Open Access
Journal of Electronics and Telecommunication Engineering

RESEARCH TITLE

Engineering Solutions in the Era of COVID-19 Choosing a CNN Architecture for a Computer-Based Covid-19 Diagnosis

Lucy Nwosu and Cajetan M Akujuobi*

Center of Excellence for Communication Systems Technology Research (CECSTR), Department of Electrical and Computer Engineering Prairie View A&M University, USA.

***Corresponding Author:** Cajetan M Akujuobi, Center of Excellence for Communication Systems Technology Research (CECSTR), Dept. of Electrical and Computer Engineering Prairie View A&M University, USA, Tel: +1-832-375-9893, E-mail: cmakujuobi@pvamu.edu

Citation: Lucy Nwosu and Cajetan M Akujuobi (2021) Engineering Solutions in the Era of COVID-19 Choosing a CNN Architecture for a Computer-Based Covid-19 Diagnosis. J Electron and Telecommun Eng 1: 1-11

Copyright: © 2021 Cajetan M Akujuobi. This is an open-access article distributed under the terms of Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

ABSTRACT

COVID-19, a disease caused by the SARS CoV-2 virus has become a global pandemic and has crippled most areas of human life as well as the economy. Researchers all over the world are hard-pressed to find a lasting solution to this pandemic. This paper evaluates the use of engineering principles as a solution to the various issues associated with COVID-19 such as the provision of accurate testing, early identification of symptoms, enforcement of social distancing to mitigate spread, data acquisition for further research, making predictions as well as monitoring the trend and effect of the disease. This paper also compares three convolutional neural network (CNN) architecture used for computer-based COVID-19 Diagnosis. A dataset of 9610 chest x-ray images from the Covid-19 radiography database is used to train five models and the performance is measured using accuracy, f-score, recall, and precision.

Keywords: Engineering, COVID-19, Pandemic, Performance, Machine Learning, Convolutional Neural Network (CNN)

Introduction

The global spread of the coronavirus (COVID-19) has affected every aspect of daily life as well as the economy. This illness which has a death rate of 0.6% [1] in the United States, is caused by the Severe Acute Respiratory Syndrome Coronavirus 2 (SARS CoV-2). It can cause permanent damage to body organs such as the lungs, heart, and brain. The impact [2] of the virus is huge, ranging from overburdening of the healthcare professionals and facilities, challenges in the testing and treatment of confirmed cases, reduction in local, national, and international businesses. The journey towards reducing transmission rate and finding a cure has been tedious and many engineering principles have been enlisted to speed-up the process. This paper aims to evaluate how engineering research and development can bring permanent solutions in the fight against covid19.

Literature Review

Proper testing and treatment, quarantining of exposed persons, social distancing are some of the recognized strategies listed by the world health organization (WHO) for controlling the COVID-19 spread. Research has shown that engineering principles and algorithms can be employed to provide solutions.

Unavailability of data is the main ingredient needed to boost research on the COVID-19. Engineering has employed techniques from data science, statistics, artificial intelligence, and machine learning in reviewing recent research and making forecasts on the changing trend of the disease. A K-Means Clustering, Agglomerative Clustering, and Density-Based Spatial Clustering of Applications with Noise (DBSCAN) clustering algorithm [3] are used to analyze the impact of national epidemic policies on the current epidemic results. Predictions such as the number of newly infected cases, the number of deaths, and the number of recoveries [4] are made from data using logistic regression. In a bid to keep a real-time analysis of recent researches, [5] presents a live repository of the latest research papers and datasets on COVID-19.

Although COVID–19 can be either asymptomatic or symptomatic, the most common symptoms associated with it include Cough, Shortness of breath, Fatigue, Headache, Sore throat, and Congestion or runny nose. To alert patients and remote medical staff [6, 7], simple sensors and microcontrollers are used to design a wearable device that can track key COVID-19 symptoms. A real-time location system (RTLA) is also used for data acquisition from post symptom patients [7] for smart quarantine. Ensuring a minimum social distance of 6 feet especially in crowded places is used to reduce infection due to person-to-person contact. A cellular network is used in [8] to identify at-risk areas, while the frequency of handover and cell (re)selection events is highly reflective of the density of mobile people. Engineering machinery has been used in the vast production of personal protective equipment (PPE) such as masks, gloves, face shields, cover-all Etc. to meet the increased demand for personal and medical use.

