J. ICT Res. Appl., Vol. 17, No. 1, 2023, 99-113

CNN Based Covid-19 Detection from Image Processing

Mohammed Ashikur Rahman[1,*], Mohammad Rabiul Islam[2], Md. Anzir Hossain Rafath[3] & Simron Mhejabin[1]

[1]Department of Computer Science, University of Liberal Arts Bangladesh, 688, Beribadh Road, Mohammadpur, Dhaka-1207, Bangladesh
[2]Department of Computer Science, American International University Bangladesh, 408/1, Kuratoli, Khilkhet, Dhaka 1229, Bangladesh
[3]Department of Computer Science & Engineering, University of South Asia, Amin Bazar, Savar, Dhaka-1348, Bangladesh
*E-mail: ashikur.rahman@ulab.edu.bd

Abstract. Covid-19 is a respirational condition that looks much like pneumonia. It is highly contagious and has many variants with different symptoms. Covid-19 poses the challenge of discovering new testing and detection methods in biomedical science. X-ray images and CT scans provide high-quality and information-rich images. These images can be processed with a convolutional neural network (CNN) to detect diseases such as Covid-19 in the pulmonary system with high accuracy. Deep learning applied to X-ray images can help to develop methods to identify Covid-19 infection. Based on the research problem, this study defined the outcome as reducing the energy costs and expenses of detecting Covid-19 in X-ray images. Analysis of the results was done by comparing a CNN model with a DenseNet model, where the first achieved more accurate performance than the second.

Keywords: *Covid-19 detection; CNN; DenseNet; image processing; pneumonia detection.*

1 Introduction

In the global humanitarian disaster related to Covid-19, the biomedical community is looking for new ways to track Covid-19 (coronavirus) outbreaks and contain the spread of the virus. Artificial intelligence is a platform that scientists can embrace since it can detect high-risk individuals in real time and track the virus's spread in order to effectively manage the outbreak. Detecting Covid-19 from medical images such as chest X-rays and CT scans has been an active area of research since the start of the pandemic. Convolutional neural networks (CNNs) have shown promising results in detecting Covid-19 from medical images. Doctors cannot say with certainty if someone is Covid positive without running tests. Covid testing is done by using the saliva or a swab of the person being tested [1]. Covid attacks only the lungs of people who have the disease. Covid-19 can only be detected by utilizing image processing of a

Received October 7th, 2022, Revised March 12th, 2023, Accepted for publication April 3rd, 2023.
 ISSN: 2337-5787, DOI: 10.5614/itbj.ict.res.appl.2023.17.1.7

patient’s chest X-ray image by training a neural network model to distinguish Covid-positive chest x-rays from Covid-negative chest X-rays.

Radiographic images of the lungs, X-rays and CT scans, can provide adequate detectable information on Corona-virus invasion. The application of cross-sectional radiography to diagnose lung infections is a cost-effective method. Multiple research centers and researchers have been involved in putting together a collection of Covid patients’ chest X-ray scans.

Chest X-rays are a non-invasive diagnostic tool to identify Covid-19 in patients who have been exposed to the virus, which is useful because of the paucity of diagnostic kits and inaccurate RT-PCR predictions [2]. Convolutional neural networks have been utilized to detect Covid-19 in patients who participated in a study using CT check photos. Other trials with low accuracy have been done using diagnostic tests to detect infection with Covid-19 in the pulmonary system [3]. Moreover, traditional neural networks are not well-suited for image processing tasks because they treat each pixel in the image as a separate input, which can lead to a very large number of parameters and high computational costs. Therefore, CNNs are commonly used to process images, because they are highly effective at extracting features from images [17].

Deep learning applied to X-ray imaging can be used to develop methodological approaches for detecting Covid-19 infection [4]. When it comes to Corona-virus tests, there are few options. The present study’s major purpose was to make predictions with the highest possible accuracy while reducing energy costs and expenses. It demonstrates the complete infrastructure that has been developed for distinguishing illustrations of coronavirus-infected lungs from other lung illnesses by using chest X-rays. The originality of this study is that it compared two types of models (CNN and DenseNet). The CNN model achieved an accuracy of 89.44 percent.

