An automated COVID analysis using Deep Learning

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***Abstract*—Advancements in technology has put a rapid and huge impact on every field of life, be it defence, commerce, medical or any other field. Artificial intelligence has exhibited affirmative results in health care industry through its decision-making capability by analysing the data. More than 100 countries got affected by COVID-19 during a matter of no time. In the coming future, people are highly vulnerable to its incoming consequences. It is crucial to find out and develop a control system which will help in detecting the corona virus. To control the current mayhem, one of the solutions can be to use various AI tools in the diagnosis of this disease. According to a clinical study of COVID-19 infected patients, it was depicted that these patients, after coming in contact with this virus, are highly infected from a lung infection. The more efficient imaging techniques for detecting lungs related problems are chest x-ray (i.e., radiography) and chest CT. A chest x-ray is considerably a lower cost process in comparison to a chest CT. One of the most efficacious technique of machine learning is considered to be deep learning. It provides numerous beneficial analysis to study a very large number of images of chest x-rays which can have crucial effect on screening of Covid-19. In this work, we have taken into consideration the chest x-ray and CT scans of healthy patients as well as covid-19 affected patients and then trained our model to produce the results for the detection of virus.**

***Keywords:* Covid-19, X-Ray, CT scan. Deep Learning, Convolution neural network.**

I.INTRODUCTION

Starting in Wuhan, the capital of the Chinese province of Hubei, the COVID-19 or Corona virus spread rapidly to other parts of the world. Coronavirus is caused by the Severe Acute Respiratory Syndrome Coronavirus2 (SARS-CoV-2). It originally came from animals and developed quickly into a global pandemic. The most common ways for the transmission of this virus are by means of air and also by the physical contact with a person who is already infected. It enters into the human body through the respiratory system and infects the lungs. Some of the common symptoms of the coronavirus are fever, coughing and shortness of breath [1].

More than 170 million COVID-19 cases were confirmed worldwide by the end of May 2021. And more than 150 million people globally had successfully recovered from the disease [2].

It is critically important to identify the infection of COVID-19 in its early stages. The conventional method which is prescribed by WHO to identify the covid cases is Reverse Transcription Polymerase Chain Reaction (RT-PCR) which is not time efficient. Therefore, medical imaging, particularly X-Ray imaging, could be performed for preliminary detection of the coronavirus, before conducting this test. In recent times, a number of deep learning-based architectures that use GAN, CNN, etc. have been used to build models which try to identify and predict coronavirus cases from the x-ray image samples of chest, collected from various sources [1]

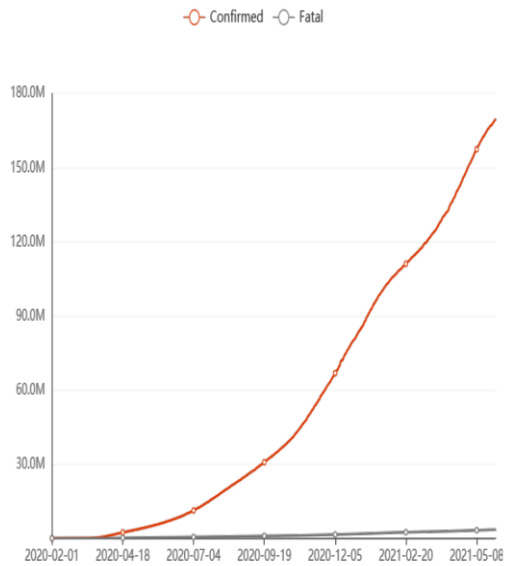

Fig. 1. COVID-19 outbreak over time [3]

II. RELATED WORK

In a study in this area, Rustam et al. tried to predict numbers of patients which will have COVID-19 in the future [4]. They tried to estimate the number of patients that recovered, and also the number of patients who died, in addition to the number of patients infected, over the next 10 days. As a result of their research, the best result among all the models used was given by exponential smoothing. After exponential smoothing, least absolute shrinkage, linear regression, and selection operator gave the best result. The worst accuracy rate was shown by Support Vector Machine (SVM). In this study, longitude, latitude, country, city, number of patients recovered, number of deaths, and the number of cases were used for estimation.

