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COVID-19 Image Classification Using VGG-16 & CNN based on CT Scans

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***Abstract:** The main purpose of this work is to investigate and compare several deep learning enhanced techniques applied to CT-scan medical images for the detection of COVID-19. In this proposed work we are going to build two Covid19 Image classification models. Both the model uses Lungs CT Scan images to classify the covid-19. We build the first Classification model using VGG16 Transfer leaning framework and second model using Deep Learning Technique Convolutional Neural Network CNN to classify and diagnose the disease and we able to achieve the best accuracy in both the model.*
***Keywords:** Visual Geometry Group-VGG16, Convolutional Neural Network-CNN, CT Images, X-Ray, rTPCR*

I. INTRODUCTION

COVID-19 is the disease caused by the Corona Virus called SARS-CoV-2. COVID-19 is the name given by the World Health Organization (WHO) on February 11, 2020. Since the discovery of the first case, the disease has spread to almost every country, causing deaths of over 4.9 million people among nearly 244 million confirmed cases based on the statistics of the World Health Organization by October 2021.

Symptoms of COVID-19 are variable, but often include fever, cough, headache, fatigue, breathing difficulties, and loss of smell and taste. Symptoms may begin one to fourteen days after exposure to the virus.

COVID-19 transmits when people breathe in air contaminated by droplets and small airborne particles containing the virus. The risk of breathing these in is highest when people are in close proximity, but they can be inhaled over longer distances, particularly indoors.

Several testing methods have been developed to diagnose the disease. The standard diagnostic method is by detection of the virus' nucleic acid by real-time reverse transcription polymerase chain reaction (rRT-PCR)

Several COVID-19 vaccines have been approved and distributed in various countries, which have initiated mass vaccination campaigns. Other preventive measures include physical or social distancing, quarantining, and ventilation of indoor spaces, covering coughs and sneezes, hand washing, and keeping unwashed hands away from the face. The use of face masks or coverings has been recommended in public settings to minimize the risk of transmissions.

The proposed work we are going to build two Covid19 Image classification models. Both the model uses Lungs CT Scan images to classify the covid-19. We build the first Classification model using VGG16 Transfer leaning framework and second model using Deep Learning Technique Convolutional Neural Network CNN to classify and diagnose the disease and we able to achieve the best accuracy in both the model.

II. RELATED WORK

A. *Deep Learning for the Detection of COVID-19 Using Transfer Learning and Model Integration.*

Abstract—we researched the diagnostic capabilities of deep learning on chest radiographs and an image classifier based on the COVID-Net was presented to classify chest X-Ray images. In the case of a small amount of COVID-19 data, data enhancement was proposed to expand COVID-19 data 17 times. Our model aims at transfer learning, model integration and classify chest X-ray images according to three labels: normal, COVID-19 and viral pneumonia. According to the accuracy and loss value, choose the models ResNet-101 and ResNet-152 with good effect for fusion, and dynamically improve their weight ratio during the training process. After training, the model can achieve 96.1% of the types of chest X-Ray images accuracy on the test set. This technology has higher sensitivity than radiologists in the screening and diagnosis of lung nodules. As an auxiliary diagnostic technology, it can help radiologists improve work efficiency and diagnostic accuracy.

B. Classification of COVID-19 from Chest X-ray images using Deep Convolutional Neural Network.

Abstract—The COVID-19 pandemic continues to have a devastating effect on the health and well-being of the global population. A vital step in the combat towards COVID-19 is a successful screening of contaminated patients, with one of the key screening approaches being radiological imaging using chest radiography. This study aimed to automatically detect COVID-19 pneumonia patients using digital chest x-ray images while maximizing the accuracy in detection using deep convolutional neural networks (DCNN). The dataset consists of 864 COVID-19, 1345 viral pneumonia and 1341 normal chest X-ray images. In this study, DCNN based model Inception V3 with transfer learning have been proposed for the detection of coronavirus pneumonia infected patients using chest X-ray radiographs and gives a classification accuracy of more than 98% (training accuracy of 97% and validation accuracy of 93%). The results demonstrate that transfer learning proved to be effective, showed robust performance and easily deployable approach for COVID-19 detection.

