



Employing X-ray images Characteristics For Early Corona Virus Detection Based on Deep Learning Techniques

Mohammed L. Muammer¹, Omar Ibrahim Alsaif²

¹ Department of Computer Engineering Technology, Northern Technical University, Mosul, Iraq

² Department of computer systems technologies, Northern Technical University, Mosul, Iraq

mohammed.loay@ntu.edu.iq, Omar.alsaif@ntu.edu.iq

5664

Abstract.

SARS-CoV2 is a new virus that began rapidly spreading in Wuhan Province, China, on December 2019 and has since spread around all the world. The infections methods can be considered as transportation techniques were one of the key factors that contributed to the global pandemic that occurred on March, 2020. The virus has the ability to infect various organs of the human body, including lungs, heart, kidneys, and others, causing severe damage and maybe death. As the virus spreads quickly, numerous ways for detecting the infection have emerged to assist doctors in treating the patient. This paper concentrate about using X- ray images that are collected from Kaggle data set to detect the infections of corona virus. These data are pre-trained (fine-tuned) to specific networks like Visual Geometry Group (vgg19) and MobileNet to get benefit of the CNN properties (image processing, segmentation and classification). The motivation of this paper include section (1) introduction with related work, section (2) (CNN)algorithm with details, section (3) contain the the data set properties while section (4) included the results and discussions. The proposed technique (vgg19 network) performed the best result (99%) validation accuracy.

Keywords: . SARS-CoV2 disease, deep learning, CNN, Visual Geometry Group (VGG19), X-ray images.

DOI Number:10.14704/nq.2022.20.8.NQ44594

NeuroQuantology 2022; 20(8): 5664-5673

1. Introduction

In December 2019, a cluster of strange pneumonia cases was discovered in the Chinese province of Wuhan, which subsequently spread to the rest of the world. COVID 19 is a recently identified coronavirus that causes an infectious illness. It was not recognized until December 2019, when an epidemic in Wuhan city, China, began. Fever, fatigue, and a dry cough are the most relevant early signs of COVID-19. The majority of people (about 80%) are recovering from the ailment without the need for additional therapy. COVID-19 affects around one out of every six persons, causing major

illness and respiratory problems. Seniors and those with long-term medical disease conditions like increased blood pressure, heart problems, or diabetes are more vulnerable to acquiring severe illnesses[1][2].

There is currently no medication for this virus that has been authorized. COVID-19 has been detected and classified a pandemic illness by the World Health Organization (WHO)[3]. This virus is evolving at a breakneck speed, making it more lethal than ever before. This is one of the most rapidly progressing diseases that has ever been observed[4].



Meanwhile, COVID-19 targets the epithelial cells that line our respiratory system, and X-ray

may be utilized to examine a patient's lungs, as shown in figure (1).

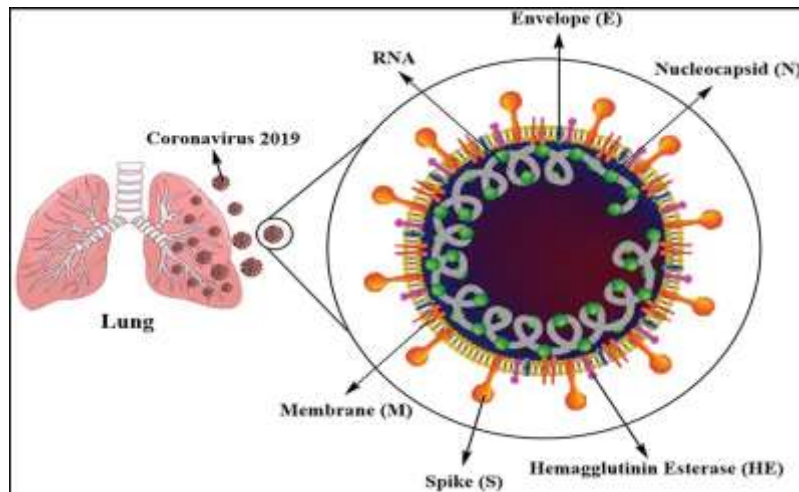


Figure (1). An illustration of the shape of an infected lung with Covid 19.