2 Literature Review

AI techniques are used in a variety of medicinal imaging applications. Additional appropriate segmentation techniques and computerized vision are the best practices in the context of diagnosing Covid-19 disease. Covid comes from Influenza-A viral pneumonia and normal cases can be detected with the use of computer tomography (CT) images. The goal of CT images is to distinguish between Covid, non-Covid, and pneumonia cases [5]. CNN is a deep learning technique with a wide and deep structure. Pixels are extracted from the image and transferred to a neural network. In order to reduce the complexity of the model, the images must be preprocessed.

Pillalamarry and Prathyusha [6] found that X-ray images can be used to identify Covid and non-Covid cases, which is necessary to train the machine learning model by giving it two image sets, where one is Covid and the other one is non-Covid. Rahul, *et al.* [7] conducted a similar study in 2022 to optimize the classification of chest X-ray images by improving the quality of the model using supervised machine learning algorithms, decision tree, and deep neural networks.

AI methods that have been used to detect Covid-19 are:

1. Chest X-ray analysis: AI algorithms have been trained to analyze chest X-rays for patterns that are indicative of Covid-19. This method provides a quick and non-invasive way to screen patients for the virus. CT scan analysis is similar to chest X-ray analysis. AI algorithms can also be trained to analyze CT scans of the chest for signs of Covid-19.
2. Natural language processing (NLP): NLP techniques can be used to analyze text-based data such as medical records, social media posts, and news articles to identify potential Covid-19 cases.
3. Machine learning-based models: Machine learning algorithms can be trained on large datasets of Covid-19 cases to identify patterns and predict new cases. These models can be used for early detection and to inform public health strategies.
4. Temperature screening: AI-powered thermal cameras can be used to detect elevated body temperatures, which is a common symptom of Covid-19.

It is important to note that while AI methods can be helpful in detecting Covid-19, they should not be used as a replacement for traditional diagnostic methods such as PCR tests. AI methods can help to augment and streamline the diagnostic process but should always be used in conjunction with other diagnostic tools [16].

A prototype was integrated into a web app, presenting annotated images corresponding to the binary classes ‘Covid’ and ‘Normal’ in [7]. In this case, supervised machine learning algorithms were used first. The labeled photos had already been assigned to the correct class and the model learned from the annotated training data. Another research developed a programmed framework for distinguishing coronavirus-infected lungs in chest CT scan images and other lung conditions. The goal of the study was to predict the most accurate result in order to save time and budget [8].

In 2021, Kaheel, *et al.* [9] found that deep learning had been cited as the source of significant advancements in a variety of AI technologies. These achievements attracted researchers into the field of computational medical imaging to explore the potential of using deep learning on medical images captured using X-ray radiography, positron emission tomography (PET), MRI, CT, and other imaging techniques. In order to successfully participate in the global fight against the Covid-pandemic, data were analyzed using an AI therapeutic framework that aimed to acquire heterogeneous information from numerous sources, including both infrastructure and healthcare sensory systems. Kaggle was the source of all the data used to develop the model, which was tweaked on a local machine. Although chloroquine and hydroxychloroquine have been found to be effective in reducing the severity of pneumonia, enhancing lung imaging results, and promoting a virus-negative conversion, they do not provide a satisfactory cure because of the rapid rise in cases of Covid infection. When the spread is not effectively managed, many more people will be infected [10]. Therefore, identifying cases at an early stage and quarantining the infected persons is an important intervention.

Taking a conventional Covid test is bothersome, as testing is done using an antiquated approach using a swab or saliva from the person being tested. This research tried to find a model that uses CT images and neural networks in order to save time and energy. The following are examples of deep learning implementations for image classification, cell structure recognition, tissue segmentation, and computer-assisted disease diagnosis [11]. In order to comprehend and learn from hidden patterns through a large number of observations, artificial neural networks are AI models that mimic the way the human cerebral system works. The first one-layer trainable neural network was the perceptron [12]. Even when nonlinear functions are utilized in the output layer, the modified perceptron is a linear model with several output units that helps applications in handling complicated input patterns. By placing a hidden layer between the input and output layers, this limitation is effectively eliminated.

A two-layer neural network with a finite number of hidden layers may estimate any continuous function when certain assumptions on the activation function are taken into account and is hence referred to as a universal approximator [13]. However, a complex construction with two or perhaps more layers and a smaller total number of units may typically predict functions with the same precision [14]. As a result, the number of trainable parameters can be lowered, which makes training with a data set easier. [15]. The objective of the present research was to train innovative models to classify data from chest X-rays into ‘Normal’, ‘Pneumonia’, or ‘Covid-19’.

