Near East University, Northern Cyprus. His main research interests are biosensors, crispr and. application to artificial intelligence.

1 Introduction

Epidemic outbreaks have led to the deaths of billions over the decades. The novel Coronavirus (COVID-19) is a dangerous disease that first appeared in China in December 2019 and was later declared a pandemic by the World Health Organisation (WHO) at the beginning of 2020 [1,2]. The disease is typically spread by exposure to respiratory droplets while a person is in direct contact with someone who has COVID-19, and typical signs of COVID-19 include cough, fever, lack of appetite, fatigue, chest pain and high temperatures [3,4]. To date, the Covid-19 epidemic has infected more than 76 million people with an estimated total of 1.6 million deaths around the world [5].

Rapid and early diagnosis of suspected patients is important to monitor the dissemination of COVID-19, it will increase the efficacy of medical services, consequently, decrease mortality and the need for intensive care [6–8]. Covid-19 can be detected using Reverse Transcription Polymerase Chain Reaction (RT-PCR) with approximately 71% sensitivity. However, the use of RT-PCR is associated with certain deficiencies, including the lack of supply of RT-PCR kits, especially in developing countries, and time-consuming, which makes their use difficult and complicated. Several types of research have proposed that computer tomography (CT) imaging may serve as a feasible option for the detection of COVID-19 with better sensitivity compared to RT-PCR [9].

Despite the continuous rise in cases of COVID-19, many experts assumed that CT had a major role to play in the detection and management of COVID-19 at early-stage, chest CT scan was able to recognise COVID-19 by revealing irregular imaging findings [10]. Other benefits of CT include high sensitivity, a high positive rate of moderate turnaround time and more details on pathology [9,10]. Although chest CT has shown an immense capacity for the identification of COVID-19, the manual detection of radiographic characteristics has low accuracy in distinguishing COVID-19 from common pneumonia [11]. The rapid growth of COVID-19 patients and multiple CT scans (average 300 slices per scan) of each patient have also resulted in a large number of CT images, which is a severe challenge for radiologists, especially in the epidemic [12].

Deep learning has been applied to many problems in different fields [13–19]. Several deep learning models were developed to improve the performance and generality of the models, the major setbacks face by these models are associated with the deep learning architecture [20], a low number of datasets [21,22], noise and variation of scale levels in medical images [12,23–25]. To detect COVID-19 on CT scan images using deep learning, transfer learning is the widely used method, it is easier to train and achieve higher accuracy [26–30]. With few datasets, deep learning may overfit or may not perform very well, data augmentation can reduce overfitting, robustness and improve the performance of the model [21,31,32]. In this study, hybrid models which use pre-trained deep learning models as feature extractor and support vector machine (SVM) as the classifier was proposed. SVM is easier to train and very efficient. Similar architectures have been applied to problems like classifying the texture of plants [33] facial recognition [34]. In Patalas-maliszewska [16] SVM shows better performance and takes less time to train compared to a Softmax classifier of the pre-trained models.

By linking most of the real objects around us to the internet, IoT technology helps us to integrate the physical and virtual environments. It gives everyday objects computational power and network access, allowing them to produce and disseminate data. These objects could include home appliances, wearable devices, medical equipment, and vehicles. IoT pushes us closer to artificial intelligence, smart access, and automation with less human interference [35]. To reduce human interaction and fasten COVID-19 detection [36] proposed an intelligent system that makes use of thermal and optical cameras as sensors, the thermal camera checks the temperature of the suspect and if the suspect temperature is high, the optical camera will capture the suspects face, the GPRS sensor will also provide the location of the suspect, both the GPRS and the captured image will be sent to the authority, this system will reduce the spread of the virus. Remote diagnostics, such as radiological services and online image processing, may benefit from the image database with advanced analysis, which allows physicians to diagnose critical illnesses without having to travel to remote locations. Improvements in biomedical and healthcare environments are apparent when combined with machine learning (ML) algorithms that can analyse and develop sophisticated simulations. Every day, millions of images are created, allowing different types of artificial intelligence (AI) to open up new frontiers in big data analytics. The machine learning algorithms mainly clean structured data from raw datasets, converting it into expectations and assumptions to aid in the adoption of immediate actions [37]. The IoT has spurred the development of a wide range of smart IoT applications across several industries. Successful IoT implementations and experiments are needed to advance the various technical aspects of these solutions. Low-cost and modular approaches such as mathematical modelling and simulation are commonly used to solve this. However, such techniques are limited in their ability to realistically capture physical characteristics and network conditions. To address this issue, a revolutionary IoT testbed device that allows for the realistic testing of various IoT solutions in a controlled environment. The testbed was built to provide multidimensional general-purpose support for various IoT properties such as sensing, connectivity, portal, energy storage, data processing, and security [38–40]. IoT and big data analytics, in general, are two main innovations that can change the biomedical and healthcare industries and improve people's lives [41].

Convolutional neural networks (CNNs) have attained state-of-the-art performance in the field of medical imaging based on previous studies [42–44]. This degree of reliability is obtained by using labelled data to train and fine-tuning the system's millions of parameters. CNN can easily overfit small datasets due to the huge number of parameters, so generalisation efficiency is proportional to the size of the labelled data. Due to the limited number of datasets, limited datasets prove to be the most challenging problem in the medical imaging domain [45–47]. Medical image collection is a very expensive and tedious process that requires the participation of radiologists and researchers [46]. Also, since the COVID-19 outbreak is recent, sufficient data of chest CT scan images is difficult to gather, unlike [42] were by the detection of COVID-19 was performed on synthetic CT scan images, we proposed an offline data augmentation were by several data augmentations employed in many studies were performed on each of the three datasets such as random reflection, random rotation, random rescale, random translation.

Feature extraction is a critical component of a detection system's performance [15]. CNN features are automatically trained. One of CNN's advantages in the case of transformations such as translation, scaling, and rotation is that they can be invariant. Invariance, rotation, and scale are three of CNN's most unique advantages, particularly in image recognition problems such as object detection, since they allow the network to abstract identity, enabling it to recognise the object even though the image's pixel values vary greatly. Feature extraction increases the accuracy of the models learned by extracting the features from the input data. This move in the general framework reduces data dimensionality by removing redundant data. It also increases the speed and inference of model training. Methods of extraction of features generate new features by rendering the variations and transformations of the original features. Colour, shape, texture or pixel value is the type of characteristics that can be obtained from medical images. Any diagnostic image, such as CT scan images, does not contain any colour detail. This is appreciated in this field.