X-ray scans are frequently used by doctors to identify pneumonia, lung irritation, swellings, and/or swollen lymph nodes. Because X-ray imaging devices are readily available in all hospitals, X-rays might be used to examine COVID-19 without the need of specialized examination kits; however, this necessitates the presence of a radiology professional, which takes time, which is valuable when people are sick all over the world. As a result, planning and constructing a computer-based system is required to save significant time for medical practitioners[5][6]

The availability of an Artificial Intelligence (AI) methods might aid in the rapid and accurate identification of COVID-19 patients utilizing X-ray and CT scans[7]. The main aims of this study is to design an accurate, simple, and faster approach of classifying COVID-19 patients. This is crucial for the prevention and control of the pandemic. Most significantly, (AI) methods may have the ability to save millions of lives all across the world. Also provide deep learning technique based radiologist image analysis algorithms that, compared to existing approaches, might deliver testing accuracy. Several Deep Learning (DL) technique-based approaches for COVID-19 identification from CT scans have recently been developed and demonstrated to be very

accurate[2]. Some previous works about covid19 are explained in this section.

- In 2020, Batista .AFM et al. suggested COVID-19 diagnosis used a machine learning algorithm. Five machine learning methods are used in their study; random forests(RF), neural networks (NNs), logistic regression, gradient boosting trees, and support vector machines(SVM). The collected dataset was 235 cases from the Hospital in Sao Paulo, Brazil, 102 cases were a positive diagnosis of COVID-19 and the rest of cases were negative diagnosis. The support vector machines method produced the best predicting results; (accuracy: 85%, sensitivity: 68%, specificity: 85%)[8].

- In 2020 Xueyan .M et al. suggested recognition of COVID-19 diseases based on neural networks. There are three methods used in this study; CNN model, MLP model, and Joint model. 905 CT scan images have been collected from eighteen medical centers in thirteen provinces in China; 419 of these images are a positive case and remainder is a negative case. The best accuracy obtained was in the joint model with 92%[9].

- Wei Tse. L et al. presented the detection of COVID-19 using machine learning of clinical data in 2021. eXtreme Gradient Boosting algorithm (XGBoost) is utilized to



detect COVID-19 patients and influenza patients. They also use 3 other machine learning techniques ; RIDGE, LASSO, and random forest to compare results achieved from these networks with the results achieved by XGBoost. They use 413 patients to gather the data set for training the networks. The XGBoost model was able to detect COVID-19 cases from influenza cases with a sensitivity of 92.5% and with a specificity of 97.9% than other networks[10].

2. Convolutional neural network (CNN) Algorithm

Convolutional neural network (CNN), is a one of important type of artificial neural network that has gained popular in computer vision applications[11]. CNN uses some of building blocks such as convolution layers, pooling layers, and fully linked layers to learn and provides special information automatically and adaptively across back propagation [12], as shown in figure (2).

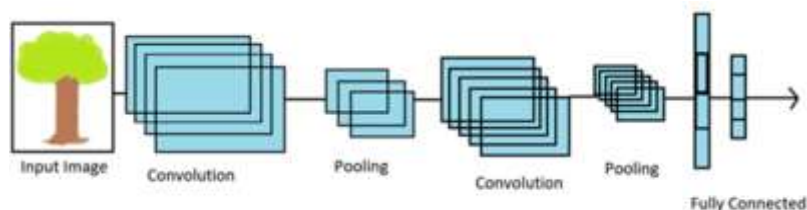


Figure (2). CNN block diagram

In machine learning approaches , the CNN achieves quite well. Especially image-related applications, like as the biggest image classification data collection[13].

(CNN) is universal, which means that, when the depth of the neural network is big enough. It may be utilized to estimate any continuous function to an arbitrary precision[14].

2.1 Convolution layer

Feature maps, are created by the convolution layer. The feature map highlights the unique properties of the original image. The

$$A_j = f(\sum_{i=1}^N I_i * K_{ij} + B_j) \dots\dots\dots(1)$$

Where: I_i :input image
 K_{ij} : kernel
 B_j : bias

2.2 Pooling Layer Characteristics

The pooling layer also referred to as sub-sampling, it aims is to down the size of an input image. These image will be in other way, further more shrink the input image dimensions (height and width). Thus, the number of parameters is decreased and the complexity of computational

convolution layer differs from the other neural network layers, it operates in a completely different manner. This layer has no linked weights or a weighted sum. It contains image-converting filters instead. Convolution filters will be used to describe these filters. By moving an image across the convolution filters, the feature map is formed.[15].

