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Predictive Analysis of Covid-19 Disease Severity in X-ray images: using Deep Learning Techniques

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Abstract:
Healthcare systems are evolving in order to deal with the issues of death in human. The most current worldwide pandemic, COVID-19, which first appeared in 2019, has spread throughout the world. Covid sickness is currently one of the leading causes of death in humans. The signs of COVID-19 include fever, coughing, exhaustion, body pains, and shortness of breath. These symptoms can range in severity from moderate to severe. Also possible for some people are sore throats, congestion, runny noses, and loss of taste or smell. The COVID-19 pandemic has prompted researchers to create imaging-based medical treatments, allowing medical staff to detect COVID-19-infected patients more quickly and begin necessary treatments on schedule. The new coronavirus (COVID-19) illness is extremely contagious, thus there are often too many patients waiting in line for chest X-rays. This burdens the radiologists and physicians and has a detrimental impact on the patient's treatment and pandemic management. Due to this highly contagious condition, there aren't as many clinical amenities available, such as hospitals with critical care units and ventilatory machines, it is now crucial to categorise the patients according to their severity levels. Using deep learning techniques, we categorized the individual based on the severity levels of moderate, severe, and extreme if they tested positive for COVID-19. The COVID-19 patient severity divided into three groups: moderate, serious, and extreme, using Convolution Neural Network (CNN) three architecture: VGG19, ResNet-50 and DenseNet201 model that was constructed with an average accuracy of VGG19-89.63%, ResNet-50 with 92.62% and DenseNet201 with 96.4% with the input of chest X-ray pictures.

Keywords: Chest X-ray, COVID-19, Severity analysis, Bigdata Analysis, Deep learning, CNN, DenseNet-201, VGG19, ResNet-50.

I. INTRODUCTION

The SARS-CoV-2 virus is the source of the extremely contagious respiratory illness COVID-19, sometimes referred to as the corona virus disease. In December 2019, the illness made its initial appearance in Wuhan, China, and soon expanded to affect the entire world. The coronavirus epidemic was listed as a "International Concern based on Public Health Emergency" by the World Health Organization on January 30, 2020. [1]. The COVID-19 classification for the coronavirus disease was given by the WHO in February 2020. There have been 178,364 recoveries from the 859,965 verified cases around the world, while 42,344 people have died as a result. The US experienced 188,592 incidents of COVID-19, compared to 105,972 instances in Italy, 95,923 instances in Spain, 81,554 instances in China, 71,808 instances in Germany, 52,128 instances in France, and 44,605 instances in Iran.

A broad family of viruses known as coronaviruses can infect either people or animals. Typically, infections only cause relatively little symptoms, similar to a cold. No one is naturally resistant to COVID-19 because it does not exist in humans, thus anyone can get it. Shortness of breath (4%), a dry cough (78%), and a fever (98%) are all signs of a COVID-19 infection. Additionally, to exhaustion and muscular problems, some COVID-19 patients have also mentioned taste or smell loss (anosmia). Diarrhea, pneumonia, and the seasonal flu are other associated diseases that have the same symptoms.

Most COVID-19 instances are moderate, however in other groups, it has led to more severe symptoms. Aged over 65, very overweight individuals, and immunocompromised individuals are at increased risk. Pregnant women and those with pre-existing diseases including diabetes, heart disease, underlying lung disease, and diabetes is particularly vulnerable.

COVID-19 is more harmful and contagious than the common flu.

Individual contact is the primary method of COVID-19 transmission. Each time an infected person speaks, coughs, or sneezes, droplets are released that carry the viruses. Other people's mouths or noses may catch these droplets, which they may then inhale into their lungs. It appears that the likelihood of transmission increases with the length and proximity of contact between an infected and uninfected individual.

A viral screening can identify if you have been diagnosed with SARS–CoV[1] the virus that causes COVID-19, using samples from your nose or mouth. Rapid testing and laboratory tests are the two different virus test kinds. Along with immunization, masking, and physical separation, One of the ways to reduce risks that protects you and others by lowering the possibility of COVID-19 transmission is COVID-19 testing.