1.1 Related works

The deadly disease of COVID-19 has had an impact on the world by debilitating operations, multiple methods have been taken into account in combating the spread of deadly disease, mathematical models have been studied to estimate the spread of the disease by considering the number of infected, susceptible and recovered patients, and this analysis is a classic approach. The maximum number of sick people, as well as the scale and speed at which the disease spreads through migration, was analysed using a time-varying SIR model, these analyses can help estimate the number of infectious individuals and the disease's replication number [48]. To attain real-time prediction, AI models coupled with IoT have been used to help medical practitioners diagnose and track COVID-19 by looking at parameters such as temperature, blood pressure and heart rate, considering the high number of incidents, the privacy of data transmission and the energy efficiency of the low power system used to gather information is very critical [49]. To reduce the effect of the economic impact caused by COVID-19 [50] Proposed AI model that is data-driven to forecast lock-down and non-lock-down region boundaries to minimise the economic effect of the COIVD-19 pandemic, the embraced form of lock-down by several countries was absolute lock-down, this method is not good for the economy. with the proposed model by Rahman [50], near to real-time prediction of areas with high active cases was predicted and this can serve as an avenue to smart cities [51]. IoT based system was proposed to identify COVID-19 by gathering information from patients such as X-ray images, temperature, breathing ventilation, sweat change, and heart signals. The system classifies X-ray images and predicts the state of patients using three deep learning models, namely ResNet50, InceptionV3 and InceptionResNetV2. This research would allow health professionals to treat and detect COVID-19 patients.

Medical imaging and deep learning have contributed a lot in detecting respiratory diseases and other medical conditions like brain surgery, pulmonary diseases, and cardiology [32,51–56]. By employing transfer learning via the Resnet50 pre-trained model, retraining at 41 epochs an accuracy of 96.3% was achieved in all classes. RT PCR findings were compared with CT scan images in COVID-19 identification, the earlier RT PCR results are negative while the CT scan results are positive, this indicates the efficacy of the medical imaging in COVID-19 profiling as it can identify the virus at an early stage [57]. Multi-Scale Convolutional Network was used to distinguish COVID-19 and common pneumonia CT scan images, the performance of the Deep Learning model was compared to the results of the radiologist, it was observed that the AI model outperforms the radiologist, achieves an accuracy of 97.7%, a sensitivity of 0.995, a specificity of 0.956 and an AUC of 0.962, while the radiologist achieves an accuracy of 97%, a sensitivity of 0.995, a specificity of 0.956 and an AUC of 0.962 [21].

In the study carried out by Umar et al. [58], X-ray images were trained using a pre-trained AlexNet to differentiate between COVID-19 pneumonia NON-COVID-19 Viral pneumonia, Bacterial pneumonia and healthy patients, binary classification was performed by considering two of the above classes, then multi-class classification for three classes except healthy individual X-rays, and the last four classes were considered for training. The performance of the models was calculated using precision, sensitivity and specificity, the highest performance is of the binary classification which COVID-19 and healthy X-ray were considered, the accuracy obtained was 99.16%, the sensitivity was 97.44% and the specificity was 100% [42]. Improving the efficiency of the CNN model proposed in the study by adding an Auxiliary Classifier Generative Adversarial Network (ACGAN), ACGAN generates synthetic images to maximise the number of training images, achieving 95% accuracy, which is 10% higher than the accuracy attained by the proposed CNN model.

1.2 Contributions

In this study, seven pre-trained deep learning models AlexNet, GoogleNet, ResNet-50, ResNet-101, ShuffleNet, VGG16 and VGG19 were used as feature extractors and multi-class SVM as a classifier for COVID-19 detection. The idea behind this hybrid model is to improve the performance of the state of the art model in the detection of COVID-19. The different deep learning models employed in the study have different depth in architectures and features, the multiclass SVM classifier is very efficient and easier to train. Our contributions to this study are:

- i proposed a hybrid model which is deep learning-based feature extraction and classification based on multi-class SVM classifier
- ii seven pre-trained deep learning models were proposed as feature extractors and a multi-class SVM as a classifier
- iii the proposed model outperformed the state of the art model
- iv to improve the performance of the models and reduce overfitting, data augmentation was carried out on the datasets
- v three datasets were merged to generalised the performance of the model and improve the training of the model.

2 COVID-19 detection

This section describes the characteristics of the dataset used and the proposed pre-trained deep learning models for COVID-19 detection. All abbreviations are listed in Table 1.

Table 1 Abbreviations

WHO	World Health Organisation
RT-PCR	Reverse-transcription polymerase chain reaction
SVM	Support vector machine
CT	Computer tomography
IoT	Internet of things
ACGAN	Auxiliary classifier generative adversarial network
CNN	Convolutional neural network
DL	Deep learning
AI	Artificial intelligence
ML	Machine learning

2.1 Dataset

In this research, three datasets have been used to classify CT scan images. The datasets obtained provide three classes: positive COVID-19, healthy individuals and common pneumonia. The first collection of data [59], contains 349 COVID-19 positive and 397 healthy individuals CT scan images, collection of data [60] contains 328 common pneumonia and 371 COVID-19 positive CT scan images and the third collection of data [22] contains 1252 COVID-19 positive class and 1229 healthy individuals. Meanwhile, to generalised the dataset the three datasets were merged. The overall dataset comprises 1608 healthy individuals, 1972 COVID-19 positive and 328 patients with common pneumonia. The details of the dataset is presented in Table 2.

Table 2 Compiled dataset

Dataset	*COVID–19 Positive*	*Common Pneumonia*	*Healthy Individuals*
Yang et al. [59]	349	NA	397
Yan et al. [60]	371	328	NA
Soares et al. [22]	1252	NA	1229
Total Number of CT scan images per class	1972	328	1608

2.2 Transfer learning

Transfer learning is a research problem in machine learning. It focuses on storing knowledge gained while solving one problem and applying it to a different but related problem [51,61–64]. In training the pre-trained network for another problem, some features of the pre-trained models will be changed, such changes are layers to be frozen, layers to be added and change of some hyperparameters values.

2.3 ResNet

ResNet or Residual Network [14] is a deep learning algorithm used in classifying images. The key concept behind ResNet is to deal with disappearing gradients that degrade network output induced by piling up a convolution layer over a pooling layer in deep network architecture, shortcuts that include identity is a residual block, the idea of inserting skip connections effectively removes a high training error, other deep networks do not contain an identity connection that is why ResNet is different, the ResNet-50 has 50 layers while ResNet-101 has 101 layers. The input layer accepts an image of size 224 × 224.

2.4 AlexNet

AlexNet [65] is a deep learning model which consist of five convolution layers, three fully connected layers and 3 max-pooling layers, the AlexNet was the first to win the ImageNet challenge in 2012, Rectified Linear Unit was first introduced in AlexNet, this makes it to train faster compared to CNN with tahn function. The AlexNet input layer admits images with the size 227 × 227.