The core feature of CNN is convolutional neuron layers. The procedure for calculating a single output matrix is specified as explained in equation (1)[16].

is also decreased. There are two techniques of pooling layer; max pooling and average pooling. Figure 3 shows both max pooling and average pooling. The pooling layer of the 2x2 dimension divides the feature map into sub-matrices (sub-windows), each with a 2x2 dimension. In the Max pooling way, the highest



pixel value is chosen from the window. In the average pooling way, the average value is chosen from the window. Max pooling aids the neural network in terms of recognizing the salient features of the input image. Average pooling aids the models in the term of

distinguishing the whole extent of the input image. the average pooling technique maintains a greater amount of data when comparing it with the max pooling technique[17]. Figure (3) shows max and average pooling

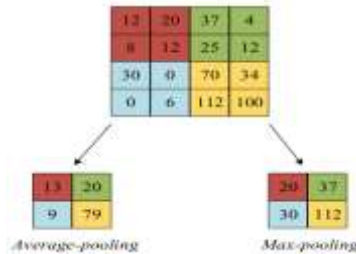


Figure (3). Max and average pooling [12]

5667

2.3 Fully Connected Layer

At the end of a convolutional neural network, the result of the final Pooling Layer is passed into the Fully linked Layer. It's possible that one or more of these levels are present. The term

"completely linked" refers to the fact that every component in the first layer is connected to every component in the second layer[18]. Figure (4) shows Fully connected layers.

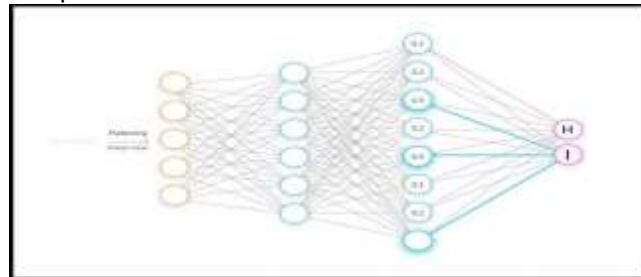


Figure (4). Fully connected layers [13]

2.4 Transfer Learning Technology

Transfer learning (TL) is a type of machine learning in which pre-trained models are reused for new tasks[19]. A huge number of samples are required to train a convolutional neural network as a supervised learning method[20]. Transfer learning is a potential machine learning technology for solving problems since it focuses on transferring information across domains.

Transfer learning, which is inspired by people's ability to transfer information across domains, tries to increase learning performance or reduce the number of labeled examples necessary in a target domain by using knowledge from a related domain (called source domain)[21]. Figure (5) shows Transfer learning.



Figure (5). Transfer learning

2.4.1 The VGG19 Neural Network

The VGG-19 Neural Network is a deep neural network with 19 layers and higher weight. In terms of completely linked nodes, the VGG-19 network is 574 MB in size. DNN accuracy

improves as the number of layers grows. The VGG 19 model consists of 19 convolutional deep trainable layers that are completely coupled to max pooling and dropout layers[22]. Figure (6) shows VGG19 network

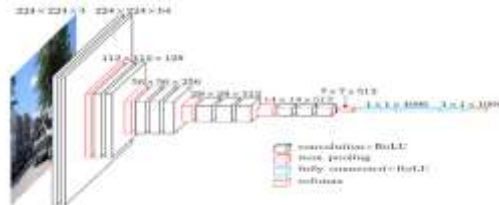


Figure (6). VGG19 network

5668

2.4.2 MobileNet network

MobileNet employs a technique known as depth wise separable convolution. It costs around one-eighth as much to compute using depth wise separable convolution and has just a little reduction in accuracy. The fundamental layer of MobileNet is depth wise separable convolution, which is a type of factorized convolution. Its feature is that it splits the conventional convolution into a depth wise convolution and a 1x1 convolution called

pointwise convolution. The depth wise convolution in MobileNet refers to the fact that each of the filters only requires a single input channel to perform convolution. The pointwise convolution then takes the result of the depth wise convolution and performs a 1x1 convolutions. Depth wise separable convolution has a processing cost of 8 to 9 times less than ordinary convolution [23]. Figure (7) shows MobileNet network