Viral tests:

- **Rapid Point-of-Care tests,** Antigen and certain NAATs are examples of rapid point-of-care tests, which can be completed in a matter of minutes and are conducted or interpreted by someone other than the person being tested. Self-tests are quick assessments that may be completed anywhere, at any time, and they yield results quickly.
- **Laboratory tests** such as RT-PCR and other NAATs might take days to complete.

Antibody tests:

- An **antibody test** (also known as a serology test) You can check your blood for SARS-CoV-2 antibodies using an antibody test, sometimes referred to as a serology test. Your immune system produces antibodies, which are proteins, to help fight infection and guard against future illness.

CT scans and x-rays:

- As of the spring of 2020, the virus, formally known as COVID-19, the new coronavirus, or SARS-CoV2, has spread globally. According to the most recent study, chest images and CT images often aren't enough to identify or rule out COVID-19 on their own. Imaging does, however, have a very small function to perform. CT scans or x-rays can be helpful for identifying COVID-19 or determining the severity of the condition in some persons when paired with blood testing, a medical history, and a physical examination.

Although they are not always necessary to diagnose COVID-19, CT scans and x-rays may be useful in some circumstances. People with severe symptoms may use imaging to assess the disease's severity. Additionally, CT scans or x-rays can be useful in determining a patient's treatment plan when combined with lab tests, a thorough medical history, and a physical examination.

Furthermore, the use of artificial intelligence (AI) techniques is crucial in resolving issues associated with COVID diagnosis that are used in conjunction with medical imaging techniques to automatically identify the behavior of input samples. The ultimate goal of artificial intelligence models is to identify the set of properties that are inherent to data using machine learning (ML) and deep learning (DL) techniques. Machine learning approaches such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Logistic Regression are used to solve Covid diagnostic models, however DL outperforms ML techniques in many ways. Due to the DL model's ability to automatically learn features and successfully accomplish the desired output [1]. The forecasting model must, however, be processed using a variety of datasets.

Research Approach:

This research has now revealed the techniques for classifying and identifying COVID sickness. Following is a summary of our work's main contributions:

- Creating a cutting-edge hybrid quantum dilated convolution neural network (HQDCNet[1]) to recognize multi-class COVID-19 data.
- Creating a brand-new Deep Learning method called DenseNet121 to determine the severity of the Covid-19 and to control a patient's treatment course.
- In comparison to published state-of-the-art methodologies, quantitative validation of the proposed model demonstrates superior performance.
- The suggested deep learning model is customized to choose the best parameters and has the ability to automatically extract intrinsic characteristics.

Following is the organization of the remaining text. The background information is explored and discussed in Section 2. Section 3 details the suggested approach's detailed methodology. Section 4 about the accuracy and evaluation metrics. Section 5 experimental findings and related work. The article's conclusion is covered in section 6 in its entirety.

2. Literature Survey

2.1 COVID-19 **identification:**

Nagamani.T et al. [2] used Bigdata analytics for storing the covid diagnosis images for teh detection. It is challenging to make an early diagnosis of COVID when using diverse medical imaging modalities and a vast number of medical information. utilising big data analytics to overcome the challenge.

S. Ying et al. [11] developed the DRENet architecture that allows the utilization of 3D computed tomography images for fast identification of COVID-19 infection. The DRENet architecture identifies Covid-19 with an accuracy of 86%.

D.P.Bhatt et al. [19] explains about early covid detection using CT scans. Covid detection typically involves the use of CT and Xrays. CT scans and X-rays are vital instruments in medical imaging. To determine COVID-19 disease, segmentation, and categorization models are utilized.

D. Singh et al. [20] determined whether or not people with the corona virus were infected with 93 percent accuracy using chest CT images. The datasets were categorised and their COVID-19 infection status was assessed by feature extraction, according to authors M. Barstugan et al. [21]. and achieved 99.6% accuracy in results.