2.5 GoogleNet

GoogleNet is a 22 layer network comprising of the input layer, convolution layers, max-pooling and softmax classifier, the main things that make the GoogleNet different is the 1 × 1 convolution, network in network and the global average pooling. The GoogleNet won the ILSVRC 2014 competition with a low error rate compared to VGG [66].

2.6 ShuffleNet

ShuffleNet [67] is a deep learning model that has 50 layers, it utilises the group convolution from AlexNet on 1 × 1 convolution layer, the group convolution reduces computation significantly, but the drawbacks of the group convolutions is that output of certain channels are driven from a small fraction of the input, to address this issue, the channels which are also differentiable are shuffled in ShuffleNet to address this issue.

2.7 VGG

VGG [68] is a deep learning model which utilises small filters and max pooling after every convolution, the VGG16 which contains 16 layers, out of the 16 layers 5 are convolutional layers, 3 trainable layers and the remaining layers are max-pooling layers, while the VGG19 has 19 layers. This architecture was the 1st runner up of the Visual Recognition Challenge of 2014 i.e., *ILSVRC-2014*.

2.8 Support vector machines (SVM)

The SVM [69] classification is referred to as a process whereby the supervised binary classification method is used and when a training set is introduced, wherein the algorithm develops a hyperplane that maximises the margin that exists between two input classes. For instance, considering linearly separate data with two distinct classes, the system can have numerous hyperplanes which separate two classes. SMV identify the most ideal hyperplane that has a maximum margin between all available hyperplanes, whereby the margin is the distance difference between the hyperplane and the support vectors. Given a set of training data $\{(x_i, d_i)\}_i^N$ (d_i is the actual value, x_i represents the input vector and N is the data number), given that the SVM function is:

$$y = f(x) = w\phi(x_i) + b \tag{1}$$

where $\phi(X)$ is mapped non-linearly from input vector x, which are input feature spaces.

Then, the SVM equation is given as [69]:

$$f(x, \alpha_{j,} \alpha_{i^*}) = \sum_i^N (\alpha_i - \alpha_{i^*}) K(x, x_i) + b \tag{2}$$

$k(x_i, x_j)$ is the kernel function in the feature space after performing non-linear mapping and b is bias term. The most commonly used kernel function is Gaussian radial basis function (RBF) because it performs better than linear and polynomial kernel as it is not only capable to map non-linearly training data into infinite-dimensional space but also easier to implement [69] and it is given as:

$$k(x_1, x_2) = exp(-\gamma \parallel x_1 - x_2 \parallel^2) \tag{3}$$

where γ is the kernel parameter.

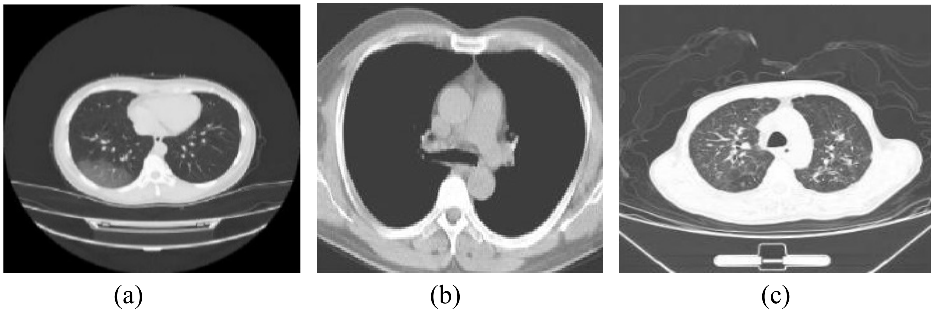
3 Data pre-processing and training

Data preprocessing in deep learning is the process of perfecting data in such a way that it can fit the input of a network and also, clean and increase the number of the dataset for robust and better training. There are several types of data preprocessing such as resizing, augmentation and smoothing in training medical images.

3.1 Data augmentation

Data augmentation is a method of obtaining additional data from the initial dataset, an increase in data increases training performance and prevents over-fitting [21,32]. Several data augmentations employed in many studies were performed on each of the three datasets such as random reflection, random rotation, random rescale, random translation along X-axis and random translation along Y-axis. After data augmentation, a total number of 10,000 COVID-19 positive CT scan images were produced and 10,000 healthy individuals CT scan images were produced and a total number of 10,000 Common Pneumonia CT images were produced, in total, we generated 30,000 CT scan images for the study. Samples of CT scan images are presented in Figure 1.

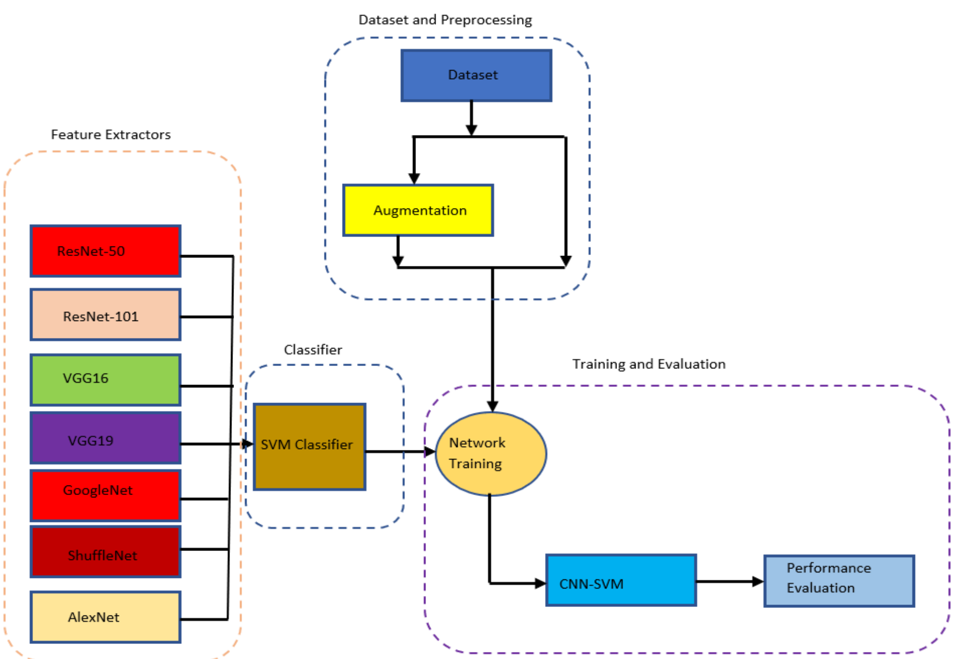
Figure 1 CT scan images samples: (a) COVID-19 positive; (b) healthy individuals and (c) common pneumonia



3.2 *Training*

In this study, seven pre-trained deep learning models AlexNet, GoogleNet, ResNet-50, ResNet-101, ShuffleNet, VGG16 and VGG19 which serves as feature extractor coupled with multi-class SVM classifier were used in classifying COVID-19, common pneumonia and healthy individuals CT scan images, the pre-trained models serve as feature extractors while the multi-class SVM as classifier. The training is in two stages, firstly the training was carried out on the original set of CT scan images, while the second training was carried out on augmented CT scan images. The performance of the two training types was compared to find the best models. Figure 2 show the detailed training process in this study.