In another study, Roy et al. investigated solutions based on deep learning for lung diseases [5]. In their study, the dataset of LUS images collected from several Italian hospitals was presented. The dataset contained labels with videos and pixel levels. Their experiments showed satisfactory results in the used data set. The study confirmed that COVID-19 can be detected using the LUS data. This study has also guided the future deep learning studies on COVID-19. The most successful rate of 97% was shown by U-net++ [5].

Another study by Sethi et al. made emotion detection in Tweets containing COVID-19 in the literature [6]. Automatically created dataset through the Twitter API was used in this study. In this study a total of three different data sets were used, and they made binary, multiple, and cross-classification. The most successful results were achieved by the binary classification among these classification tasks. In this classification process, tweets were classified as positive and negative. Machine learning algorithms SVM and Decision Tree achieved a success rate of about 90% [6]. In the multiple classifications, tweets were classified as positive, negative and neutral. Same algorithms of machine learning when used in this classification process achieved less success rate than the binary classification. They replicated this achievement in different data sets. The most unsuccessful process in this article was the cross-dataset classification.

In another tweet-based study, Long et al. inspected text-based tweets and proposed a system for the governments and municipalities to understand their citizens during the epidemic [7]. Developed Need Full system gathered the data from Twitter during the pandemic and analysed the emotional needs of the people with the methods of machine learning created after the feature selection and normalization stages [7].

A recent study [8] proposed a model for the detection of coronavirus by using transfer learning that performs both the binary and multiclass classification. Their model called Darknet-19 is selected as the beginning point. The architecture of this system is designed for spotting objects. The authors have designed an architecture DarkCovidNet [Fig.1] specifically for COVID-19. The specified model has a total number of 17 convolution layers where each layer is subsequently followed by batch normalisation operations and rectified linear activation. The batch normalisation operation is used to standardise the inputs. This operation has other benefits as well like escalating model stability and minimising the training time. The maxpool layer reduces the inputs size by taking the limit of the region defined by its filter. This specified approach performed the assignment of coronavirus detection while operating with binary labels and multiclass labels. This method detects the coronavirus automatically without requiring any custom techniques for the feature extraction. A technique called Grad-CAM was also used in understanding which parts of the image had contributed more to the model's final output. The k-fold validation technique was utilized for model validation, and yielded an accuracy of 98.08%, a sensitivity of 95.13%, and 95.30% specificity for binary classification and for multiclass classification it yielded 87.02% accuracy, 85.35% sensitivity, 92.18%.

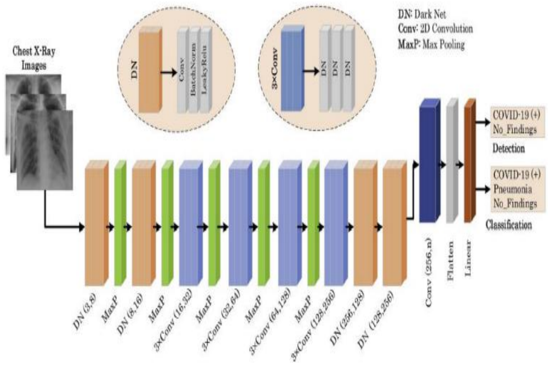

Fig. 1. DarkCovidNet [8].

Another study [9] proposed a model based on auxiliary classifier generative adversarial network [Fig.2] which generated synthetic samples and used this model for augmentation of training dataset, and then used a convolutional model (VGG16 architecture) for the diagnosis of coronavirus, with SoftMax classifier. This method performed binary classification of the dataset. Small datasets are the greatest challenge in the medical imaging domain. To tackle this challenge, data augmentation technique is used. The study was implemented on a data set with limited number of images; 403 covid positive x-ray image samples and 721 normal x-ray image samples. The results obtained for the actual data were 85% accuracy, 69% sensitivity and 95% specificity, and for actual data with synthetic augmentation, 95% accuracy, 90% sensitivity and 97% specificity.