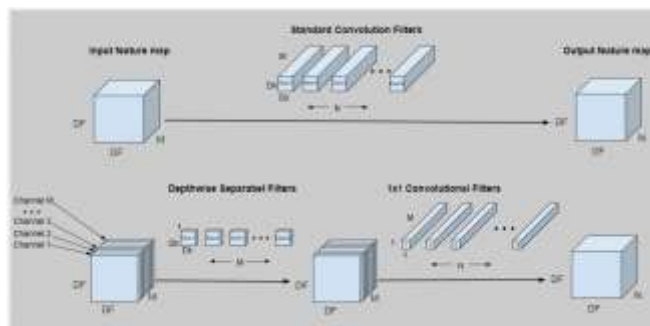


Figure (7). MobileNet network[17]

3. Research Methodology

The proposed method has been divided into many steps, these steps are, image acquisition, preprocessing data, classification of the Covid

19 images, finally sending to remotely doctor. Figure (8) explains the steps that are worked for the proposed method.



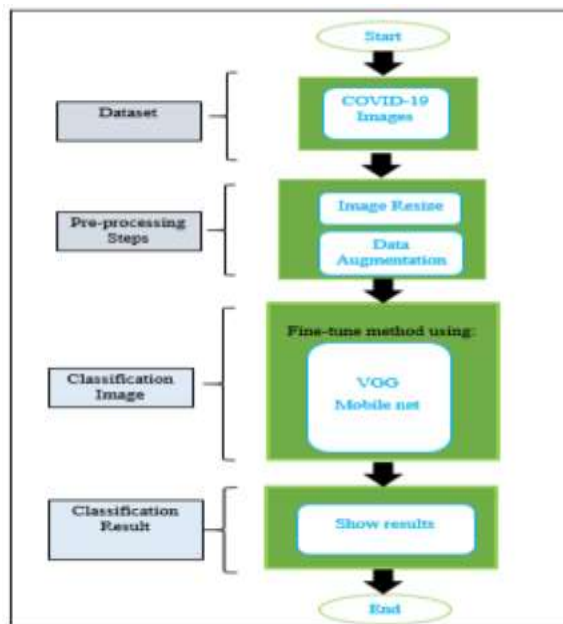


Figure (8). Steps of the proposed method

3.1 Dataset Characteristics

The kaggle dataset consisted of a thousand photos for two-dimensional chest x-rays, 500 of which were diagnosed as covid19 and the rest as normal, with 80% of the X-rays scan utilized

for training and 20% used for testing. The images used for testing were picked at random. Figure (9) shows X-ray for lung images of infected and uninfected with covid 19.



Figure (9) X-ray for lung images of infected and uninfected with covid 19..

3.1.1 Pre-Processing Step: There are two stages in this step as follows:

1- Image Resize: because of the CNN network accept the image with fixed size, all the images in the dataset are resized into 224*224 pixels.

2- Data augmentation: After resizing the dataset images, the augmentation step is utilized in the training datasets. There are different geometric transformations performed on training images such as; rotation, rescaling, shifting, shear, and zoom. The augmentation processes applied to training datasets are explained below.

- The rotation range is 10 which rotates all training images by 10 degrees.

- The width shift range is 0.2 which increases the width by 2.
- height shift range is 0.2 which increases height by 2.
- The zoom range is 0.2 which zooms in the image by 0.2.

3.2 Fine-Tune Method Process

In this step the fine-tune based on transfer learning has been implemented using the following networks; VGG19, and Mobilenet. There are several steps to perform fine-tune method, in the first step, the pre-training network is invoked with its weights. in the



second step, the FCL of the pre-training network is removed and replaced with new fully connected layers, then set the number of last fully connected layer according to the number of classes in the dataset, in the third step, randomly initialization the weight of the FCLs, in

the fourth step, all of the feature extraction (convolutional and pooling) layers is frozen, preventing them from being modified (during the back-propagation), in the last step, the new fully connected layers is only trained. Figure 10 explains how to fine-tune works.