Figure 2 Training process (see online version for colours)



The images were resized to the size of 224 × 224 for GoogleNet, ResNet-50, ResNet-101, ShuffleNet, VGG16 and VGG19 and 227 × 227 for AlexNet, from the input of the pre-trained networks to the last pooling layer of the networks were used for feature extraction, the top of the pre-trained models which include the fully connected layers and the softmax classifier were replaced by multi-class SVM classifier, 805 of the total images were used for training and the 20% were used for testing. The feature extraction part is responsible for extracting features that will be used by the classifier to classify the CT scan images, after training the hybrid model, the model's performance will be evaluated based on the performance evaluation criteria.

4 Results and discussion

In this study, seven pre-trained models were employed to classify COVID-19, common pneumonia and healthy individuals CT scan images, the performance of the first and second training sets was compared to find the model with the best performance, also the performance of the best model between the two training was compared with the state of the art model that performed multi-class classification to detect COVID-19 on CT scan images.

The first training carried out on the original training set and the results of the model performance are presented in Table 3. The models with the best performance in terms of accuracy is the VGG16 with an accuracy of 93.8% followed by VGG19 and GoogleNet with an accuracy of 93.6% and 93.1% respectively, in terms of specificity, VGG16 achieves the highest with 0.943, also VGG16 achieves the highest AUC with 0.936, this show that VGG16 outperformed the remaining models trained in this model for the first training, the results are also visually presented in Figures 3 and 4.

Table 3 Proposed models performance for the first training

Models	*Accuracy* (%)	*Sensitivity*	*Specificity*	*F1 score*	*Precision*	*Yonden index*	*AUC*
Resnet–101	88.3	0.9	0.86	0.886	0.873	0.76	0.880
ResNet–50	91.9	0.918	0.918	0.918	0.919	0.836	0.918
GoogleNet	93.1	0.944	0.918	0.932	0.921	0.862	0.931
ShuffleNet	86	0.852	0.867	0.859	0.866	0.719	0.860
AlexNet	91	0.93	0.893	0.911	0.893	0.823	0.912
VGG16	93.8	0.934	0.943	0.939	0.944	0.877	0.939
VGG19	93.6	0.949	0.923	0.937	0.926	0.872	0.936

For the second training, the training was carried out on the augmented training set and the results are presented in Table 4. The models with the best performance in terms of accuracy is VGG19 with an accuracy of 96% followed by VGG16 and GoogleNet with an accuracy of 94.9 each. In terms of specificity and AUC, VGG19 outperformed the remaining models in the second training with 0.967 and 0.952 specificity and AUC respectively, the visual representation of the results is presented in Figures 5 and 6.

Figure 3 Models performance for the first training (see online version for colours)

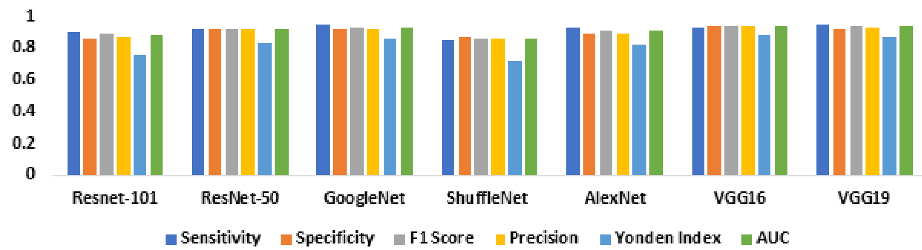


Figure 4 Models accuracy for the first training (see online version for colours)

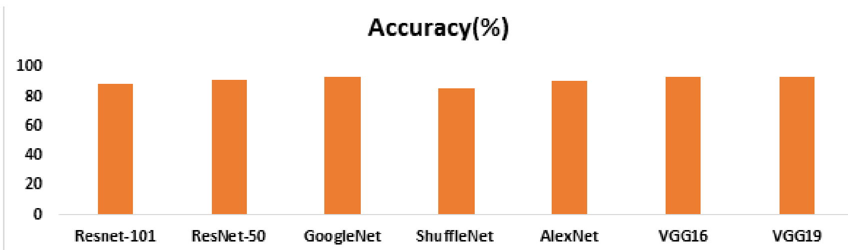


Table 4 Proposed models performance for the second training

Models	*Accuracy* (%)	*Sensitivity*	*Specificity*	*F1 Score*	*Precision*	*Yonden Index*	*AUC*
ResNet–101 + Augmentation	93.4	0.912	0.948	0.905	0.898	0.86	0.930
ResNet–50 + Augmentation	93	0.905	0.945	0.899	0.892	0.85	0.925
GoogleNet + Augmentation	94.9	0.926	0.964	0.927	0.928	0.89	0.945
AlexNet + Augmentation	92	0.886	0.941	0.885	0.883	0.827	0.914
ShuffleNet + Augmentation	87	0.846	0.892	0.848	0.851	0.738	0.869
VGG16 + Augmentation	94.9	0.92	0.96	0.922	0.925	0.88	0.940
VGG19 + Augmentation	96	0.936	0.967	0.935	0.934	0.903	0.952

The state of the art model [70] proposed a new deep learning model in which they trained to classify CT scan images with three different classes COVID-19, other pneumonia and healthy patients, in training, they consider two different images resolutions, first training on 512 × 512 resolution CT scan images and the second training on 256 × 256 resolution CT scan images. The best models [70] achieve an accuracy of 94.67%, a sensitivity of 0.96, specificity of 0.92 and AUC of 0.97 in Table 5. The proposed model's performance was compared to the state of the art model. The proposed architecture which utilises pre-trained deep leaning as feature extractor and SVM as classifier shows how great it can perform in detecting COVID-19 CT scan images.