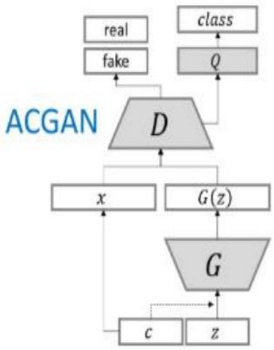

Fig. 2. Auxiliary Classifier Generative Adversarial Network architecture [9]

III. PROPOSED SYSTEM

We aim to use deep learning methodology on the x-rays of suspected patients to speed up the process of COVID-19 testing. The X-rays of the patients' chest contains information which helps us to determines whether the person has COVID-19 or not. In this article, we compare the different available models and then modify them to meet our needs of testing the virus. Specifically, we were focused on CNN, InceptionV3 and ResNET in this article and compared these models on the basis of their accuracy and the ability to detect viruses. Here we have used the neural networks' ability to act like a human brain so that with each class, we get different image details, also known as medical image processing.

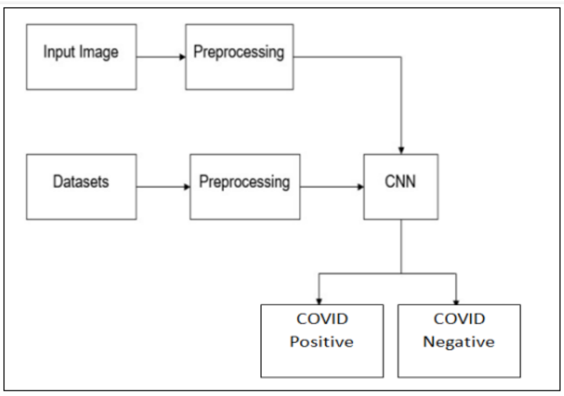

Fig. 3. Proposed System

There are three main strategies to use CNNs successfully for medical image classification:

- Training CNNs from scratch,
- Using features of pre-trained CNN off the market and
- Refining unsupervised learning.

Transfer learning or fine-tuning of pre-trained (supervised) CNN models from natural image datasets to medical imaging problems, is an effective technique for doing this although the field between two sets of medical image data can also be transferred. It is difficult to train a deep complex neural network (CNN) if you train it from scratch, as a lot of training data that is labelled is required and also a lot of experience is must so as to ensure good, well-matched convergence. We can fine tune the pre-trained CNN to do this better. A confusion matrix is used to describe how well a classification model (or "classifier") performs on a set of test data. It is used in evaluating the deep learning models' performance. It is a matrix in which actual values and target predictions are compared to evaluate the classifications used in deep learning algorithms [10]. In itself, a confusion matrix is pretty straightforward, but the terms associated might be perplexing.

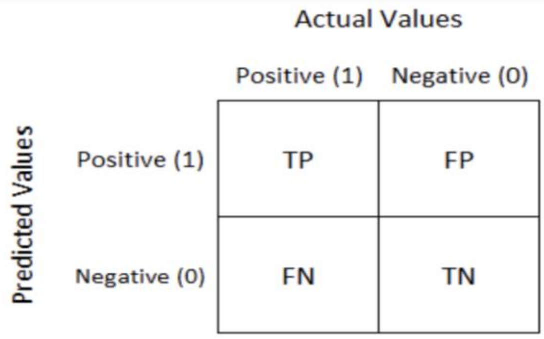

Fig. 4. Sample Confusion Matrix table [13].

In this matrix, there are four different combinations of actual values and predicted values.

- True Positive (TP): It is predicted positive and it is true.
- True Negative (TN): It is predicted negative and it is true.
- False Positive (FP): It is predicted positive and it's false.
- False Negative (FN): It is predicted negative and it is false.