The unavailability of widespread and accurate testing has been identified as one of the major factors militating against the control of COVID-19. The medical diagnosis of this illness is based on Reverse Transcription Polymerase Chain Reaction (RT-PCR) testing. This testing method has a high level of false negatives and turnaround time, preventing early treatment. Engineering is currently providing a solution by using chest CT imaging for both diagnosis and prognosis of COVID-19 patients using deep learning algorithms. A high infection detection rate has been achieved in [9] which uses a weakly supervised deep learning strategy for detecting and classifying COVID-19 infection from CT images. This method is disadvantaged by the scarcity of data needed to train the detection model, [10] tries to overcome this disadvantage by using a machine-agnostic method that can segment and quantify the infection regions on CT scans from different sources to augment available data. However, other engineering and Nano technological innovations have started to make inroads to solving the problems of COVID-19 [11].

The rest of the paper is arranged as follows. In Section III, relevant background information on different engineering principles applied in the solution of Covid-19 issues. Section IV discusses a simple experiment that focuses on choosing a CNN architecture for covid-19 diagnosis. Section V analyses the result from section IV and Section VI concludes this research.

Engineering Solutions for COVID-19

Almost every human-made object in the world is created by using engineering principles to solve problems. Engineering covers fields such as Software, Electrical, Computer, Electronics, Civil, Mechanical, and Biomedical. This section summarizes how engineering has contributed to tackling COVID-19 issues. Figure 1 show a summary of areas where engineering can be applied in the fight against COVID-19.

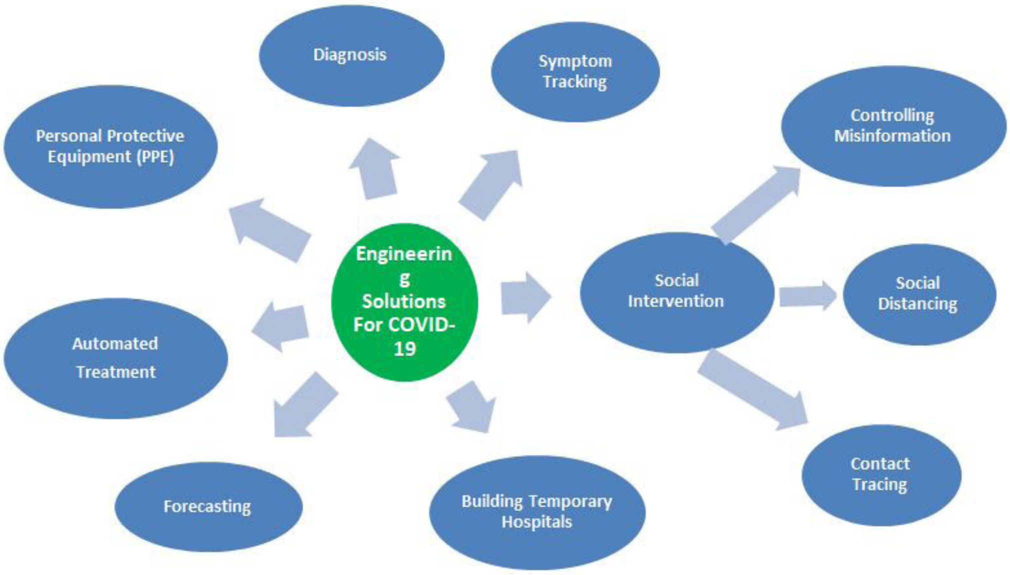

Figure 1: Summary of Engineering Applications for COVID-19

Diagnosis

The nucleic acid detection is considered the standard for testing the COVID-19 virus but this method has a high false-negative rate especially in the early stages of the virus infection. A lot of research has been put into a computer-based alternative to the above method which applies artificial intelligence in detecting COVID-19 patterns on chest-x-ray (CT scan) images. Different engineering approaches to this machine-agnostic method use data segmentation, classification [9], and deep learning [10]. All these approaches have produced rapid and more accurate results when compared to the nucleic acid alternative.

Symptom Tracking

Early detection and treatment are paramount in the treatment of the COVID-19 virus. Most people only go in for testing when they experience the symptoms associated with the virus. Engineering has helped in the design and manufacture of low-cost electronic devices built using simple sensors, and general-purpose microcontrollers for the monitoring of body temperature, heart rate, respiration rate, and other vital signs, which are important to alert patients of the possibility of having contracted the virus. Engineers have designed several wearable devices [6] that are immune to noise and artifacts and is capable of detecting COVID-19 symptoms [9].