Table 5 Proposed models performance with state of the art model

References	*Models*	*Accuracy (%)*	*Sensitivity*	*Specificity*	*F1 Score*	*Precision*	*Yonden Index*	*AUC*
Amyar et al. [70]	T1 and T2 & T3 512 × 512	91.13	0.94	0.85	NA	NA	NA	0.94
	T1 & T2 & T3 256 × 256	94.67	0.96	0.92	NA	NA	NA	0.97
Proposed models	Resnet–101	88.3	0.9	0.86	0.88	0.87	0.76	0.88
	ResNet–50	91.9	0.91	0.91	0.91	0.91	0.83	0.91
	GoogleNet	93.1	0.94	0.91	0.93	0.92	0.86	0.93
	ShuffleNet	86	0.85	0.86	0.85	0.86	0.71	0.86
	AlexNet	91	0.93	0.89	0.91	0.89	0.82	0.91
	VGG16	93.8	0.93	0.94	0.93	0.94	0.87	0.93
	VGG19	93.6	0.94	0.92	0.93	0.92	0.87	0.93
	ResNet–101 + Augmentation	93.4	0.91	0.94	0.90	0.89	0.86	0.93
	ResNet–50 + Augmentation	93	0.90	0.94	0.89	0.89	0.85	0.92
	GoogleNet + Augmentation	94.9	0.92	0.96	0.92	0.92	0.89	0.94
	AlexNet + Augmentation	92	0.88	0.94	0.88	0.88	0.82	0.91
	ShuffleNet + Augmentation	87	0.84	0.89	0.84	0.85	0.73	0.86
	VGG16 + Augmentation	94.9	0.92	0.96	0.92	0.92	0.88	0.94
	VGG19 + Augmentation	96	0.93	0.96	0.93	0.93	0.90	0.95

Figure 5 Models performance for the second training (see online version for colours)

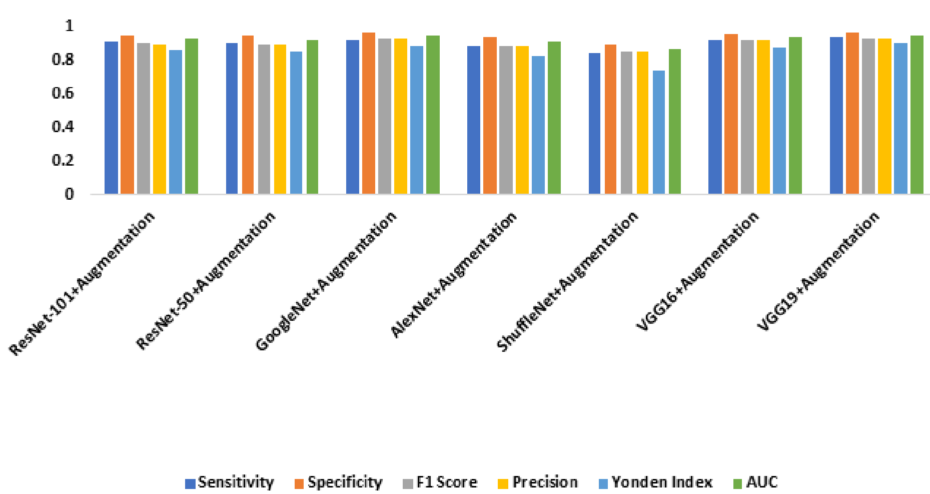
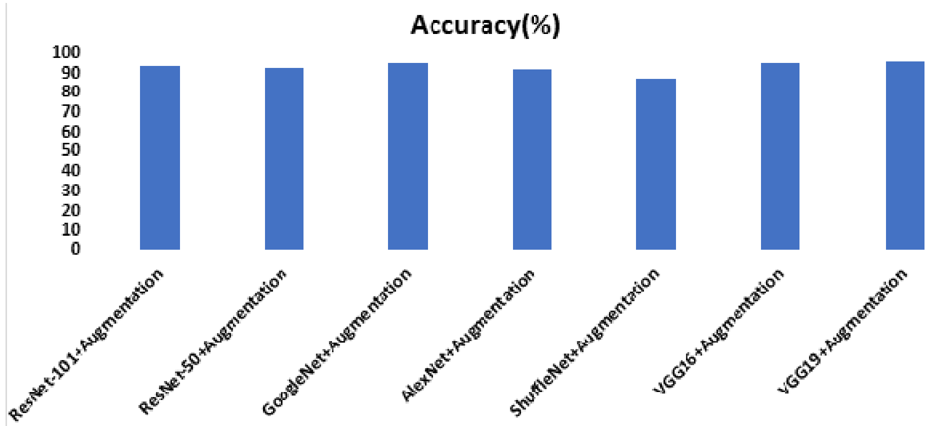


Figure 6 Models accuracy for the second training (see online version for colours)



5 Conclusion

Seven pre-trained models AlexNet, GoogleNet, ResNet-50, ResNet-101, ShuffleNet, VGG16 and VGG19 were employed in this study as feature extractors and a multi-class SVM as the classifier to classify COVID-19, common pneumonia and healthy individual CT scan images, detecting COVID-19 at an early stage is very important, it will reduce the spread of the virus and putting the patient on the right diagnosis, that is why in this study, we improved the performance of deep learning models by augmenting the images and changing the classifier of the pre-trained models with a classifier that is efficient and takes less time to train. With this approach, we are confident that COVID-19 can be detected at an early stage with high accuracy and reliability.

In the future, the authors will explore more preprocessing techniques, also more classifiers such as Decision Tree, SVM, K Nearest Neighbour and ensemble classifiers will be explored to improve the performance of the detection. The authors will also try to incorporate the proposed model with IoT for easy detection of COVID-19.

References

1 Bianco, S., Cadene, R., Celona, L. and Napoletano, P. (2018) 'Benchmark analysis of representative deep neural network architectures', *IEEE Access*, Vol. 6, pp.64270–64277, https://doi.org/10.1109/ACCESS.2018.2877890

2 Caliendo, A.M., Couturier, M.R., Ginocchio, C.C., Hanson, K.E., Miller, M.B., Walker, K.E. and Frank, G.M. (2020) 'Maintaining life diagnostic testing for the novel coronavirus', *Clinical Infectious Diseases: An Official Publication of the Infectious Diseases Society of America*, Vol. 323, No. 15, pp.1437–1438, https://doi.org/10.1093/cid/ciw260

3 Emperador, D., Dittrich, S., Domen, J., Sra, H.A.V.D.B. and Diagnostic, C.C. (2020) 'Signs and symptoms to determine if a patient presenting in primary care or hospital outpatient settings has COVID-19 disease (Review)', *Cochrane Database of Systematic Reviews, CD013665*, pp.1–93, https://doi.org/10.1002/14651858.CD013665.www.cochranelibrary.com

4 Wang, H.Y., Li, X.L., Yan, Z.R., Sun, X.P., Han, J. and Zhang, B.W. (2020) 'Potential neurological symptoms of COVID-19', *Therapeutic Advances in Neurological Disorders*, Vol. 13, pp.1–2, https://doi.org/10.1177/1756286420917830

5 WHO (2020) WHO *Coronavirus Disease (COVID-19) Dashboard*, World Health Organization.

6 Zivkovic, M., Bacanin, N., Venkatachalam, K. and Nayyar, A. (2021) *COVID*-19 *Cases Prediction by Using Hybrid Machine Learning and Beetle Antennae Search Approach*, Vol. 66, November 2020.