3 Research Method

The developed model predicts Covid-19 from chest X-rays that are analyzed by applying deep learning and CNNs. The dataset was downloaded from the Kaggle repository and modified for further use. It consisted of 1,500 X-rays of lungs infected with Covid, 1,500 X-rays of healthy lungs, and 1500 X-rays of lungs infected with pneumonia. The images were manually divided into testing and training data at a ratio of 20:80. This section reviews the materials and procedures used to implement the system. The system's categorization and dataset building procedures are discussed in the first subsection. The platform's fundamentals are presented in the following section. Following that, we will focus on the system's layout and the experimental set-up.

In general, deep learning and CNNs are very powerful tools that can carry out a wide range of tasks, including image classification, object detection, natural language processing, and speech recognition. CNNs are particularly useful for image analysis tasks because they can automatically learn to detect patterns and features in images. This study proposes to use chest X-ray images to classify Covid-positive and Covid-negative cases as well as pneumonia cases using a CNN- and deep learning-based algorithm that is simple and effective. Figure 1 depicts the system's process.

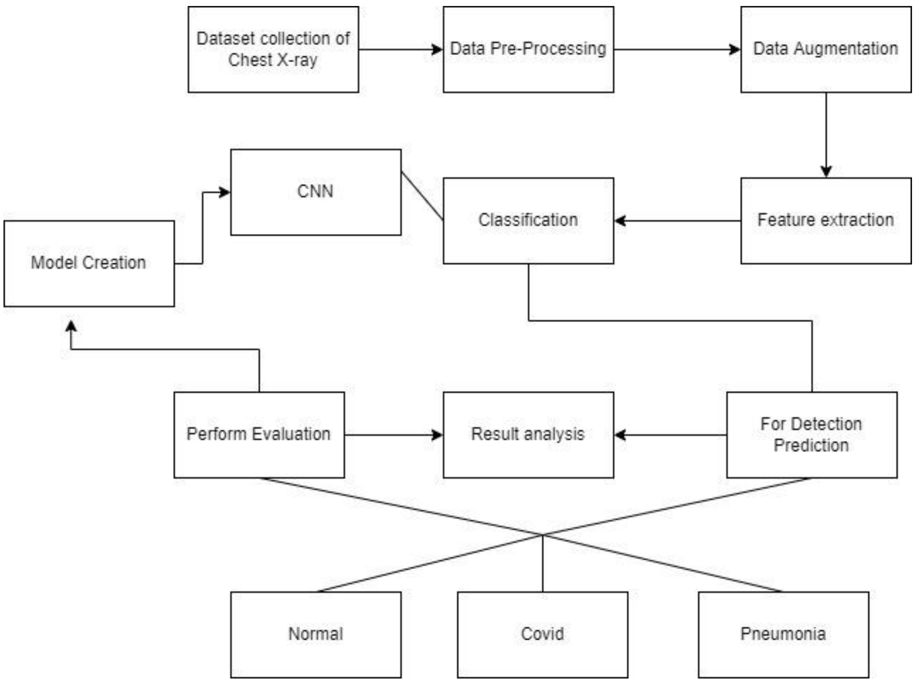

Figure 1 The system's block flow diagram.

The system is implemented with a data source containing Covid, Normal and Pneumonia chest X-ray images. The data were processed by splitting them at a ratio of 80:20 to increase accuracy. Then the features were extracted and labeled as 0 for Covid, 1 for Normal, and 2 for Pneumonia. AI technologies can be used to determine the presence of the Covid plasmodium based on X-rays. Utilizing deep learning helps data enhancement and the development of the prediction model. Pair-wise comparison of X-rays is better compared to prior image classification tests, which can easily lead to departure from the framework, creating overfitting concerns, lowering the network's generalization performance, and complicating the image classification task. It is a necessary and vital stage in image-based machine learning.

Then there is data augmentation, which is done with TensorFlow and Keras on the CNN. First, the images are resized. Most often, code cases and image representations after preprocessing, known as image enhancement, are used. The data will refer to similar images from now on and this feature will be removed. Classification can be an administered learning strategy in machine learning and measuring. The computer application adapts the information from the provided data and creates a display, which may be used to analyze the results as well as to assess the system's performance. Following CNN image generation and X-ray image testing on the chest X-ray image collection, the system will display the coronavirus detection result.