Social Intervention

People all over the world are afraid of being infected by the COVID-19 virus, this fear has harmed daily life activities and the global economy. Researches in engineering have aimed to intervene by applying engineering principles to contact tracing, social distancing, and control of misinformation [12]. The engineering industry has massively explored the deployment of information and communication technologies to track and curb the spread of the virus. On the front-line of these efforts, is the Mobile Contact Tracing Applications (MCTA) [13]. These refer to mobile apps that use mobile sensors (e.g., location, proximity) [2, 3] and social networks to facilitate the process of identification of persons who may have been previously into contact with a COVID-19 infected person and subsequent collection of further information about these contacts[7]. Mobile apps have also been created to ensure that a minimum of six feet of social distance is maintained between individuals. This app is built in such a way that it alerts a person once the acceptable social distance is violated [8]. The general public is frequently being faced with a lot of conspiracy theories and false information about the virus through social media. Fact-Check software is used to check the authenticity of the information put up on platforms such as YouTube and Facebook.

Building Temporary Hospitals

The high infection rate of the virus has made various countries all over the world to build mobile and temporary intensive care centers to meet the demand of increased hospitalization. Engineers have designed and built temporary hospitals with available resources. There have been cases where empty shipping containers and tents have been converted to ICU's to admit and help save the life of COVID-19 patients., examples are the NHS Nightingale built in London and the pre-fabricated ICUs made from shipping containers in Massachusetts, United States[7].

Forecasting

The government, medical professionals, and the general public all need to make the right decision in one way or another on how best to tackle the issues associated with covid-19. A major tool in decision making is forecasting. In engineering, machine learning models are used to make predictions, forecasting the number of deaths, the number of hospitalizations, the number of recoveries, and the number of newly infected cases in a specified period [13]. Linear regression (LR), support vector machine (SVM), and exponential smoothing (ES) using time series data collected over a given period have demonstrated the capability to forecast the threatening factors of COVID-19[4].

Automated Treatment

Due to the burden on the hospitals, there is a need for remote and automated treatment options. Engineering principles such as system integration, digital signal processing, and networking is used in creating telemedicine networks in figure 2, which automatically connects a patient to remote medical staff. Figure 2 shows a network connection between a patient and medical personal.

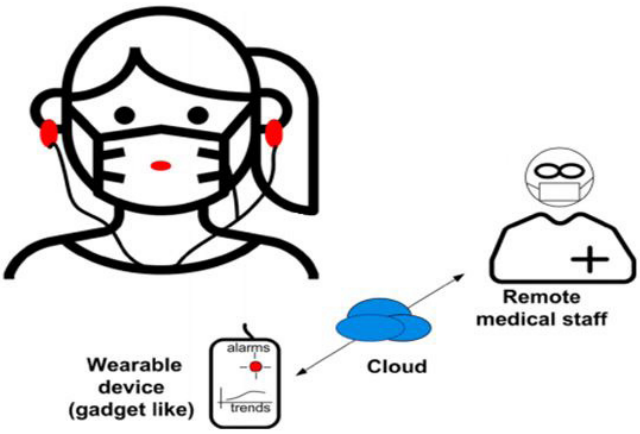

Figure 2: Network between patient and remote medical staff

A sensor that can detect changing body vital signs triggers the system [6]. It is networked via mobile devices to the cloud and communicates to a remote medical staff of the patient's need for medical attention.

Provide Personal Protective Equipment (PPE)

The use of Personal Protective Equipment is recommended for everyone who is going to be outdoors and close to other people. It is also used in protecting the medical staff as well as patients in hospitals. Various engineering companies have helped in the massive production of PPE's to meet the unprecedented high demand. 3-D printing has played a major role in the printing of face masks. Various engineering companies and researchers have also created machines for mass sterilization of PPE's for reuse. Designed and manufactured at the University of Michigan (UM), is an Electronic sterilizer that is currently licensed to operate at a frequency of 50Hz, and producing an average electron current of 20 µA. Under these licensed operating conditions, the X-rays produced can deliver dose rates sufficient for PPE sterilization in minutes [14].