7 Guan, W., Ni, Z., Hu, Y., Liang, W., Ou, C., He, J., Liu, L., Shan, H., Lei, C., Hui, D.S.C., Du, B., Li, L., Zeng, G., Yuen, K-Y., Chen, R., Tang, C., Wang, T., Chen, P., Xiang, J. and Zhong, N. (2020) 'Clinical characteristics of coronavirus disease 2019 in China', *N. Engl. J. Med.*, Vol. 382, No. 18, pp.1708–1720, https://doi.org/10.1056/nejmoa2002032

8 Zhu, N., Zhang, D., Wang, W., Li, X., Yang, B., Song, J., Zhao, X., Huang, B., Shi, W., Lu, R., Niu, P., Zhan, F., Ma, X., Wang, D., Xu, W., Wu, G., Gao, G.F. and Tan, W. (2020) 'A novel coronavirus from patients with pneumonia in China, 2019', *N. Engl. J. Med.*, Vol. 382, No. 8, pp.727–733, https://doi.org/10.1056/nejmoa2001017

9 Fang, Y., Zhang, H., Xie, J., Lin, M., Ying, L., Pang, P. and Ji, W. (2020) 'Sensitivity of chest CT for COVID-19: comparison to RT-PCR', *Radiology*, Vol. 296, No. 2, pp.E115–E117, https://doi.org/10.1148/radiol.2020200432

10 Pan, Y., Guan, H., Zhou, S., Wang, Y., Li, Q., Zhu, T. and Hu, Q. (2020) 'Initial CT findings and temporal changes in patients with the novel coronavirus pneumonia (2019-nCoV): a study of 63 patients in wuhan, China Yueying', *Eur. Radiol.*, Vol. 30, December 2019, pp.3306–3309.

11 Bai, H.X., Hsieh, B., Xiong, Z., Halsey, K., Choi, J.W., Tran, T.M.L., Pan, I., Shi, L.B., Wang, D.C., Mei, J., Jiang, X.L., Zeng, Q.H., Egglin, T.K., Hu, P.F., Agarwal, S., Xie, F.F., Li, S., Healey, T., Atalay, M.K. and Liao, W.H. (2020) 'Performance of radiologists in differentiating COVID-19 from non-cOVID-19 viral pneumonia at Chest CT', *Radiology*, Vol. 296, No. 2, pp.E46–E54, https://doi.org/10.1148/radiol.2020200823

12 Yan, T., Wong, P.K., Ren, H., Wang, H., Wang, J. and Li, Y. (2020) 'Automatic distinction between COVID-19 and common pneumonia using multi-scale convolutional neural network on chest CT scans', *Chaos, Solitons Fractals*, Vol. 140, p.110153, https://doi.org/10.1016/j.chaos.2020.110153

13 Bermejo-Peláez, D., Ash, S.Y., Washko, G.R., San José Estépar, R. and Ledesma-Carbayo, M.J. (2020) 'Classification of interstitial lung abnormality patterns with an ensemble of deep convolutional neural networks', *Sci. Rep.*, Vol. 10, No. 1, pp.1–15, https://doi.org/10.1038/s41598-019-56989-5

14 He, K. and Sun, J. (2016) *Deep Residual Learning for Image Recognition*, https://doi.org/10.1109/CVPR.2016.90

15 Niu, X.X. and Suen, C.Y. (2012) 'A novel hybrid CNN-SVM classifier for recognizing handwritten digits', *Pattern Recognit.*, Vol. 45, No. 4, pp.1318–1325, https://doi.org/10.1016/j.patcog.2011.09.021

16 Patalas-maliszewska, J. (2019) *A Model for Generating Workplace Procedures Using a CNN-SVM Architecture*, pp.1–15.

17 Ameen, Z.S, Ozsoz, M. and Saleh, A. (2021) 'C-SVR crispr: prediction of CRISPR/Cas12 guideRNA activity using deep learning models', *Alexandria Eng. J.,*, Vol. 60, No. 4, pp.3501–3508, https://doi.org/10.1016/j.aej.2021.02.007

18 Soltanian-Zadeh, H., Windham, J.P., Peck, D.J. and Yagle, A.E. (1992) 'A comparative analysis of several transformations for enhancement and segmentation of magnetic resonance image scene sequences', *IEEE Trans. Med. Imaging*, Vol. 11, No. 3, pp.302–318, https://doi.org/10.1109/42.158934

19 Ameen, Z., Saleh, M. and Aşırm, S. (2019). *Development of CNN Model for Prediction of Cpf1 Guide RNA Activity*, https://doi.org/10.1007/978-3-030-35249-3_90

20 Barstugan, M., Ozkaya, U. and Ozturk, S. (2020) 'Coronavirus (COVID-19) classification using CT images by machine learning methods', *Computer Vision and Pattern Recognition*, Vol. 5, pp.1–10, http://arxiv.org/abs/2003.09424

21 Loey, M., Smarandache, F. and Khalifa, N.E.M. (2020) *A Deep Transfer Learning Model with Classical Data Augmentation and CGAN to Detect COVID*-19 *from Chest CT Radiography Digital Images*, April, pp.1–17, https://doi.org/10.20944/preprints202004.0252.v1

22 Soares, E., Angelov, P., Biaso, S., Higa Froes, M. and Kanda Abe, D. (2020) *SARS-CoV-2 CT-Scan Dataset: A Large Dataset of Real Patients CT Scans for SARS-CoV-*2 *Identification*, pp.1–8, https://doi.org/10.1101/2020.04.24.20078584

23 Grapov, D., Fahrmann, J., Wanichthanarak, K. and Khoomrung, S. (2018) 'Rise of deep learning for genomic, proteomic, and metabolomic data integration in precision medicine', *OMICS*, Vol. 22, No. 10, October, pp.630–636, doi: 10.1089/omi.2018.0097, Epub 2018 Aug 20, PMID: 30124358; PMCID: PMC6207407.

24 Mayasari, R. and Heryana, N. (2019) *Reduce Noise in Computed Tomography Image Using Adaptive Gaussian Filter Reduce Noise in Computed Tomography Image Using Adaptive Gaussian Filter Abstract*, September, pp.16–20.