Zheng et al. [22] COVID-19 disease identification on CT scans using 3D deep CNN. The lung region is divided using a U-Net initial-training design. Additionally, the categorized 3D lung areas are used as an input to a network that accurately predicts the likelihood of infection 90% of the time. A Deep Learning model with a 91.4 percent accuracy rate for detecting COVID-19 and pneumonia infections was created by M. Rahimzadeh and A. Attar [23] using CXR. Two deep learning models, ResNet50V2 and Xception, were combined by the researchers.

Md. Z. Islam et al. [24] used CNN and LSTM in conjunction with X-ray scans to examine COVID-19. While LSTM performs detection using those features, CNN retrieves deep features. The proposed approach, which has a 98.5 percent accuracy rate, categorises the X-ray images into three categories: normal, Corona-infected, and pneumonia.

P. K. Sethy and S. K. Behera [25] proposed a deep learning-based classification model using X-ray images as the input dataset. A number of already-trained deep learning models are used by the SVM (Support Vector Machine) classifier to extract deep properties. authors' recommendations. With an accuracy of 95.38, the ResNet50 model with SVM outperforms other previously trained deep learning models.

S. Hu et al. [26] developed a poorly supervised DL model using CT scans, that has a 96.2 accuracy rate for identifying and classifying COVID-19 infection. The presented system performs recognition and identification using picture-level labels and is inspired by VGG architecture. A CT scan evaluation method was given by O. Gozes et al. [19] that could identify, quantify, and follow individuals who had the COVID-19 disease with a high degree of accuracy. 2D and 3D deep learning models with clinical understanding have been modified and adjusted by the current system. CT images were used to study 157 individuals from China as well as the United States. To gauge how infected patients are doing, a proposed "Corona score" is used.

A. Narin et al. [28] predicted COVID-19 using X-rays using a deep CNN-based transfer model that had a 98 percent accuracy rate. The researchers contend that images from X-rays are a useful diagnostic tool and that ResNet50 is a more efficient model than the trained InceptionV3 ad Inception-ResNetV2 models.

2.1 COVID-19 severity analysis

The COVID-19 pandemic has significantly impacted public health and healthcare systems worldwide. Accurate and timely identification of patients at risk of developing severe symptoms is crucial for effective resource allocation and appropriate medical interventions. This study aims to develop a deep learning-based model for predicting the severity of COVID-19 cases.

Kelei He et al. [4] the progression of COVID was monitored by using lung CT scans. It is impossible to accurately anticipate the disease using these CT images. A multitask multi-instance deep network, commonly known as M2UNet, is used to assess the seriousness of COVID-19 patients with a rate of success of 98.5 percent. A machine learning approach was suggested by Zhenyu Tang et al. [5] to automatically determine the COVID-19 disease severity with an accuracy of 87.5%by checking the opacity and lung involvement. Deep-learning convolutional networks were employed by Jocelyn Zhu et al. [6]

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to predict the severity scores. The severity of the disease will be determined using the severity scores compared to traditional learning. CNN outperforms.

Aswathy et al. [7] used back propagational neural networks, including the ResNet- 50 and DenseNet- 201 models, and transfer learning for the severity diagnosis of COVID-19. Daignosed COVID scored 98.5 out of 100, and its severity scored 97.84.

Fei Shan et al. [8] to detect COVID-19, a deep neural categorization technique was developed infection areas in chest CT scans. It is challenging to precisely identify the many infection sites in the lungs and determine the disease's severity. Kelei He et al. [4] present an effective learning framework for multi-instance classification and lung area separation for determining the degree of seriousness of COVID-19 in 3D CT scans.

Zhang Li et al. [9] created an AI system to independently partition and measure the COVID-19-infected lung areas on thick-section lung computed tomography (CT) images were used to accurately and precisely assess the severity and course of the disease.

Lu-Shan Xiao et al. [10] developed a deep learning-based model was created by predicting illness severity and assessing the chance of developing severe disease in COVID-19 patients by employing residual convolutional neural network (ResNet34) and multiple instance learning.