Engineering in COVID-19 Diagnosis

It is highly infectious, and testing must be done to control the spread. Standard **COVID-19** tests are called **PCR (Polymerase chain reaction).** It is time-consuming with significant false-negative results and expensive for large scale implementation. Therefore, the need for this research, which aims at predicting if a patient has COVID19 by using an image recognition and analysis model based on a convolutional neural network (figure 3). Five different CNN structures are built, and their performance is compared using traditional metrics such as Classification Report, Confusion Matrix, Predictions Results, and Learning Curves.
The Convolutional Neural Network architecture consists of four layers [15].

The convolutional layer (CL) receives the input image and is designed to identify the features of an image by using a running a filter across the image. Usually, it goes from the general features such as shapes to specific objects such as a face. The mathematical operation of convolution between the input image and a filter (or kernel) of size (M * M) is achieved using kernel convolution. A matrix is formed by sliding the kernel over the input image and the dot product between the kernel and the input image is taken based on the kernel size. This operation is repeated until the image area is completely covered.

$$G[m,n] = (x * y)[m,n] = \sum_j \sum_k y[j,k]x[m-j,\ n-k] \qquad (1)$$

Feature map values are calculated according to equation 1, where the input image is denoted by x and our kernel by y. The indexes of rows and columns of the result matrix are marked with m and n respectively. The Rectified Linear Unit layer (ReLu) is an extension of a convolutional layer. The rectifier function is applied to increase non-linearity in the CNN as images are made of different objects that are not linear to each other.

$$f(x) = \begin{cases} 0, if\ x < 0 \\ x, if\ x \geq 0 \end{cases} \qquad (2)$$

The output of ReLu in equation 2 is equal to zero when the input value is negative and equal to the input value when the input is zero or positive.

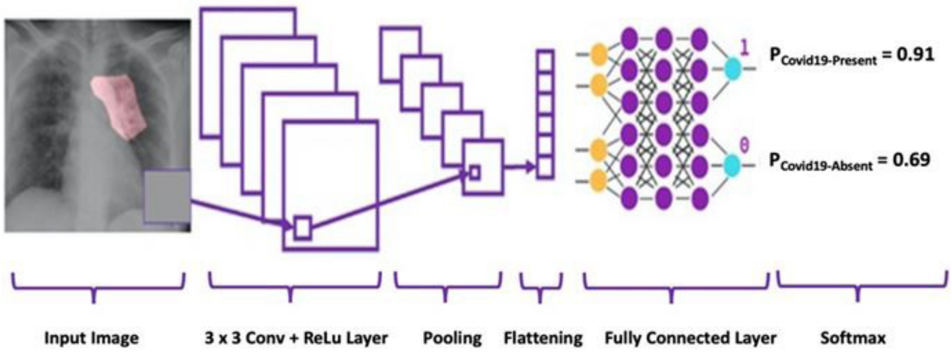

Figure 3: Standard Architecture of a Convolutional Neural Network

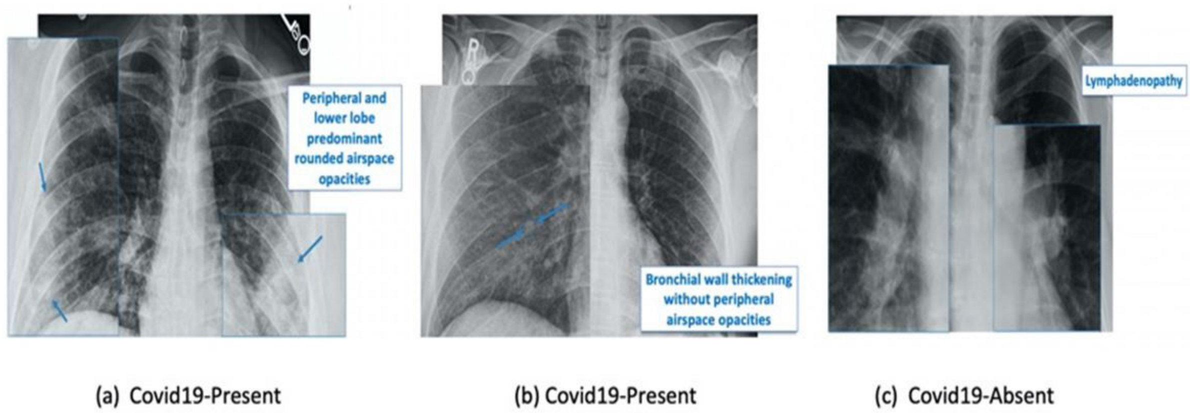

Figure 4: Chest X-ray showing infection pattern on covid-19 present images and covid-19 absent images