C. COVID-19 Future Forecasting Using Supervised Machine Learning Models.

Abstract—Machine learning (ML) based forecasting mechanisms have proved their significance to anticipate in perioperative outcomes to improve the decision making on the future course of actions. The ML models have long been used in many application domains which needed the identification and prioritization of adverse factors for a threat. Several prediction methods are being popularly used to handle forecasting problems. This study demonstrates the capability of ML models to forecast the number of upcoming patients affected by COVID-19 which is presently considered as a potential threat to mankind. In particular, four standard forecasting models, such as linear regression (LR), least absolute shrinkage and selection operator (LASSO), support vector machine (SVM), and exponential smoothing (ES) have been used in this study to forecast the threatening factors of COVID-19. Three types of predictions are made by each of the models, such as the number of newly infected cases, the number of deaths, and the number of recoveries in the next 10 days. The results produced by the study proves it a promising mechanism to use these methods for the current scenario of the COVID-19 pandemic. The results prove that the ES performs best among all the used models followed by LR and LASSO which performs well in forecasting the new confirmed cases, death rate as well as recovery rate, while SVM performs poorly in all the prediction scenarios given the available dataset.

III. SYSTEM REQUIREMENT SPECIFICATION

System requirement specifications gathered by extracting the appropriate information to implement the system. It is the elaborative conditions which the system needs to attain. Moreover, the SRS delivers a complete knowledge of the system to understand what this project is going to achieve without any constraints on how to achieve this goal. This SRS does not providing the information to outside characters but it hides the plan.

A. Hardware Requirements

1) System Processor : i7
2) Hard Disk : 500 GB.
3) RAM : 8 GB / 12 GB.

Any desktop / Laptop system with above configuration or higher level.

B. Software Requirements

1) Operating system : Win 8/10(64bits OS)
2) Programming Language : Python 3
3) Framework : Anaconda
4) Libraries : Keras, TensorFlow, OpenCV
5) IDE : Jupyter Notebook

IV. EXISTING SYSTEM

The global spread of the COVID-19 pandemic has caused significant losses. The most critical issues, medical and healthcare departments are facing is the fact that the COVID-19 was discovered promptly. Therefore, it is of great importance to check the diagnosis of the suspected case, not only to facilitate the next step for the patients, but also to reduce the number of infected people. X-Ray examination is considered to be the most commonly used Chest X-Ray examination method because of its low cost, wide range of application, and fast speed. It plays a pivotal role in COVID-19 patient screening and disease detection.

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Because COVID-19 attacks human respiratory epithelial cells, we can use Chest X-Ray to detect the health of the patient's lungs. How to detect these features from Chest X-Ray has become a top priority.

V. PROPOSED SYSTEM

In this proposed work we are going to build two Covid19 Image classification models. Both the models use Lungs CT Scan images to classify the covid-19. We build the first classification model using VGG16 Transfer leaning framework and second model using Deep Learning Technique Convolutional Neural Network-CNN to classify and diagnose the disease and we able to achieve the best accuracy in both the model.

In the face of the potential for using CT images as a complementary screening method for COVID-19, alongside the challenges of interpreting CT for COVID-19 screening, extensive studies have been conducted on how to detect COVID-19 using CT images.

A. VGG16-Visual Geometry Group

VGG16-Visual Geometry Group is a convolutional neural network model.

VGG16 is a convolution neural net (CNN) architecture which was used to win ILSVR (ImageNet) competition in 2014. It is considered to be one of the excellent vision model architecture till date. Most unique thing about VGG16 is that instead of having a large number of hyper-parameters they focused on having convolution layers of 3x3 filter with a stride 1 and always used same padding and maxpool layer of 2x2 filter of stride 2. It follows this arrangement of convolution and max pool layers consistently throughout the whole architecture. In the end it has 2 FC (fully connected layers) followed by a softmax for output. The 16 in VGG16 refers to it has 16 layers that have weights. This network is a pretty large network and it has about 138 million (approx.) parameters.

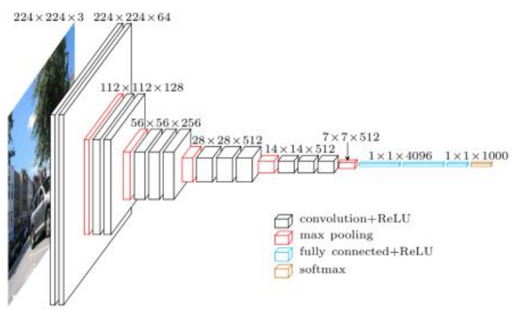


Fig.1. Architecture of VGG-16

B. Convolutional Neural Network (CNN)

In deep learning, a convolutional neural network (CNN or ConvNet) is a class of deep neural networks, most commonly applied to analyzing visual imagery. They are

also known as shift invariant or space invariant artificial neural networks (SIANN), based on their shared-weights architecture and translation invariance characteristics. They have applications in image and video recognition, recommender systems, image classification, medical image analysis, and natural language processing.