After the competition that was organized in 2012 by ImageNet, deep learning algorithms became more and more popular and started to be used more often in academic research. One of the deep learning networks which is used for computer vision is Convolutional neural network (CNN). CNN has become, in recent years, one of the most advanced methods that is used in artificial intelligence (AI). It has been actively used in analysing medical images, such as X-ray, CT scan, MRI and ultrasound. It is also very efficient in natural language processing, audio recognition, computer vision, speech recognition, pattern recognition and image processing. The famous architecture of CNN consists of one or more convolution layers, grouping layers and one or more fully connected layers, like a standard multilayer neural network [11]. The main block of CNN is convolution layer [12]. It is responsible for extracting the features from the image. Several parameters and hyperparameters are associated with CNNs, namely filters and kernels. This layer uses these filters to extract the entities and then learn from them. Therefore, convolution layer is also called a feature extraction layer. The order goes to the nonlinear layer after convolution layer. This layer is called the Relu layer where the activation process is done. This layer's task is to reduce the number of parameters and the sheer size of representation and calculations within the network. Incompatibility in the network can be checked in this way. Here, the main purpose is to minimise the number of parameters and keep the most critical parameters only. This reduces the total number of entries for the next layer which in turn reduces the computational cost for following layers and prevents memorization. The main purpose of the flattening layer is to prepare the data for the last layer i.e., Fully Connected layer. This layer converts the matrices from Convolutional and Pooling layers into an array of one-dimension [12]. The Fully Connected Layer then takes the data from the Flattening layer and performs the learning process through the Neural network. CNN model flow is shown in Figure 5.

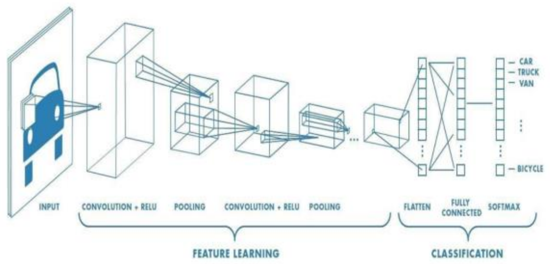

Fig. 5. Sample CNN model flow [14]

The core idea behind adding ResNet is introducing a so-called "identity shortcut connection" which bypasses one or more layers. To solve a complex problem, we usually stack extra layers into our deep neural network to improve the accuracy and its performance. The main idea behind adding some extra layers is that these layers will gradually learn some more complex features. For example, in case of image recognition, the first layer may learn to detect the edges, the second layer may learn to recognize the textures, the third layer may learn to detect the objects, and so on. To handle the complex tasks, deep neural networks can be used. However, adding too many layers can cause the gradient problem to disappear, and also the weights of the first few layers cannot be modified through backpropagation. Adding an identity connection can solve this problem. The ResNet's structure allows the gradient to flow from the last layer to the initial filter directly through the identification connection. ResNet is the continuation of the deep neural network. It enhances the architecture of CNN through residual learning and also provides an effective method for the deep network training.

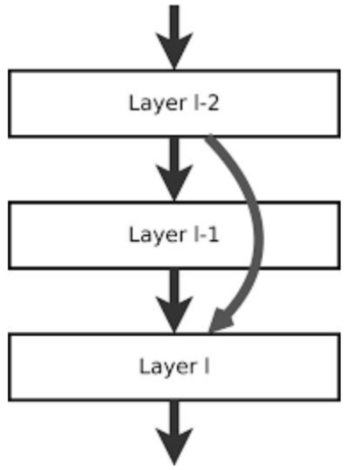

Fig. 6. ResNet Layers Skipping [15].