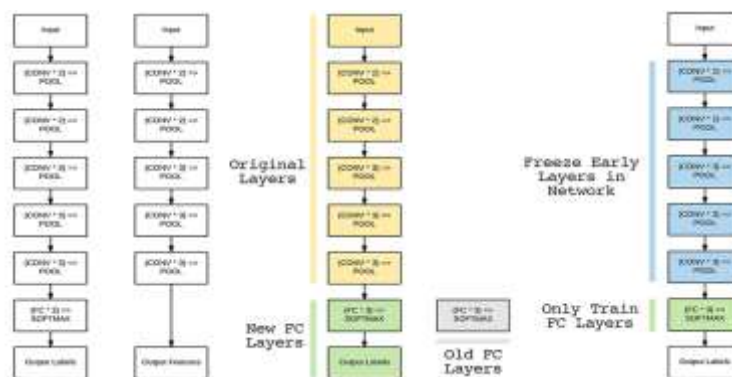


Figure (10). Fine-tuning process. (a) VGG16 network
 (b) Removing FC layers from VGG16
 (c) freeze FE layers

The suggested way to fine-tune the pre-trained networks can be described as follows, all of the feature extraction layers (Convolution and pooling layers) are frozen at the training stage, and the final layers (classifier layers) are removed, and three of new fully connected layers are added. The model's final three layers are adjusted as follows: Flatten layer, Dense FC including ReLU AF (512 neurons), Dense FC including ReLU AF (256 neurons), Dense FC including Soft max function with a classification output layers (2 neurons).

The suggested model has been trained using the following parameter; ADAM optimizer, learning rate of 10⁻³, 32 batch size (batch size represents, how many images are passed to the network at once), Epoch of 50, and One hot-encoding for label the dataset. The loss function was calculated using categorical cross-entropy, and then the trainable parameters of the fully

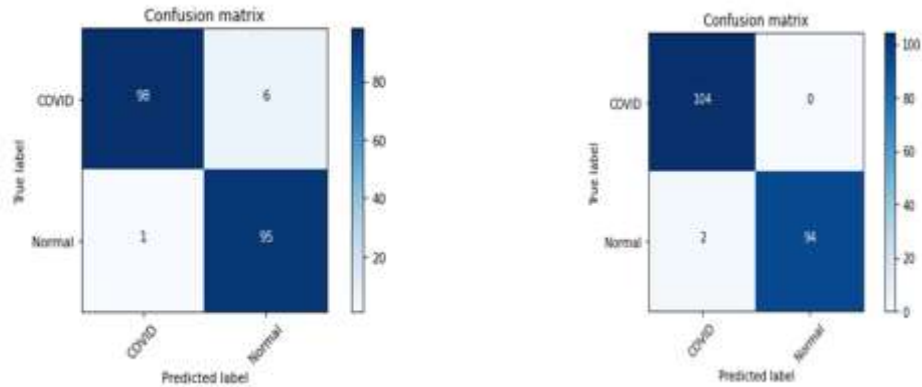
connected layers were modified to reduce the loss function prediction.

4. Results And Discussion

This section shows the performance of the proposed CNN (pre-training networks (VGG 19, and Mobilenet)) and the proposed system for recognition of COVID_19 diseases by applying a deep learning model. From the results that are obtained and shown in this section, the proposed system has been successfully tested and gives good results. Each pre-training network has been trained with and without augmentation process.

The confusion matrix of validation samples for vgg 19. In figure (11.a) vgg 19 with augmentation, there is 7 incorrectly classified samples. But, in figure (11.b) vgg 19 without augmentation only 2 samples incorrectly classified.