3.1 Detection Object

The images are loaded and resized with OpenCV. This photo pattern recognition aids in instrument recognition based on the coloration, texture, and geometry of the images. Recognition techniques aid in object recognition using image color, scale, and contour. A number of benchmarks are learned by the CNN models to make separate predictions. The models are then merged to predict a class value by using the new weighted average assembling procedure. The Covid-19 detection system is able to detect particles in chest X-ray images by utilizing TensorFlow. Computer vision techniques aid to detect the image's colors and structure. All have been trained to generate a prediction independently, since the CNN models have benchmarks within the range of Keras and TensorFlow for specified parameters to train the models.

With the exception of the first convolutional layer, each convolutional layer gets the output of the previous convolutional layer and produces an output feature map that is then passed on to the next convolutional layer in a conventional feed-forward CNN (which takes in the input). As a result, for L layers, there are L direct connections between each layer and the next layer.

The 'vanishing gradient' problem emerges when the number of layers in the CNN grows. This means that when the communication channel between the input and output layers is extended, some data may 'disappear' or are lost, lowering the network's capacity to train successfully. DenseNet tackles this problem by simplifying the layer connectivity pattern and changing the standard CNN design. A DenseNet architecture has each layer directly connected to every other layer, hence the name 'densely connected convolutional network'. For L levels, L(L+1)/2 direct connections are used.

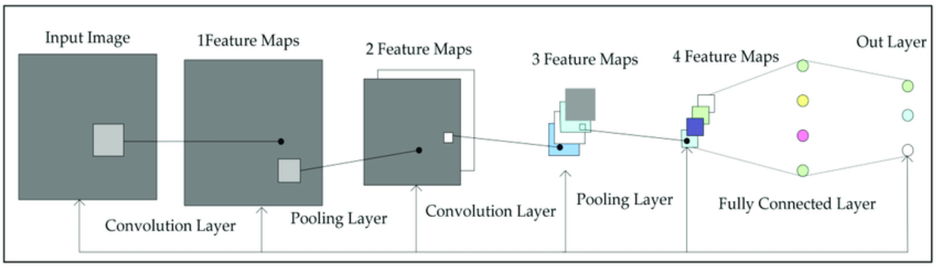

Figure 2 DenseNet architecture layer that produces the output feature map.

Convolution layers are designed to tackle activities involving object recognition with little data preprocessing and no need for manual features. CNN models use the nonlinear activations of the preceding layers to get knowledge of low-level to high-level characteristics. CNN employs feature algorithms or filters that are specialized in detecting the existence of a smaller subset of the supplied image's attributes. As CNN's layers become more complex, it begins to discover global structures and processes in addition to the information retrieved in earlier layers.

Using appropriate filters or kernels, CNN can capture the spatial and temporal variance in an image. These filters are based on multifunctional spatial learning matrices rather than pixel values, and the filtration remains constant throughout the learning process. This method drastically minimizes the number of learnable factors. In absence of the kernel trick, when an image is supplied to an artificial neural network (ANN), the information is provided by individual pixels. The number of learnable factors will become unsustainable for greater image sizes in this case.

As demonstrated in Figure 3, the CNN model is made up of three components. Convolution layers: These strata oversee the mastering of the input image's slightly elevated attributes. Multiple convolution layers can be used to learn visual functions in a step-by-step method. Pooling layer: This layer shrinks the geographical extent of the volume that is concatenated, lowering the amount of computing resources required to process the data. Extracting the dominant traits is also beneficial. Noise suppression is also performed by this layer.

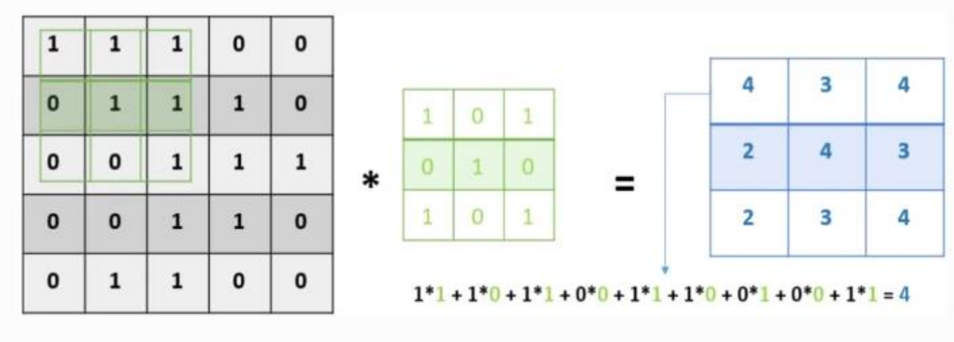

Figure 3 Illustration of the kernel trick used in CNN models.