InceptionV3 is a type of CNN model which was developed by Christian Szegedy in 2015 for assisting in object detection and image analysis. Its design was intended to allow deeper networks but at the same time keeping the number of parameters low. Instead of stacking convolutional layers and sequentially grouped layers one by one, some layers are parallel, and their results are periodically merged. The key idea of this network is to stack Inception modules, which are composed of convolutional layers and grouping layers. The computational cost of InceptionV3 is suitable for mobile or big data scenarios. Inception V3 mainly focuses on consuming less computing power by modifying the previous Inception architecture. Inception Networks (GoogleNet / Inception v1) has been proven to be more computationally efficient, both in terms of the number of parameters generated by the network and the economic costs (memory and other resources) generated. If you want to make changes to your home network, you must take care to ensure that you do not lose computing advantages. Therefore, due to the uncertainty of the efficiency of the new network, adjusting the initial network for different use cases becomes a problem. In the Inception v3 model, several techniques have been proposed to optimize the network to relax constraints and promote model adaptation. Techniques include decomposition and convolution, regularization, dimensionality reduction and parallel computing.

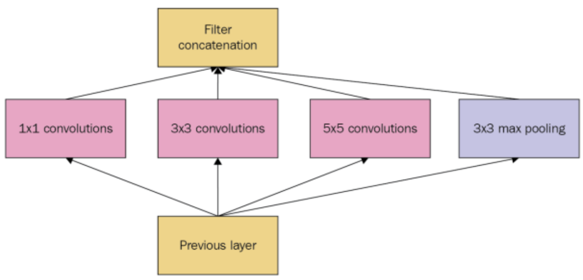

Fig. 7. Inception V3 architecture [16].

IV. EXPERIMENTAL RESULTS

We trained different models and upon testing they produced different results. Any detection problem that was solved using CNNs, the interpretation of the results was done by means of Confusion Matrix. The same is shown in Figures 8-12.