25 Wang, M., Zheng, S., Li, X. and Qin, X. (2014) 'A new image denoising method based on gaussian filter', *Proceedings – 2014 International Conference on Information Science, Electronics and Electrical Engineering, ISEEE. 2014*, Vol. 1, No. 1, pp.163–167, https://doi.org/10.1109/InfoSEEE.2014.6948089

26 Ahsan, M.M., Gupta, K.D., Islam, M.M., Sen, S., Rahman, M.L. and Hossain, M.S. (2020) *Study of Different Deep Learning Approach with Explainable AI for Screening Patients with COVID*-19 *Symptoms: Using CT Scan and Chest X-Ray Image Dataset*, http://arxiv.org/abs/2007.12525

27 El Asnaoui, K. and Chawki, Y. (2020) 'Using X-ray images and deep learning for automated detection of coronavirus disease', *J. Biomol. Struct. Dyn.*, pp.1–12, https://doi.org/10.1080/07391102.2020.1767212

28 Ozturk, T., Talo, M., Yildirim, E.A., Baloglu, U.B., Yildirim, O. and Rajendra Acharya, U. (2020) 'Automated detection of COVID-19 cases using deep neural networks with X-ray images', *Comp. Bio. Med.*, Vol. 121, April, p.103792, https://doi.org/10.1016/j.compbiomed.2020.103792

29 Wang, S., Kang, B., Ma, J., Zeng, X., Xiao, M., Guo, J., Cai, M., Yang, J., Li, Y., Meng, X. and Xu, B. (2020) *A Deep Learning Algorithm using CT Images to Screen for Corona Virus Disease (COVID-19)*, pp.1–27.

30 Wang, S., Kang, B., Ma, J., Zeng, X., Xiao, M., Guo, J., Cai, M., Yang, J., Li, Y., Meng, X. and Xu, B. (2020). *A deep learning algorithm using CT images to screen for Corona Virus Disease (COVID-19)*, 1–19. https://doi.org/10.1101/2020.02.14.20023028

31 Rasheed, J., Ali, A., Chawki, H., Akhtar, D., Fadi, J. and Turjman, A. (2021) 'A machine learning-based framework for diagnosis of COVID-19 from chest X-ray images', *Interdiscip. Sci.*, Vol. 13, No. 1, pp.103–117, https://doi.org/10.1007/s12539-020-00403-6

32 Ghassemi, N., Shoeibi, A. and Rouhani, M. (2020) 'Deep neural network with generative adversarial networks pre-training for brain tumor classification based on MR images', *Biomed. Signal Process. Control*, Vol. 57, p.101678, https://doi.org/10.1016/j.bspc.2019.101678

33 Simon, P., Uma, V., Simon, P. and Uma, V. (2020) 'Deep learning based feature extraction for texture classification deep learning based feature extraction for texture classification', *Procedia Computer Science*, Vol. 171, No. 2019, pp.1680–1687, https://doi.org/10.1016/j.procs.2020.04.180

34 Almabdy, S. and Elrefaei, L. (2019) 'Deep convolutional neural network-based approaches for face recognition', *Applied Sciences (Switzerland)*, Vol. 9, No. 20, p.4397, https://doi.org/10.3390/app9204397

35 Alsukayti, I.S. (2020) *A Multidimensional Internet of Things Testbed System: Development and Evaluation*, https://doi.org/https://doi.org/10.1155/2020/8849433

36 Chakraborty, C. and Abougreen, A.N. (2021) 'Intelligent internet of things and advanced machine learning techniques for covid-19', *EAI Endorsed Transactions on Pervasive Health and Technology*, Vol. 7, No. 26, pp.1–14, https://doi.org/10.4108/eai.28-1-2021.168505

37 Xing, E.P., Ho, Q., Xie, P. and Wei, D. (2016) 'Strategies and principles of distributed machine learning on big data', *Engineering*, Vol. 2, No. 2, pp.179–195, https://doi.org/10.1016/J.ENG.2016.02.008

38 Schuß, M., Boano, C.A., Weber, M. and Kay, R. (n.d.), *A Competition to Push the Dependability of Low-Power Wireless Protocols to the Edge*, pp.54–65.

39 Mu, J., Rincon, F., Chang, T., Vilajosana, X., Vermeulen, B., Walcarius, T., Van De Meerssche, W. and Watteyne, T. (2019) *OpenTestBed: Poor Man's IoT Testbed*, pp.467–471.

40 Reshi, A.A., Madinah, A., Munawarah, A., Madinah, A., Munawarah, A., Madinah, A. and Munawarah, A. (2019) 'Development and web performance evaluation of internet of things testbed', *2019 International Conference on Computer and Information Sciences (ICCIS)*, pp.1–6.

41 Banerjee, A., Chakraborty, C., Kumar, A. and Biswas, D. (2020) 'Emerging trends in ioT and big data analytics for biomedical and health care technologies', *Handbook of Data Science Approaches for Biomedical Engineering*, Elsevier Inc., https://doi.org/10.1016/B978-0-12-818318-2.00005-2

42 Waheed, A., Goyal, M., Gupta, D., Khanna, A., Al-turjman, F., Pinheiro, P.R. (2020) *CovidGAN: Data Augmentation Using Auxiliary Classifier GAN for Improved Covid*-19 *Detection*, pp.1–9, https://doi.org/10.1109/ACCESS.2020.2994762

43 Wang, Sun, S.J., Chen, Y., Zhang, Y. and Mehmood, I. (2019) *Cerebral Micro-Bleeding Identification based on a Nine-Layer Convolutional Neural Network with Stochastic Pooling*, May, pp.1–16, https://doi.org/10.1002/cpe.5130

44 Wang, S., Tang, C., Sun, J., Zhang, Y., Kingdom, U. and Kingdom, U. (2019) *Cerebral Micro-Bleeding Detection Based on Densely Connected Neural Network*, https://doi.org/10.3389/fnins.2019.00422

45 Roth, H.R., Lu, L., Member, S., Liu, J., Yao, J., Seff, A., Cherry, K., Kim, L. and Summers, R.M. (2015) *Improving Computer-Aided Detection Using Convolutional Neural Networks and Random View Aggregation*, pp.1–12, https://doi.org/10.1109/TMI.2015.2482920

46 Greenspan, H., van Ginneken, B. and Summers, R.M. (2016) 'Guest editorial deep learning in medical imaging: overview and future promise of an exciting new technique', *IEEE Trans. Med. Imaging*., Vol. 35, No. 5, pp.1153–1159.