Hossein Aboutalebi et.al.[11], A convolutional neural network called COVID-Net was developed based on a CXR image of the patient's chest to predict the severity of the airway in a SARS-CoV-2 positive patient. More specifically, employing over 16,000 CXR images from a global cohort of over 15,000 SARS-CoV-2 positive and negative patient cases, we employed transfer learning to incorporate representational information into a unique network architecture for severity evaluation.

Viacheslav V. Danilov et. al. [12] used a mix of DeepLabV3 + for lung segmentation and MA-Net for disease segmentation, and it is based on a combined dataset of 580 COVID-19 patients and 784 people without diseases. Four publicly accessible X-ray datasets of COVID-19 patients and two X-ray datasets of patients without pulmonary disease were used to train and test the models for the proposed approach.

Maxime Blain et al. [13] used 48 SARS-CoV-2 RT-PCR positive patients (age 60–17 years, 15 women) data from a tertiary care hospital in Milan, Italy. He used subjects of a retrospective investigation of X-rays, clinical, and laboratory data between February 22 and March 6, 2020. Two radiologists examined 65 chest X-rays and graded the degree of alveolar and interstitial opacities on a scale from 0 to 3. Then, lung segmentation and opacity detection deep learning models were trained for the respective tasks. The unpaired student t-test or Mann-Whitney U test was used to compare imaging properties to clinical datapoints. The agreement between traditional radiologist interpretation and deep learning was assessed using Cohen's kappa analysis.

Tuan Le Dinh et al. [14] attempt to classify three types of chest X-ray, which are normal, pneumonia, and COVID-19 using deep learning methods on a customized dataset. We also carry out an experiment on the COVID-19 severity assessment task using a tailored dataset. Five deep learning models were obtained to conduct our experiments: DenseNet121, ResNet50, InceptionNet, Swin Transformer, and Hybrid EfficientNet-DOLG neural networks.

3. PROPOSED METHODOLOGY:

By creating a comparable ensemble model, this study aims to create a framework for the automated categorization of severity of COVID-19. We employed the DenseNet201 model, ResNet50 model, and VGG19 model in Fig. 1. In later sections of the text, each step will be detailed in detail.

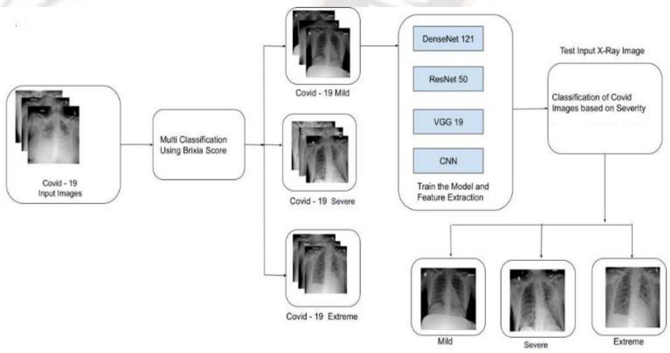

Figure 1: Proposed system architecture to detect Covid-19 Severity using Deep Learning Techniques

3.1. DATA COLLECTION:

The information we used was gathered from the Kaggle website. 9391 raw and segmented CT scans of COVID-19 patients make up the dataset. A csv file is also included with the dataset[29][30]. There are 4695 patient information in the csv file. The filename, study date,

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modality, columns, rows, manufacturer, photometric interpretation, brixia score, brixia score global, consensus test set, subject, study id, sex, and age at study date five years are the 14 columns in the csv find. The dataset in the path: https://www.kaggle.com/datasets/andrewmvd/covid19-xray-severity-scoring?resource=download . The detailed explanation of the dataset is given below:

1. Filename(Filepath),
2. grid_3x3StudyDatesort(Filename)
3. text_formatModalitysort(DICOM Photometric interpretration (already preprocessed)
4. grid_3x3Columnssort(Image modality)
5. grid_3x3Rowssort(Xray machine manufacturer)
6. text_formatManufacturersort(Original Image Width)
7. text_formatPhotometricInterpretationsort(Original Image Height)
8. grid_3x3BrixiaScoresort(Severity Score by Lung Section)
9. grid_3x3BrixiaScoreGlobalsort(Overall Severity Score)
10. grid_3x3ConsensusTestsetsort(Consensus test set is the proper testing set - evaluated by 5 radiologists rather than 1 elsewhere.)
11. subject
12. study id
13. sex
14. age