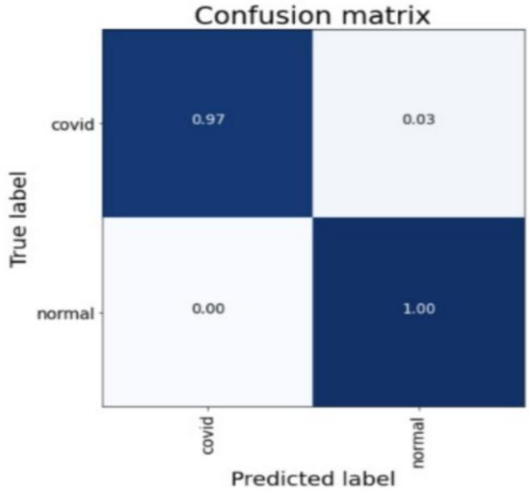

Fig. 8. CNN X-Ray Confusion Matrix

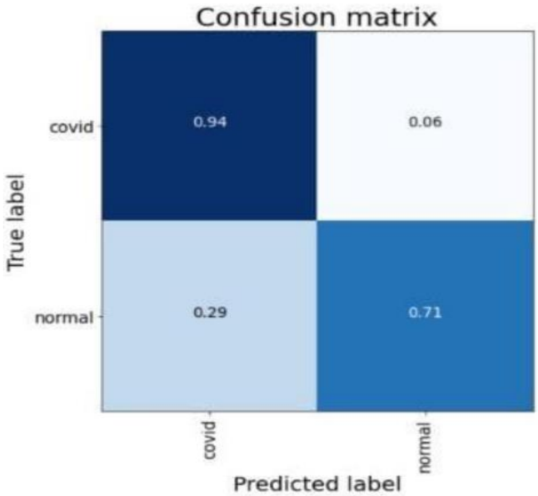

Fig. 9. ResNet X-Ray Confusion Matrix

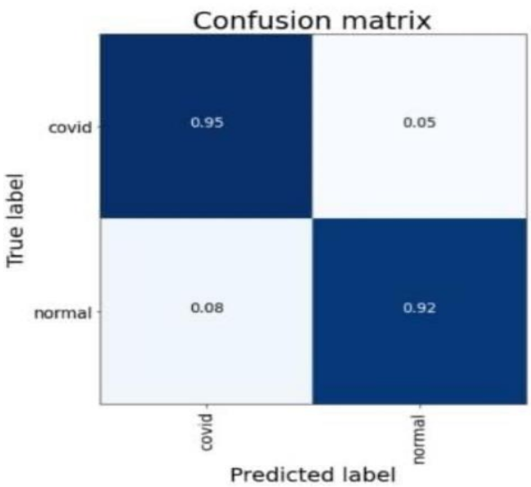

Fig. 10. Inception V3 X-Ray Confusion Matrix

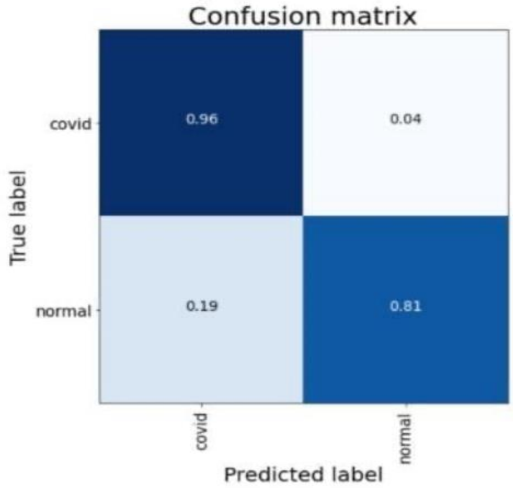

Fig. 11. Inception V3 CT-Scan Confusion Matrix

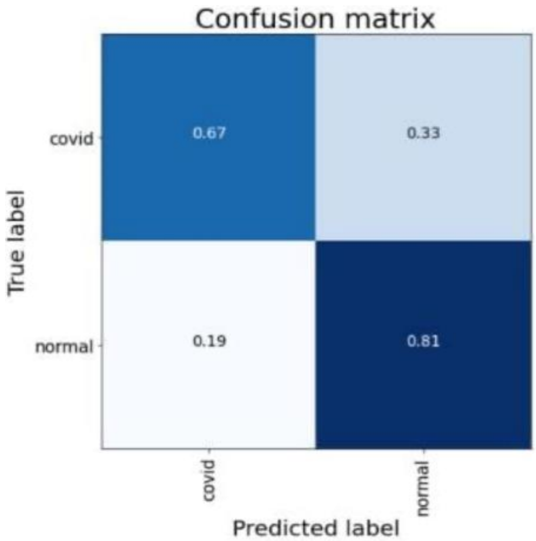

Fig. 12. ResNet CT-Scan Confusion Matrix

V. CONCLUSION AND FUTURE SCOPE.

COVID-19 has utterly threatened the lives of millions of people globally within a very short period of time. It is an ongoing pandemic disease that affects the lung cells directly and can also inflict permanent damage, even death, if not appropriately detected early on. This rapid outbreak of COVID-19 across the globe and the growing number of deaths requires immediate actions from all sectors. Future prediction of possible infections will enable the authorities to confront the consequences efficiently. By making the use of image processing approaches on x-ray images, deep learning can play a crucial role in detecting the coronavirus. In this paper, deep learning procedures were proposed to detect the COVID-19. Detection models such as the Inception V3, ResNet and CNN algorithms were used to detect the COVID19 confirmations.

Model	CoviddetectionAccuracy	Covid Detection Failure	NonCovid Detection Accuracy	Non-Covid Detection Failure
CNN for X-ray	97%	3%	100%	0%
ResNet for X-ray	94%	6%	71%	29%
ResNet for CT-scan	96%	4%	81%	19%
InceptionV 3 for X-ray	95%	5%	92%	8%
InceptionV 3 for CT-scan	67%	33%	81%	19%

Table: Comparing Accuracies among different approaches.