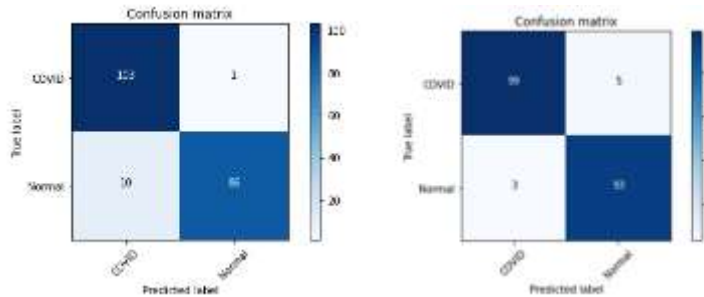
(a) VGG19 with augmentation

(b) VGG19 without augmentation

Figure (11). VGG 19 confusion matrix

The confusion matrix of validation samples for Mobilenet. In figure (12.a) Mobilenet with augmentation , there is 11 incorrectly classified samples. But ,in figure (12.b) Mobilenet without augmentation only 8 samples incorrectly classified.

5671



(a) MOBILENET with augmentation

(b) MOBILENET without augmentation

Figure (12). Mobilenet confusion matrix

Table(1) shows the comparison between our and previous studies as show in the Literature reviews ,the result has been obtained from our study give high accuracy than others.

Table(1) comparison between this work and previous studies

study	Data type	year	method	accuracy
Batista .AFM et al	x-ray	2020	support vector machines	85%
Xueyan .M et al	CT SCAN	2020	joint model	92%
Wei Tse. L et al	x-ray	2021	XGBoost	92.5%
This work	X-RAY	2022	VGG19	99%

5. Conclusions

In this study, we successfully build and develop an automatic system for detecting COVID-19 and infected region localization from x-ray

scans. For classification, we are successfully applied the deep learning application specially the CNN network with transfer learning like (VGG19, mobilenet). The observed results



presented by VGG19 are very promising classification results with 99% testing accuracy for COVID-19 from X-ray. Furthermore, the qualitative results show that COVID-19 has a high level of accuracy in classifying and detecting infected areas in X-ray scans. We'd want to collect additional samples of COVID-19-affected people in the near future so that we can design a more reliable and accurate approach.

References

- [1] R. Punia, L. Kumar, M. Mujahid, and R. Rohilla, "Computer vision and radiology for COVID-19 detection," *2020 Int. Conf. Emerg. Technol. INCET 2020*, pp. 1–5, 2020, doi: 10.1109/INCET49848.2020.9154088.
- [2] I. A. Saleh, W. A. Alawsi, O. I. Alsaif, and K. Alsaif, "A Prediction of Grain Yield Based on Hybrid Intelligent Algorithm," *J. Phys. Conf. Ser.*, vol. 1591, no. 1, 2020, doi: 10.1088/1742-6596/1591/1/012027.
- [3] S. Q. Alhashmi, K. H. Thanoon, and O. I. Alsaif, "A Proposed Face Recognition based on Hybrid Algorithm for Features Extraction," *Proc. 6th Int. Eng. Conf. 'Sustainable Technol. Dev. IEC 2020*, pp. 232–236, 2020, doi: 10.1109/IEC49899.2020.9122911.
- [4] M. Z. Alom, M. M. S. Rahman, M. S. Nasrin, T. M. Taha, and V. K. Asari, "COVID_MNet: COVID-19 Detection with Multi-Task Deep Learning Approaches," 2020, [Online]. Available: <http://arxiv.org/abs/2004.03747>.
- [5] F. M. Salman, S. S. Abu-Naser, E. Alajrami, B. S. Abu-Nasser, and B. A. M. Ashqar, "COVID-19 Detection using Artificial Intelligence," *Int. J. Acad. Eng. Res.*, vol. 4, no. 3, pp. 18–25, 2020, [Online]. Available: www.ijeais.org/ijaer.
- [6] M. A. Yahya et al., "inventions Transmit Diversity Technique."
- [7] K. H. Thanoon, S. Q. Hasan, and O. I. Alsaif, "Biometric information based on distribution of arabic letters according to their outlet," *Int. J. Comput. Digit. Syst.*, vol. 90, no. 5, pp. 981–991, 2020, doi: 10.12785/ijcds/090518.
- [8] B. Afm et al., "COVID-19 diagnosis prediction in emergency care patients: a machine learning approach," *medRxiv*, p. 2020.04.04.20052092, 2020, [Online]. Available: <https://www.medrxiv.org/content/10.1101/2020.04.04.20052092v2%0Ahttps://www.medrxiv.org/content/10.1101/2020.04.04.20052092v2.abstract>.
- [9] X. Mei et al., "Artificial intelligence-enabled rapid diagnosis of patients with COVID-19," *Nat. Med.*, vol. 26, no. 8, pp. 1224–1228, 2020, doi: 10.1038/s41591-020-0931-3.
- [10] W. T. Li et al., "Using machine learning of clinical data to diagnose COVID-19: A systematic review and meta-analysis," *BMC Med. Inform. Decis. Mak.*, vol. 20, no. 1, pp. 1–13, 2020, doi: 10.1186/s12911-020-01266-z.
- [11] A. H. MARAY, O. I. Alsaif, and K. H. TANOON, "Design and Implementation of Low-Cost Medical Auditory System of Distortion Otoacoustic Using Microcontroller," *J. Eng. Sci. Technol.*, vol. 17, no. 2, pp. 1068–1077, 2022.
- [12] A. Patil and M. Rane, "Convolutional Neural Networks: An Overview and Its Applications in Pattern Recognition," *Smart Innov. Syst. Technol.*, vol. 195, pp. 21–30, 2021, doi: 10.1007/978-981-15-7078-0_3.
- [13] S. Albawi, T. A. M. Mohammed, and S. Alzawi, "Layers of a Convolutional Neural Network," *IEEE*, p. 16, 2017.
- [14] D. X. Zhou, "Universality of deep convolutional neural networks," *Appl. Comput. Harmon. Anal.*, vol. 48, no. 2, pp. 787–794, 2020, doi: 10.1016/j.acha.2019.06.004.
- [15] P. Kim, "MATLAB Deep Learning," *MATLAB Deep Learn.*, no. November 2013, pp. 121–147, 2017, doi: 10.1007/978-1-4842-2845-6.
- [16] Q. Li, W. Cai, X. Wang, Y. Zhou, D. D. Feng, and M. Chen, "Medical image classification with convolutional neural network," *2014 13th Int. Conf. Control Autom. Robot.*