The model is densely linked or fully linked after the volume of the stream has been properly lowered by combining layers. Learning is done by using layers with sophisticated and high-level nonlinear sequences features. Fully connected layers are frequently fed a one-dimensional matrix obtained from the pooling layer's output and function as ANN models. Traditionally, a pair of convolution and pooling layers is regarded as a single CNN layer, and there can be any number of such pairs.

3.2 Dataset Generation with Model Architecture

The suggested prototype is a ten-layered CNN construction with three conv2D layers, three maxpool2D layers, one dropout layer, one flatten layer and two dense layers, and an output layer. The images are fed in RGB format in the shape 244,244,3. The dropout function is needed to avoid overfitting, and the rectified linear unit (ReLU) activation function is used to activate each of these convolution layers. A regularization strategy known as 'dropout' is used, in which a preset number of layer nodes are disregarded or dropped out at random throughout the training phase. In this training model, the parameters are calculated using this method and changed diagonally, applying a variety of designs with varying numbers of nodes and permutations. The dropout function uses probability distribution eligibility criteria to make this random selection. The proposed model uses a dropout rate of 0.4. ReLU activation is used in the dense layers only, with the exception of the SOFTMAX activation technique, which is used in the output units.

Three chest X-ray datasets were evaluated, and CNNs were employed to detect items. The dataset was downloaded from Kaggle and consisted of chest X-ray samples from Covid-positive, Covid-negative, and pneumonia patients. The radiographs in this collection were divided into three categories: Normal, Pneumonia, and Covid. It comprised roughly 3,780 photographs, which were quite large. Therefore, they were randomly divided into 1,260 Covid, Normal, and Pneumonia images. Positive and negative instances were needed to train the classifier.

Patients' chest X-ray image sets included women, men, and children of all ages. Some X-rays were taken from the front, while others were taken from the top or side. The images in the collection were separated into three segments, i.e., Covid positive images with pneumonia and normal CXR. The visuals were then normalized and transformed into 224,224 format. The images were then sorted and divided into preparation and analysis data. As a result, the training section had 2,880 images and three sectors, divided into 3 classes of 960 images. There were 900 images and three classes within the same testing section, which were in turn divided into 3 classes of 300 images. It was possible that the same X-ray images of the same individuals were used in both training and testing. Even though they are mixed, this supports the model's development, which has been checked, improving the trained model's competence. Examples of chest X-ray scans of Covid-19, pneumonia, and healthy patients are shown Figures 4 to 6.

The datasets that were used in this study was downloaded from the Kaggle dataset repository and processed for further use. There were 1,500 images of Covid, 1,500 images of healthy and 1,500 images of pneumonia patients. First, the images were divided into testing and training data at a ratio of 20:80. The total number of test images was 900 and the number of training images was 2,880. The method was repeated until the preset convergence rate was fulfilled, a set number of iterations had passed, or the arrangement remained the same for several epochs.

Figure 4 Covid-19 positive cells.

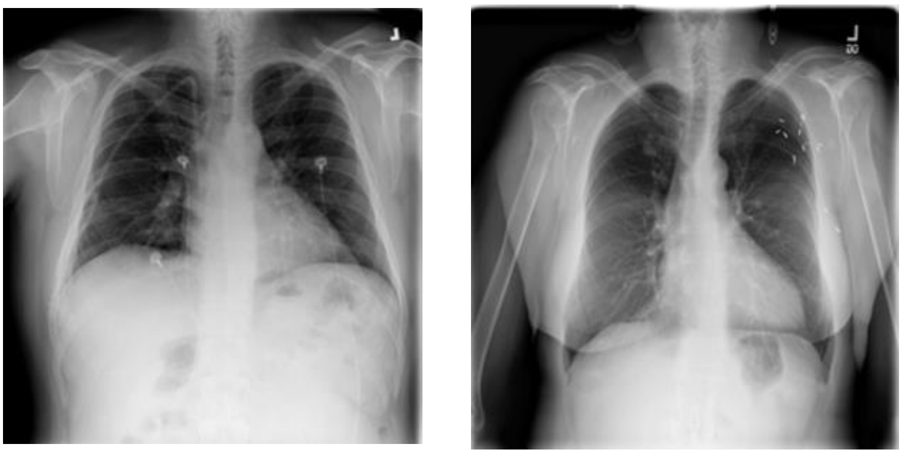

Figure 5 Covid-19 deficient cells.