In most cases, a Convolutional Layer is followed by a Pooling Layer except if otherwise specified on the model architecture. It aims to decrease the size of the convolved feature map by calculating the maximum value for each patch of the map. The max pooling is used in building the model for this research due to its advantage of reducing computational load and reducing over fitting. The fully connected layer is a standard feed-forward neural network that involves **Flattening**. It involves transforming the entire pooled feature map matrix into a single column which is then fed to the neural network for processing. With the fully connected layers, the extracted features are combined to create a model whose output is defined by equation 3. Finally, an activation function

Such as SoftMax or sigmoid is used to classify the output (z) in equation 4.

$$y=f\ (wx+b) \qquad (3)$$

$$z=f(w^{(z)}\mathbf{y}+b^{(z)}) \qquad (4)$$

Where w, b and f in equation 3 and 4 denotes the network weights, bias term, and specified activation function (ReLu) respectively.

Dataset Description

X-rays show changes in organs, such as the lungs. The presence of bilateral patchy and/or confluent, bandlike ground-glass opacity (GGO) or consolidation in a peripheral and mid to lower lung zone distribution on a chest radiograph obtained in the setting of pandemic COVID-19 is highly suggestive of SARS-CoV-2 infection and can be used in conjunction with clinical judgment to make a covid-19 diagnosis [16], especially when serologic testing is lacking. Covid-19 patterns can be identified on figure 4a and 4b with peripheral and lower lobe predominant rounded airspace opacities and nodules. Figure 4c is a non-covid chest image.
but it shows (enlarged) lymph nodes due to lymphadenopathy, therefore accuracy of prediction is important in using chest x-ray images for covid-19 predictions and diagnosis.

The dataset used in this research is a subset of the Covid-19 radiography database created by collaborations of researchers from Qatar University, Doha, Qatar, and the University of Dhaka, Bangladesh which is available at Kaggle [17]. The dataset used contains 4,610 chest X-ray images for COVID-19 positive cases labeled class 1 along with 5,000 COVID-19 absent images labeled class 0, with each image having a size of (224, 224, 3).

The dataset has four subsets with a 70% and 30% split for the train and test data respectively:

- x_train: containing 6,727 training samples
- x_test: containing 2,883 testing samples
- y_train: containing 6,727 training samples
  Class 0 = 3,500 images

  Class 1 = 3,227 images
- y_test: containing 2,883 testing samples
  Class 0 = 1,500 images

  Class 1 = 1,383 images

Model Description

Several pretrained Convolutional Networks architectures have shown great result in predicting covid-19 patterns on medical images such as x-ray images and CT scans. Such existing models include AlexNet, GoogleNet, ResNet-18, ResNet-50, VGGNet-19, MobileNet V2, and VGG-16. Due to the limited amount of available covid-19 imaging data, there is need to understand how convolutional network architecture affects model performance and covid-19 diagnosis. In this paper, five structures of the CNN architecture are designed and implemented to classify chest x-ray into covid19-present and covid19-absent. The obtained data is divided into training and testing sets. The 6,727 images in the training dataset are used for training each of the classification models. The learning rate was set to 0.0001 and the number of epochs set to 10 for all five models. The resulting models are tested using the 2,883 images in the testing dataset and various performance metrics are used to evaluate the models.

Five CNN architectures are designed to recognize chest x-ray images with COVID-19 patterns using the different structures shown in figure 5a – 5e below. The models are designed using different structures for the convolutional layer, rectified linear (Relu) and Max Pooling (MP) layer. The models end with a fully connected layer which flattens the features into a single column as seen in figure 3. The input image into the convolution layer of each of the five CNN architectures is of size 224 x 224 x 3. Without convolution this image requires 224 x 224 x 3 = 100, 352 numbers of neurons in input layer but convolution is applied to reduce the input tensor dimension to 1 x 1 x 1000, using only 1000 neurons in first layer of feed forward neural network this helps to reduce training time and complexity in the network.