CNN is the subset of deep learning; it is similar to the basic neural network. CNN is a type of neural network model which allows working with the images and videos, CNN takes the image's raw pixel data, trains the model, then extracts the features automatically for better classification.

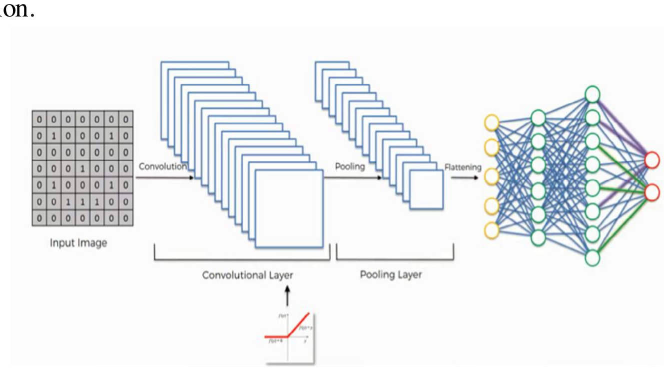
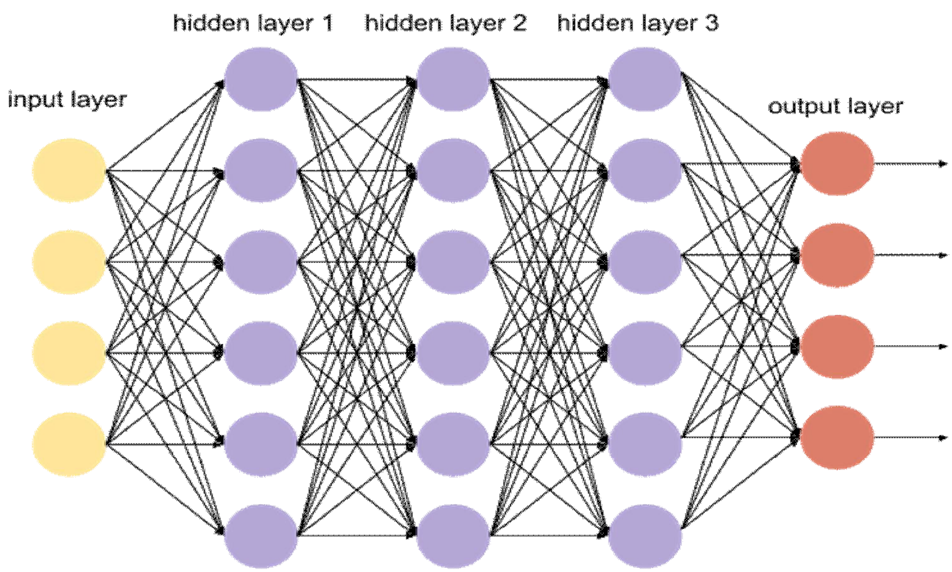


Fig.2 Basic Convolutional Neural Network

A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics.
The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlaps to cover the entire visual area.



C. What does Convolutional Neural Network Do?

Convolutional neural networks are used to find patterns in an image. You do that by convoluting over an image and looking for patterns. In the first few layers of CNNs the network can identify lines and corners, but we can then pass these patterns down through our neural net and start recognizing more complex features as we get deeper. This property makes CNNs really good at identifying objects in images.

VI. IMPLEMENTING AND ANALYSIS

A. Implementing

In this work, a business intelligent model has been developed, to classify Dataset, based on a specific business structure deal with Dataset using a suitable machine learning technique. The model was evaluated by a scientific approach to measure accuracy. We are using Traditional Algorithm to build our model.

B. Analysis

In this final phase, we will test our classification model on our prepared image dataset and also measure the performance on our dataset. To evaluate the performance of our created classification and make it comparable to current approaches, we use accuracy to measure the effectiveness of classifiers.
After model building, knowing the power of model prediction on a new instance, is very important issue. Once a predictive model is developed using the historical data, one would be curious as to how the model will perform on the data that it has not seen during the model building process. One might even try multiple model types for the same prediction problem, and then, would like to know which model is the one to use for the real-world decision making situation, simply by comparing them on their prediction performance (e.g., accuracy). To measure the performance of a predictor, there are commonly used performance metrics, such as accuracy, recall etc. First, the most commonly used performance metrics will be described, and then some famous estimation methodologies are explained and compared to each other.