3.2. CLASSIFICATION:

Pandas Data Frame is a tabular data structure with labelled axes (rows and columns) that is two-dimensional, size-mutable, and possibly heterogeneous. Data is arranged in rows and columns in a data frame, which is a two-dimensional data structure. The data, rows, and columns are the three main parts of a Pandas Data Frame. We created data frame which consist of brixia score global value.

The so-called brixia score created by the original authors divides the lung into six zones in order to evaluate the intensity of COVID-19 development:

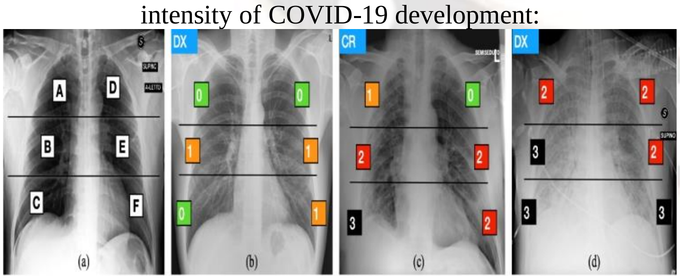

Fig 2: Brixia score created by the original authors divides the lung into six zones in order to evaluate the intensity of COVID-19 development

The multi-region 6-valued Brixia-score was created by the Radiology Unit 2 of ASST Spedali Civili di Brescia which is utilized in normal reporting; it was later verified for risk classification in a sizable population. As shown in the above figure, It asserts that the lungs are divided into six zones, three for each lung, in anteroposterior (AP) or posteroanterior (PA) views:

Upper zones (A and D): above the aortic arch's inferior wall;
Middle zones (B and E): the hilar structures, which are situated beneath the inferior wall of the aortic arch and above the inferior wall of the right inferior pulmonary vein;
Lower zones (C and F): beneath the bases of the lungs, or beneath the inferior wall of the right inferior pulmonary vein.

Each lung may be divided into three equal zones where it is technically impossible to distinguish certain anatomical markers (for instance, during bedside CXR in critically ill patients). Based on the discovered lung anomalies, each zone is given a score (from 0 to 3).

• 0: no pulmonary abnormalities;
• 1: interstitial infiltrates;
• 2: interstitial (dominant), and alveolar infiltrates;
• 3: interstitial, and alveolar (dominant) infiltrates.

We divided the data into three folders according to the brixia score. They range from mild to extreme. If the brixia score is less than or equal to 5, the condition is mild; if it is between 6 and 12, the condition is severe; and if it is more than 12, the condition is intense. By dividing accordingly dataset 4695 image classified 1,312 photos make up the mild file. 2526 photos make up the severe file. 857 photos make up the extreme file.

```
Normal=[]
mild=[]
serious=[]
extreme=[]
for i in range(len(df1['s'])):
    if(int(df1.loc[i]['s'])<=5):
        mild.append(df1.loc[i]['pic'])
    elif(int(df1.loc[i]['s'])<=12):
        serious.append(df1.loc[i]['pic'])
    else:
        extreme.append(df1.loc[i]['pic'])
```

Fig3: Code snippet for Classification of X-ray images based on Brixia Global Score value

3.3. DATA PRE-PROCESSING:

Data preparation is the process of transforming raw data into a practical, comprehensible format. Actual or unprocessed data occasionally is incomplete, frequently has human errors, and frequently has erroneous formatting. Data preparation helps to address these issues while also enhancing the usefulness and completeness of datasets used for data analysis.

Training data is the initial set of data used to develop machine learning algorithms. Models utilise these data to create and enhance their rules. In order to train a machine learning model using examples, its parameters are fitted to several data specimens. All the scenarios that the model could face in the real world are described in a clean dataset called test data. The validation data are a set of data preserved independently from the most recent training data. It is used to assess how well a network would perform with data that has not been specifically used to train it.