- Vision, ICARCV 2014*, pp. 844–848, 2014, doi: 10.1109/ICARCV.2014.7064414.
- [17] D. Miao, W. Pedrycz, D. Ślęzak, G. Peters, Q. Hu, and R. Wang, “Rough Sets and Knowledge Technology: 9th International Conference, RSKT 2014 Shanghai, China, October 24–26, 2014 Proceedings,” *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 8818, no. October 2014, 2014, doi: 10.1007/978-3-319-11740-9.
- [18] S. Tammina, “Transfer learning using VGG-16 with Deep Convolutional Neural Network for Classifying Images,” *Int. J. Sci. Res. Publ.*, vol. 9, no. 10, p. p9420, 2019, doi: 10.29322/ijsrp.9.10.2019.p9420.
- [19] I. A. Saleh, O. I. Alsaif, and M. A. Yahya, “Optimal distributed decision in wireless sensor network using gray wolf optimization,” *IAES Int. J. Artif. Intell.*, vol. 9, no. 4, pp. 646–654, 2020, doi: 10.11591/ijai.v9.i4.pp646-654.
- [20] C. Tan, F. Sun, T. Kong, W. Zhang, C. Yang, and C. Liu, “A survey on deep transfer learning,” *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 11141 LNCS, pp. 270–279, 2018, doi: 10.1007/978-3-030-01424-7_27.
- [21] F. Zhuang *et al.*, “A Comprehensive Survey on Transfer Learning,” *Proc. IEEE*, vol. 109, no. 1, pp. 43–76, 2021, doi: 10.1109/JPROC.2020.3004555.
- [22] V. Sudha and T. R. Ganeshbabu, “A convolutional neural network classifier VGG-19 architecture for lesion detection and grading in diabetic retinopathy based on deep learning,” *Comput. Mater. Contin.*, vol. 66, no. 1, pp. 827–842, 2021, doi: 10.32604/cmc.2020.012008.
- [23] H. Y. Chen and C. Y. Su, “An Enhanced Hybrid MobileNet,” *2018 9th Int. Conf. Aware. Sci. Technol. iCAST 2018*, pp. 308–312, 2018, doi: 10.1109/ICAwST.2018.8517177.