47 Tajbakhsh, N., Shin, J.Y., Gurudu, S.R., Hurst, R.T., Kendall, C.B., Gotway, M.B., Liang, J. and Member, S. (2016) *Convolutional Neural Networks for Medical Image Analysis: Full Training Or Fine Tuning?*, Vol. 35, No. 5, pp.1299–1312.

48 Srivastava, V., Srivastava, S., Chaudhary, G. and Al-Turjman, F. (2020) 'A systematic approach for COVID-19 predictions and parameter estimation', *Personal and Ubiquitous Computing*, https://doi.org/10.1007/s00779-020-01462-8

49 Al-Turjman, F. and Deebak, B. (2020) 'Privacy-aware energy-efficient framework using the internet of medical things for COVID-19', *IEEE Internet of Things Magazine*, Vol. 3, No. 3, pp.64–68, https://doi.org/10.1109/iotm.0001.2000123

50 Rahman, A. (2020) 'Data-driven dynamic clustering framework for mitigating the adverse economic impact of covid-19 lockdown practices', *Sustainable Cities and Society*, p.102372, https://doi.org/10.1016/j.scs.2020.102372

51 Pillai, S. (2020) *IoT Based Humanoid Software for Identification and Diagnosis of Covid*-19 *Suspects*, https://doi.org/10.1109/Jsen.2020.3030905

52 Hussein, S., Kandel, P., Bolan, C.W., Wallace, M.B. and Bagci, U. (2019) 'Lung and pancreatic tumor characterization in the deep learning era: novel supervised and unsupervised learning approaches', *IEEE Trans. Med. Imaging*, Vol. 38, No. 8, pp.1777–1787, https://doi.org/10.1109/TMI.2019.2894349

53 Karar, M.E., Merk, D.R., Chalopin, C., Walther, T., Falk, V. and Burgert, O. (2011) 'Aortic valve prosthesis tracking for transapical aortic valve implantation', *Int. J. Comput. Assist Radiol. Surg*., Vol. 6, No. 5, pp.583–590, https://doi.org/10.1007/s11548-010-0533-5

54 Karar, Mohamed Esmail, El-Khafif, S.H. and El-Brawany, M.A. (2017) 'Automated diagnosis of heart sounds using rule-based classification tree', *J. Med. Syst.*, Vol. 41, No. 4, https://doi.org/10.1007/s10916-017-0704-9

55 Liang, C.H., Liu, Y.C., Wu, M.T., Garcia-Castro, F., Alberich-Bayarri, A. and Wu, F.Z. (2020) 'Identifying pulmonary nodules or masses on chest radiography using deep learning: external validation and strategies to improve clinical practice', *Clinical Radiology*, Vol. 75, No. 1, pp.38–45, https://doi.org/10.1016/j.crad.2019.08.005

56 Rathore, H., Al-Ali, A.K., Mohamed, A., Du, X. and Guizani, M. (2019) 'A novel deep learning strategy for classifying different attack patterns for deep brain implants', *IEEE Access*, Vol. 7, pp.24154–24164, https://doi.org/10.1109/ACCESS.2019.2899558

57 Farooq, M. and Hafeez, A. (2020) *COVID-ResNet: A Deep Learning Framework for Screening of COVID19 From Radiographs*, http://arxiv.org/abs/2003.14395

58 Xie, X. (2020) 'Chest CT for typical covid-19 pneumonia', *Radiology*, https://doi.org/10.14358/PERS.81.12.21

59 Umar, A., Mehmet, I., Sertan, O., Fadi, S., Turjman, A., Shizawaliyi, P. (2021) 'Pneumonia classification using deep learning from chest X-ray images during COVID-19', *Cognitive Computation*, p.0123456789, https://doi.org/10.1007/s12559-020-09787-5

60 Yang, X., He, X., Zhao, J., Zhang, Y., Zhang, S. and Xie, P (n.d.), *COVID-CT-Dataset□: A CT Image Dataset about COVID-19*, pp.1–14.

61 Yan, T., Wong, P.K., Hao Ren, C., Wang, H. and Jiangtao Wang, Y.L. (n.d.) *COVID-19 and Common Pneumonia Chest CT Dataset*, https://doi.org/10.17632/3y55vgckg6.1

62 Apostolopoulos, I.D. and Mpesiana, T.A. (2020) 'Covid-19: automatic detection from X-ray images utilizing transfer learning with convolutional neural networks', *Phys. Eng. Sci. Med.*, Vol. 43, No. 2, pp.635–640, https://doi.org/10.1007/s13246-020-00865-4

63 Haque, A.B. and Rahman, M. (2020) *Augmented COVID-19 X-ray Images Dataset (Mendely) Analysis Using Convolutional Neural Network and Transfer Learning*, Vol. 19, April, https://doi.org/10.13140/RG.2.2.20474.24003

64 Loey, M., Smarandache, F. and Khalifa, N.E.M. (2020) 'Within the lack of chest COVID-19 X-ray dataset: a novel detection model based on GAN and deep transfer learning', *Symmetry*, Vol. 12, No. 4, p.651, https://doi.org/10.3390/sym12040651

65 Mahmud, T., Rahman, M.A. and Fattah, S.A. (2020) 'CovXNet: A multi-dilation convolutional neural network for automatic COVID-19 and other pneumonia detection from chest X-ray images with transferable multi-receptive feature optimization', *Comp. Biol. Med.*, Vol. 122, May, p.103869, https://doi.org/10.1016/j.compbiomed.2020.103869

66 KrizhevskyAlex, Ilya Sutskever, G.E.H. (2012) 'ImageNet classification with deep convolutional neural networks', in Gonzalez, T.F. (Ed.): *Handbook of Approximation Algorithms and Metaheuristics*, Chapman and Hall/CRC, https://doi.org/10.1201/9781420010749

67 Szegedy, C., Reed, S., Sermanet, P., Vanhoucke, V. and Rabinovich, A (n.d.) *Going Deeper with Convolutions*, pp.1–12.

68 Zhang, X., Lin, M. and Sun, J. (n.d.) *ShuffleNet□: An Extremely Efficient Convolutional Neural Network for Mobile Devices*, pp.6848–6856.

69 Zisserman Karen, S.A. (2015) *Very Deep Convolutional Networks for Large-Scale Image Recognition*, pp.1–14.

70 Wang, W.C., Xu, D.M., Chau, K.W. and Chen, S. (2013) 'Improved annual rainfall-runoff forecasting using PSO-SVM model based on EEMD', *J. Hydroinf.*, Vol. 15, No. 4, pp.1377–1390, https://doi.org/10.2166/hydro.2013.134

71 Amyar, A., Modzelewski, R., Li, H. and Ruan, S. (2020) *Multi-Task Deep Learning Based CT Imaging Analysis for COVID*-19 *Pneumonia: Classification and Segmentation*, January.