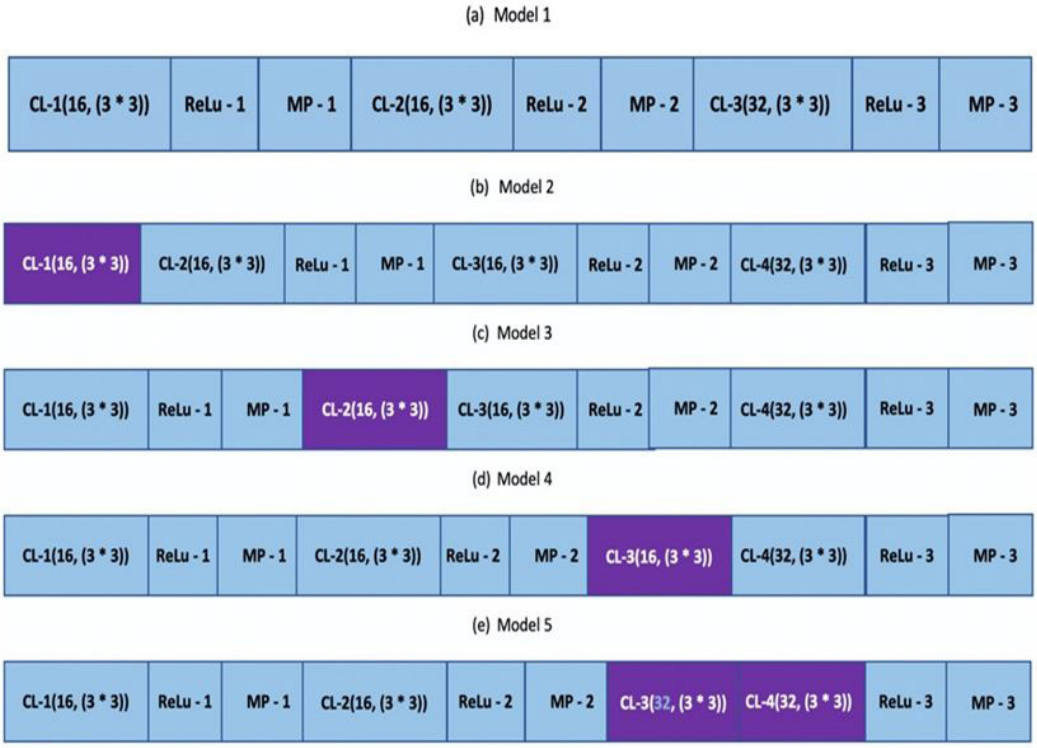

Figure 5: The structures for the five models

Model 1 is designed as a base model and it is made up of three convolutional layers, each followed by consecutive Relu and Max Pooling (MP) layers. Models 2 – 5 are different from model 1 based on the number and location of the convolutional layers as well as the number of filters present in the convolutional layer. When compared to model 1, model 2 has an additional convolution layer at the first convolutional layer, model 3 has an additional layer at the position of the second convolutional layer, Model 4 has an additional layer at the position of the third convolutional layer, and the structure of model 5 is similar to model 4 except that the number of filters in the third convolutional layer increased from 16 to 32 filters.

Result Analysis

Accuracy, Precision, Recall, F1 Score are used to evaluate the performance of the five CNN architectures shown below.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (5)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (6)$$

$$\text{F1 Score} = 2 \times \frac{\text{Precision X Recall}}{\text{Precision+Recall}} \quad (7)$$

$$\text{Accuracy} = \frac{TN+TP}{TN+FN+TP+FP} \quad (8)$$

where TP is called true positive representing the number of COVID-19 patients who are correctly identified as having the infection, FN false negative, represents the number of COVID-19 patients who are misclassified as having no infection of COVID-TN is called true negative and represents the number of non-COVID-19 subjects who are correctly identified as having no infection of COVID-19, FP false positive, represents the number of non-COVID-19 subjects who are misclassified as having the infection.

Model	Precision	Recall	F1-Score	Accuracy
Model 1	0.93	0.87	0.90	89.6%
Model 2	0.94	0.89	0.91	91.2%
Model 3	0.95	0.90	0.93	92.7%
Model 4	0.99	0.91	0.95	94.9%
Model 5	0.99	0.93	0.96	96.3%

Table 1: Comparing Model performance

Table 1 shows a comparison of the performance of the five models. Model precision tells how accurate a model is, it tells how often a prediction made by a model is correct. The question that this metric answers is, of all images labeled as a 1, how many are 1? Model 1 predicted that covid19-present images were correctly predicted 0.93 of the time. Models 2 to 5 has predictions of 0.94, 0.95, 0.99 and 0.99 respectively. This shows an improved prediction as the complexity of the model increased. Recall checks the ratio of correctly predicted positive observations to all observations in actual class - 1. The question recall answers are: of all the images that truly have a class 1 image, how many were labeled correctly? Models 1 – 5 have a recall of 0.87, 0.89, 0.90, 0.91, 0.93 respectively showing that the rate of recognition of correct labelling was high ranging from 87% to 93%.