One of the biggest and key problems in deep learning-based methods for COVID-19 detection from x-ray images is the necessity of a large and appropriately labelled data set for training the models. It was evident in most of the recent works that imbalanced open-source datasets were used, where the number of normal samples was considerably higher than the number of covid positive samples. Many approaches also have produced very high specificity and sensitivity even with small and imbalanced datasets. This illustrates that overfitting is present to some degree and also there is a lack of data to actually generalize the models for the task. Since the outbreak of COVID-19 virus is very fast, x-ray data gathered is very less, and it is very hard to implement a deep learning model from scratch. One of the techniques that may solve this issue to some extent is Data Augmentation. The training phase for these models can be improved further with more data. The excellence of the augmented data can also be enhanced with the mixing of more labelled data. and the development of a more precise deep learning model would be possible.

REFERENCE

[1] Dr. Aruna Bhat and Sachin, "A Survey on COVID-19 Detection from X-ray Images using Deep Learning" 2021 12th International Conference on Computing Communication and Networking Technologies.

[2] COVID-19 Dashboard by Johns Hopkins University. https://www.arcgis.com/apps/opsdashboard/index.html#/bda7594740fd40299423467b48e9ecf6

[3] Bing COVID-19 Tracker. www.bing.com/covid.

[4] F. Rustam et al., "COVID-19 Future Forecasting Using Supervised Machine Learning Models," in IEEE Access, vol. 8, pp. 101489- 101499, 2020, doi: 10.1109/ACCESS.2020.2997311.

[5] S. Roy et al., "Deep Learning for Classification and Localization of COVID-19 Markers in Point-of-Care Lung Ultrasound," in IEEE Transactions on Medical Imaging, vol. 39, no. 8, pp. 2676-2687, Aug. 2020, doi: 10.1109/TMI.2020.2994459.

[6] M. Sethi, S. Pandey, P. Trar and P. Soni, "Sentiment Identification in COVID-19 Specific Tweets," 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), Coimbatore, India, 2020, pp. 509-516, doi: 10.1109/ICESC48915. 2020. 9155674.

[7] Z. Long, R. Alharthi and A. E. Saddik, "NeedFull – a Tweet Analysis Platform to Study Human Needs During the COVID-19 Pandemic in New York State," in IEEE Access, vol. 8, pp. 136046-136055, 2020, doi: 10.1109/ACCESS. 2020. 3011123.

[8] Ozturk, M. Talo, E. A. Yildirim, U. B. Baloglu, O. Yildirim, and U. R. Acharya," Automated detection of COVID-19 cases using deep neu-ral networks with X-ray images," Comput. Biol. Med., vol. 121, Jun. 2020, Art. no. 103792.

[9] A. Waheed, M. Goyal, D. Gupta, A. Khanna, F. Al-Turjman, and P. R. Pinheiro," CovidGAN: Data augmentation using auxiliary classifier GAN for improved COVID-19 detection," IEEE Access, vol. 8, pp. 91916–91923, 2020.

[10] Mehmet Sevi and Ilhan Aydin "COVID-19 Detection Using Deep Learning Methods"2020 International Conference on Data Analytics for Business and Industry: Way Towards a Sustainable Economy (ICDABI).

[11] G. Gündüz, İ. H. Cedimoğlu, "Derin Öğrenme Algoritmalarını Kullanarak Görüntüden Cinsiyet Tahmini," Sakarya Unıversıty Journal of Computer and Information Sciences, 2, 9-17, 2019.

[12] K. Shankar, V. Iyer, K. Iyer and A. Pandhare, "Intelligent Video Analytics (IVA) and Surveillance System using Machine Learning and Neural Networks," 2020 International Conference on Inventive Computation Technologies (ICICT), Coimbatore, India, 2020, pp. 623- 627, doi: 10.1109/ICICT48043.2020.9112527.

[13] https://towardsdatascience.com/understanding-confusion-matrix-a9ad42dcfd62

[14] https://medium.com/@RaghavPrabhu/understanding-of-convolutional-neural-network-cnn-deep-learning-99760835f148

[15] https://en.wikipedia.org/wiki/Residual_neural_network#/media/File:ResNets.svg

[16] https://iq.opengenus.org/inception-v3-model-architecture/