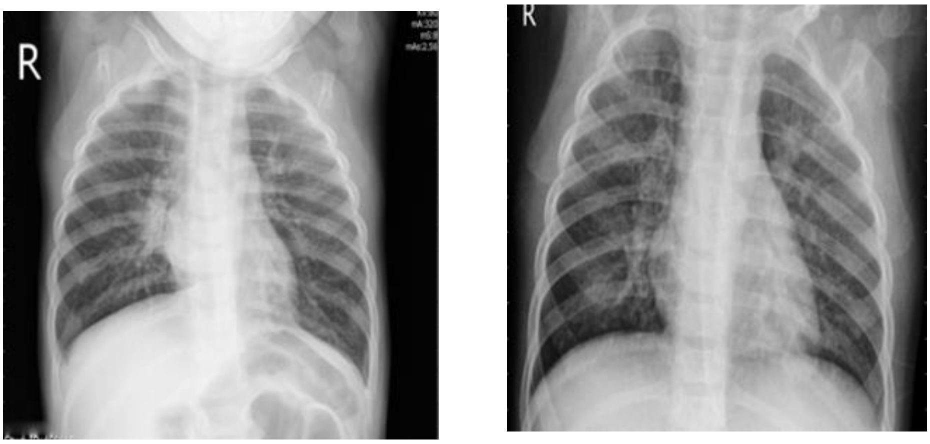

Figure 6 CXR images of a patient with pneumonia.

Table 1 Different layer types and output formats.

Layer (Type)	Output Format	Param #
Conv2d (Conv2d)	(None, 224, 224, 32)	896
Max_Pooling2d (Maxpollig2d)	(None, 112,112,32)	0
Conv2d (Conv2d)	(None, 112,112,32)	9248
Max_Pooling2d (Maxpollig2d)	(None, 56,56,32)	0
Conv2d (Conv2d)	(None, 56, 56, 64)	18496
Max_Pooling2d (Maxpollig2d)	(None, 28,28 64)	0
Flatten (Flatten)	(None, 50176)	0
Dense (Dense)	(None, 128)	6422656
Dropout (Dropout)	(None, 128)	0
Dense_1 (Dense)	(None, 3)	387

Total number of parameters: 6,451,683

Number of trainable parameters: 6,451,683

Number of non-trainable parameters: 0

The model executes a set of steps. Keras also uses a CNN-based model where different layer types and a number of formats are available. The total number of parameters was 6,451,683, of which 6,451,683 were trainable and 0 were non-trainable. The classes were 0 for Covid-positive, 1 for Normal, and 2 for Pneumonia.

4 Experimental Results and Discussion

The image classification by CNN is a vector of probabilities that represents the likelihood of the input image belonging to each class in the classification task. Having successfully trained and evaluated the model, as mentioned previously, the model's optimal accuracy on the test set was 90.87 percent. The accuracy metrics of the CNNs are covered in this section.

```
- loss: 0.3024 - accuracy: 0.9045 - val_loss: 1.5312 - val_accuracy: 0.5819
- loss: 0.2961 - accuracy: 0.9010 - val_loss: 1.5744 - val_accuracy: 0.5972
- loss: 0.2979 - accuracy: 0.9038 - val_loss: 1.5753 - val_accuracy: 0.5931
- loss: 0.2946 - accuracy: 0.9059 - val_loss: 1.5482 - val_accuracy: 0.5694
- loss: 0.2937 - accuracy: 0.9069 - val_loss: 1.5287 - val_accuracy: 0.5833
- loss: 0.2943 - accuracy: 0.9038 - val_loss: 1.5661 - val_accuracy: 0.5903
- loss: 0.2929 - accuracy: 0.9042 - val_loss: 1.5646 - val_accuracy: 0.5931
- loss: 0.2894 - accuracy: 0.9052 - val_loss: 1.6132 - val_accuracy: 0.5958
- loss: 0.2901 - accuracy: 0.9059 - val_loss: 1.5960 - val_accuracy: 0.5931
- loss: 0.2918 - accuracy: 0.9087 - val_loss: 1.5570 - val_accuracy: 0.5903
```

Figure 7 Values for testing loss, testing accuracy, training loss, training accuracy, validation loss and validation accuracy obtained after testing.