F1 Score gives the weighted average of Precision and Recall which helps check performance based on the amount of data available for each class. Models 1 to 5 have high F1-score of 0.90, 0.91, 0.93, 0.95, and 0.96. Accuracy is simply a ratio of correctly predicted observations to the total observations. It is observed that the model accuracy increased from model 1 to 5. The testing accuracies for the models 1 to 5 are 89.6%, 91.2%, 92.7%, 94.9%, and 96.3% respectively.

The difference in the performance of the evaluated models is attributed to the structure of the models. Model 5 has the best testing accuracy of 96.3% because it has the most complex structure when compared to the other models. The convolutional layers learn more specific and complex towards the end of the network which is the 4^{th} convolutional layer in our case. The increased number of filters also helped the model to learn more shapes because the number of shapes and edges learned is directly proportional to the number of filters. Therefore, it is expected that 32 filters will learn more accurate patterns than 16 filters.

Our best model, model 5 compares favorably with other high performing pretrained CNN architectures as can be seen on table 2.

Study	Model	Medical Image	Performance Accuracy
[18]	GoogLeNet ResNet18 AlexNet	Chest x- ray	81.5% 84.5% 85.2%
[19]	RexNet-50	Chest CT	86.0%
[20]	ResNet	Chest CT	86.7%
[21]	Resnet50, VGG16	Chest x- ray	94.4%
[22]	UNet++	Chest CT	95.2%
[23]	ResNet + SVM	Chest x- ray	95.38%
Proposed Model	Model 5	Chest x- ray	96.3%

Table 2: Performance comparison between model 5 and state-of-the-art pretrained CNN architectures

Model 5 is shown to perform better than existing architectures such as ResNet which has 34 convolutional layers, ResNet50; a variant of ResNet model which has 48 Convolution layers along with 1 MaxPool and 1 Average Pool layer and UNet which is specifically designed to predict infection and infection area on medical images [22].

Conclusion

Engineering input in the ERA of COVID-19 cuts across most areas of daily life such as diagnosis, testing, social intervention, the building of temporary hospitals, forecasting, and telemedicine Etc. To choose a CNN model for a computer-based covid-19 diagnosis system, five models were created using different model structures but the same learning rate and the number of epochs (Hyper-parameters). The learning rate was set to 0.0001 and the number of epochs set to 10. and both models were trained and tested using a dataset of 9610 chest x-ray images from the Covid-19 radiography database. The performances of the models were checked using the accuracy, precision, recall and f1-score. The models were compared, and results showed that the 5th model performed best among the five models. Model 5 also performed better than existing pretrained CNN architectures.

In conclusion, it is observed that if the CNN structure of a model has a more complex structure at the output convolution layer i.e. more depth and more filters then the model will learn features that are more specific and have a higher performance.

References

1. VZ Marmarelis (2020) “Predictive Modeling of Covid-19 Data in the US: Adaptive Phase-Space Approach,” in IEEE Open Journal of Engineering in Medicine and Biology, vol. 1, pp. 207-13.

2. V Chamola, V Hassija, V Gupta, M Guizani (2020) “A Comprehensive Review of the COVID-19 Pandemic and the Role of IoT, Drones, AI, Blockchain, and 5G in Managing its Impact,” in IEEE Access, vol. 8, pp. 90225-65.

3. Y Shuai, C Jiang, X Su, C Yuan, X. Huang (2020) “A Hybrid Clustering Model for Analyzing COVID-19 National Prevention and Control Strategy,” IEEE 6th International Conference on Control Science and Systems Engineering (ICCSSE), Beijing, China, 2020, pp. 68-71.

4. F Rustam, Aijaz AR, Arif M, Saleem U, Byung WO, et al. (2020) “COVID-19 Future Forecasting Using Supervised Machine Learning Models,” in IEEE Access, vol. 8, pp. 101489-99.