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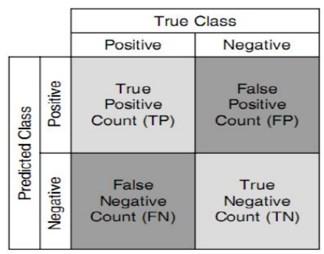
"Performance Metrics for Predictive Modelling In classification problems, the primary source of performance measurements is a coincidence matrix (classification matrix or a contingency table)". Above figure shows a coincidence matrix for a two-class classification problem. The equations of the most commonly used metrics that can be calculated from the coincidence matrix are also given in Fig 3. As being seen in above figure, the numbers along the diagonal from upper-left to lower-right represent the correct decisions made, and the numbers outside this diagonal represent the errors. "The true positive rate (also called hit rate or recall) of a classifier is estimated by dividing the correctly classified positives (the true positive count) by the total positive count. The false positive rate (also called a false alarm rate) of the classifier is estimated by dividing the incorrectly classified negatives (the false negative count) by the total negatives. The overall accuracy of a classifier is estimated by dividing the total correctly classified positives and negatives by the total number of samples.
The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlap to cover the entire visual area.



$$\text{True Positive Rate} = \frac{TP}{TP + FN}$$

$$\text{True Negative Rate} = \frac{TN}{TN + FP}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

Figure 3: confusion matrix and formulae

VII.DATA SETS AND EXPERIMENTAL RESULTS

We have used the dataset entitled "SARS-CoV-2 CT Scan Dataset", which is possibly the largest publicly available dataset of CT scans for COVID-19 identification. The dataset contains 1106 CT-scans that are diagnosed positive for the SARS-Cov-2 infection and 1057 CT-scans for normal healthy patients that are non-infected, comprising a total of 2163 CT-scan images. The dataset aims to encourage the research and development of artificial intelligence-enabled methods to identify whether a patient is infected by the deadly virus through the analysis of his/her scan.
Owing to the inconsistent number of X-ray and CT-scan images, we want to verify the effectiveness of proposed model trained for different scales of images. We divided CT-scan dataset into 2163 images for training and 1106 images for validation, which is set of COVID, Non-COVID.

```
test
Covid 141
NonCovid 167
test ----- 308
train
Covid 1106
NonCovid 1057
train ----- 2163
```

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```
['Covid', 'NonCovid']
------------------------------
Creating training images...
------------------------------
Covid 1106
Done: 0/1106 images
Done: 800/1106 images
NonCovid 1057
Done: 1600/1057 images
2163-------2
Loading done.
Transform targets to keras compatible format.
------------------------------
Creating validation images...
------------------------------
Covid 141
Done: 0/141 images
NonCovid 167
Done: 200/167 images
308
Loading done.
Transform targets to keras compatible format.
```

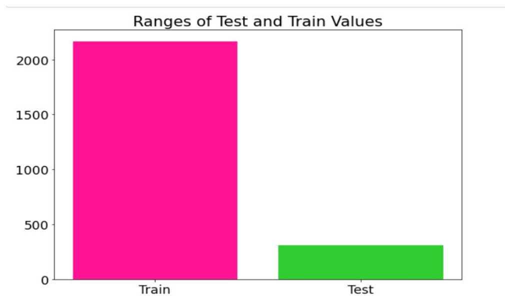

Figure 4: Ranges of Test and Train Values

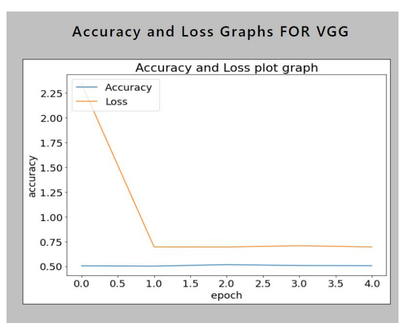

Fig.5 Accuracy and Loss Graphs for VGG

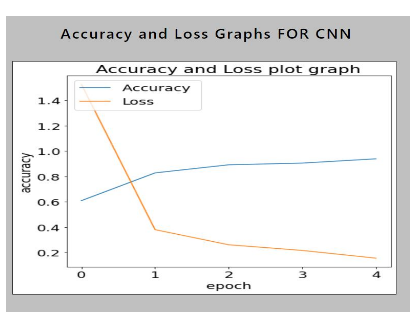

Fig.6 Accuracy and Loss Graphs for CNN

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VIII. CONCLUSION

In this work, a model for the detection of COVID-19 patterns in CT-Computed tomography images, we are going to build two Covid19 Image classification models. Both the models use Lungs CT Scan images to classify the covid-19. We build the first classification model using VGG16 Transfer leaning framework and second model using Deep Learning Technique Convolutional Neural Network CNN to classify and diagnose the disease and we able to achieve the best accuracy in both the model.
If we compare the both the models CNN will give the better accuracy than the VGG-16.

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