From the beginning to the end of the training process, the test accuracy increased to 90.87 percent. The loss percentage gradually dropped.

The loss of each step in the training process gradually decreased, as can be seen in Figure 8. The training loss is indicated by the blue line. The accuracy of the proposed method is shown in Figure 8 below, showing excellent results. The training accuracy is indicated by the blue lines. The best training accuracy was 93.19% in this case.

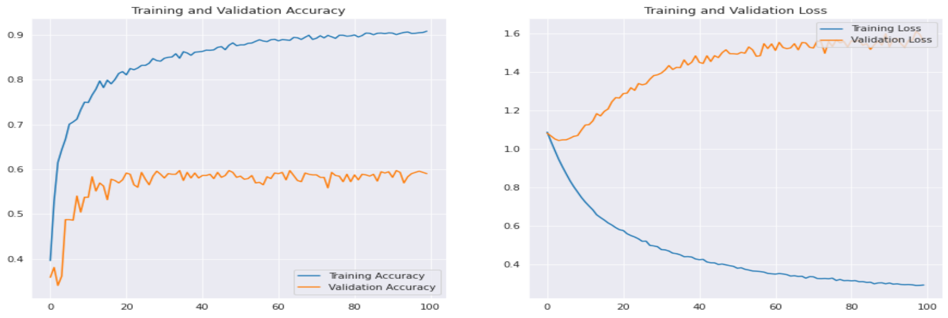

Figure 8 Training and validation graphs for loss of accuracy, training, and validation.

One of the best accuracy matrices is the confusion matrix. The confusion matrix provides a simpler technique to assess the classification problem's performance. As shown in figure 9, a confusion matrix is a two-dimensional table comprising True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN).

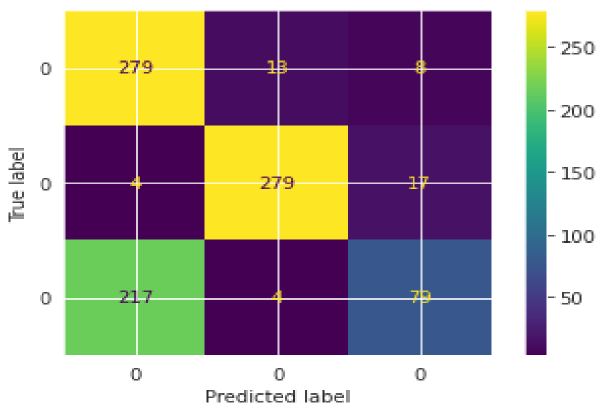

Figure 9 Confusion matrix.

The number of true positives and true negatives should be high because they represent correct classification instances. The remaining instances—false positives and false negatives—must be minimal because they are erroneous predictions. The model was trained and tested, yielding a training accuracy of 90.87 percent as the best result. Excellent results were also achieved when individual images were provided to the model.

5 Conclusion and Future Remarks

The most crucial task in fighting the Covid pandemic is to prevent Covid patients from infecting healthy people. When someone is unaware of their Covid status, they will not be able to stop Covid from spreading. This study focused on how to get the system's Covid diagnosis results as quickly as possible and at a low cost. The major goal was to use neural networks and artificial intelligence to reduce the Covid test's expenses but also to obtain answers as quickly as possible.

Another goal of the study was to execute Covid detection on chest X-ray images. The precision in predicting a correct result was 89.44 percent for the detection module of the model. This means patients can receive Covid results at no cost and from the comfort of their own home and if necessary will be able to receive treatment at their convenience. This will benefit both Covid-19 patients and healthy people who are unaffected. This could be an alternative way to save the latter from contracting Covid-19, since people infected with Covid who are quarantined are less likely to transfer the disease to others.

Typically, people look after their health by avoiding dangerous circumstances and receiving proper treatment when sick. When implemented, this approach is expected to have a significant impact on lowering the Covid-19 infection rate. The result of this research could be a crucial turning point in Covid-19 testing. However, long-term research in the same field may enhance the CNN architecture in order to improve its accuracy and improve it by comparing with deep learning models as well as other models.

References

[1] Czumbel, L.M., Kiss, S., Farkas, N., Mandel , I., Hegyi, A., Nagy, A., Lohinai, Z., Szakács, Z., Hegyi, P., Steward, M.C. & Varga, G., *Saliva as a Candidate for COVID-19 Diagnostic Testing: A Meta-Analysis Systemic Review*, Front. Med., **7**(465), 2020. DOI: 10.3389/fmed.2020.00465.