5. Siddique L, M Usman, Sanaullah M, Waleed I, Junaid Q, et al. (2020) “Leveraging Data Science To Combat COVID-19: A Comprehensive Review,” in IEEE Transactions on Artificial Intelligence.

6. R. Stojanovic, A Skraba, B Lutovac, (2020) “A Headset Like Wearable Device to Track COVID-19 Symptoms,” 2020 9th Mediterranean Conference on Embedded Computing (MECO), Budva, Montenegro, 2020, PP. 1-4.

7. J Barabas, R Zalman, M Kochlan (2020) “Automated evaluation of COVID-19 risk factors coupled with real-time, indoor, personal localization data for potential disease identification, prevention and smart quarantining,” 2020 43rd International Conference on Telecommunications and Signal Processing (TSP), Milan, Italy. PP. 645-8.

8. AAR Alsaeedy, EKP Chong (2020) “Detecting Regions At Risk for Spreading COVID-19 Using Existing Cellular Wireless Network Functionalities,” in IEEE Open Journal of Engineering in Medicine and Biology 1: 187-9.

9. Shaoping Hu, Yuan Gao, Zhangming Niu, Yinghui Jiang, Lao Li et al., “Weakly Supervised Deep Learning for COVID-19 Infection Detection and Classification from CT Images,” in IEEE Access 8: 118869-83.

10. L Zhou, Zhongxiao L, Juexiao Z, Haoyang L, Yupeng C et al. (2020) “A Rapid, Accurate and Machine-Agnostic Segmentation and Quantification Method for CT-Based COVID-19 Diagnosis,” in IEEE Transactions on Medical Imaging 8: 2638-52.

11. CM Akujuobi (2020) “Nanotechnology: An Overview of the Current Status of its Roles in the Era of COVID-19”, Vid Proc Adv Mater 1: 200822.

12. Lifang L, Qingpeng Z, Xiao W, Jun Z, Tao W et al. (2020) “Characterizing the Propagation of Situational Information in Social Media during COVID-19 Epidemic: A Case Study on Weibo,” in IEEE Transactions on Computational Social Systems 7: 556-62.

13. D Zeinalipour-Yazti, C Claramunt (2020) “COVID-19 Mobile Contact Tracing Apps (MCTA): A Digital Vaccine or a Privacy Demolition?” 2020 21st IEEE International Conference on Mobile Data Management (MDM), Versailles, France 1-4.

14. Abbas JJ, Noora BS, Christopher AM, Cameron AM, Shaun DC et al. (2020) “Review of Sterilization Techniques for Medical and Personal Protective Equipment Contaminated With SARS-CoV-2,” in IEEE Access 8: 111347-54.

15. Sumit Saha; Logistic A Comprehensive Guide to Convolutional Neural Network, https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53 201 16.

16. Jacobi A, Chung M, Bernheim A, Eber C (2020) Portable chest X-ray in coronavirus disease-19 (COVID-19): A pictorial review. Clin Imaging 64: 35-42.

17. Rahman T, Chowdhury M, Khandakar A (2020) COVID-19 Radiography Database | Kaggle,. https://www.kaggle.com/tawsifur-rahman/covid19-radiography-database.

18. M Loey, F Smarandache, NEM Khalifa (2020) Within the Lack of Chest COVID-19 X-ray Dataset: A Novel Detection Model Based on GAN and Deep Transfer Learning Symmetry, 12: 651.

19. Y Song, S Zheng, L Li, X Zhang, Z Huang, et al. (2020) Deep Learning Enables Accurate Diagnosis of Novel Coronavirus (Covid-19) with Ct Images medRxiv.

20. X Xu, X Jiang, C Ma, P Du, X Li, et al. (2019) A deep learning system to screen novel coronavirus disease 2019 pneumonia Eng 6: 1122-9.

21. LO Hall, R Paul, DB Goldgof, GM Goldgof (2020) Finding Covid-19 from Chest X-Rays Using Deep Learning on a Small Dataset. arXiv preprint arXiv: 2004.02060

22. J Chen, L Wu, J Zhang, L Zhang, D Gong, et al. (2020) Deep learning-based model for detecting 2019 novel coronavirus pneumonia on high-resolution computed tomography Sci Rep 10: 1-11.

23. S Hassantabar, M Ahmadi, A Sharifi (2020) Diagnosis and detection of infected tissue of covid-19 patients based on lung x- ray image using convolutional neural network approaches Chaos, Solitons & Fractals, 140: 110170.