[2] van Kasteren, P.B., van der Veer, B., van den Brink, S., Wijsman, L., de Jonge, J., van den Brandt, A., Molenkamp, R., Reusken, C.B.E.M. & Meijer, A., *Comparison of Commercial RT-PCR Diagnostic Kits for COVID-19, May 2020*, Journal of Clinical Virology: the Official Publication of the Pan American Society for Clinical Virology, **128**, 104412, 2020.

[3] Phan, T. & Nagaro, K., *Diagnostic Tests for COVID-19*, Advances in Experimental Medicine and Biology, **1318**, pp. 403-412, 2021. DOI: 10.1007/978-3-030-63761-3_23.

[4] Jain, G., Mittal, D., Thakur, D. & Mittal, M.K., *A Deep Learning Approach to Detect Covid-19 Coronavirus with X-Ray Images*, Journal of

Biocybernetics and Biomedical Engineering, **40**(4), pp. 1391-1405, 2020. DOI: 10.1016/j.bbe.2020.08.008.

[5] Raisa, S. & Waleed, S., *Classification of Arrhythmia Using Machine Learning Techniques*, Innovations in Information and Communication Technologies. Springer Nature Switzerland AG, 2021. DOI: 10.1007/978-3-030-66218-9_53.

[6] Pillalamarry, M. & Gnana Prathyusha, Y., *COVID-19 Detection from Chest X-Ray using Convolution Neural Networks*, Journal of Physics: Conference Series, **1804**(1), 012197, 2021. DOI: 10.1088/1742-6596/1804/1/012197.

[7] Rahul, K., *Classification of COVID-19 from Chest X-Ray Images Using Deep Features and Correlation Coefficient*, Journal of Nature Public Health Emergency Collection, **81**(19), pp. 1-25, 2022. DOI: 10.1007/s11042-022-12500-3.

[8] Meen, A.T. & Khan, M.M., *Prediction of Covid-19 Based on Chest X-Ray Images Using Deep Learning with CNN*, Computer Systems Science and Engineering; **41**(3), pp. 1223-1240, 2022.

[9] Kaheel, H., Hussein, A. & Chebab, A., *AI-Based Image Processing for COVID-19 Detection in Chest CT Scan Images*, Front. Comms. Net., 09 August 2021, Sec. IoT and Sensor Networks, 2021. DOI: 10.3389/frcmn.2021.645040.

[10] Kumar, S., Mishra, S. & Singh, S.K., *Deep Transfer Learning-Based COVID-19 Prediction Using Chest X-Rays*, Journal of Health Management **23**(10), 097206342110504, 2021. DOI: 10.1177/09720634211050425.

[11] Zheng, X., Burdick, D., Popa, L., Zhong, X. & Wang, N.X.R.W., *Global Table Extractor (GTE): A Framework for Joint Table Identification and Cell Structure Recognition Using Visual Context*, IEEE Winter Conference on Applications of Computer Vision (WACV), 2021. DOI: 10.1109/WACV48630.2021.00074.

[12] Aminzadeh, F., Temizel, C. & Hajizadeh, Y., *Artificial Neural Networks* in *Artificial Intelligence and Data Analytics for Energy Exploration and Production*, Scrivener Publishing, 2022. DOI: 10.1002/9781119879893.ch3.

[13] Halawa, K., *Selection of Activation Functions in the Last Hidden Layer of the Multilayer Perceptron*, 11th International Conference on Artificial Intelligence and Soft Computing - Volume Part I, pp. 72-80, 2012. DOI: 10.1007/978-3-642-29347-4_9.

[14] Zimmerman, D.L., *Inference for Estimable and Predictable Functions*, in *Linear Model Theory*: *With Examples and Exercises*, pp. 387-450, Chapter: 661, 2020. DOI: 10.1007/978-3-030-52063-2_15.

[15] Kalvoev, M. & Krastev, G., *Comparative Analysis of Activation Functions Used in the Hidden Layers of Deep Neural Networks*, 2021 3rd International

Congress on Human-Computer Interaction, Optimization and Robotic Applications (HORA), 2021. DOI: 10.1109/HORA52670.2021.9461312.

[16] Gouda, W., Almurafeh, M., Humayun, M. & Jhanjhi, N.Z., *Detection of COVID-19 Based on Chest X-rays Using Deep Learning. Healthcare*, **10**(2), 343, 2022.