We employed data pre-processing strategies like data augmentation in our project. Our primary methods for data augmentation are zoom, shear, and horizontal flip.

Zoom:
Using the zoom augmentation approach, the image is zoomed. Using this method, pixels are added all around the image to randomly zoom in or enlarge it. This function makes advantage of the zoom_range argument from the ImageDataGenerator class.

Shear:
Roboflow platform's data augmentation options include the shear augmentation. By modifying the original pictures programmatically, data augmentation in computer vision is a way to produce extra training data from a base training set.

Horizontal Flip:
A deep learning method called horizontal flip data augmentation flips photos horizontally to enlarge the dataset. As a result of being exposed to more variants of the same pictures, a model's accuracy may be enhanced.
The image was then scaled down to fit the model's 224X224X3 dimensions.

```
from keras.preprocessing.image import ImageDataGenerator

train_datagen = ImageDataGenerator(rescale = 1./255,
                                   shear_range = 0.2,
                                   zoom_range = 0.2,
                                   horizontal_flip = True)

test_datagen = ImageDataGenerator(rescale = 1./255)
```

Fig4: Code snippet for preprocessing X-ray images

3.4. PROPOSED MODEL:

Deep learning algorithms, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have demonstrated remarkable success in various domains, including medical imaging and natural language processing. Leveraging the power of these algorithms, we propose a deep learning framework to predict the severity of COVID-19 based on clinical and demographic features extracted from patient data.

3.4.1. DenseNet121:

Huang et al. presented the DenseNet121 convolution neural network (CNN) architecture in 2017. It is part of a family of DenseNet models that are specifically made to deal with the issue of disappearing gradients in deep neural networks. The DenseNet121 architecture is based on a dense connectivity pattern, in which each layer has a feed-forward connection to every other layer. By facilitating gradient flow through the network more easily and allowing the network to learn more robust features, this dense connection structure helps to address the issue of disappearing gradients.

The architecture consists of several dense blocks, which are consisting of a number of convolutional layers, followed by batch normalisation and ReLU activation algorithms. Each dense block is connected to the previous block and to a transition layer, which performs spatial pooling and minimises the feature maps' spatial dimensions. The final layers of the network consist of global average pooling which generates the final forecasts for the input image, a layer that is completely connected, and a function for softmax activation.

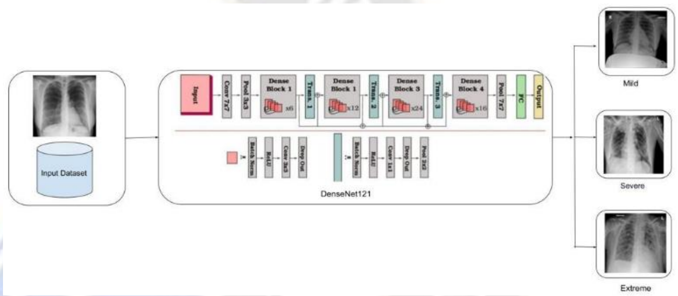

Fig5: System architecture of deep learning technique DenseNet201 to identify COVID Severity

DenseNet201 is a powerful convolutional neural network architecture that has been widely used for various computer vision tasks, including image classification. While DenseNet201 can be applied to a range of medical imaging tasks, such as detecting abnormalities or classifying diseases.

The DenseNet201 algorithm in our research work is a trainable model. The DenseNet201 model's output was then given a flatten layer. The output of the flatten layer was then added to by three dense layers. Applying the softmax function to the dense layer. K real values are converted into a vector of K real values that add up to 1 by the softmax algorithm. Even if the input values could be positive, negative, zero, or more than one, the softmax turns them into values between 0 and 1, making them understandable as probabilities.

On the test dataset, the accuracy of the DenseNet201 model was 96.4%. This suggests that it has a high degree of accuracy in accurately classifying items in photos. When compared to other studies in the field, our model performs better than the cutting-edge model, which had a 90% accuracy rate.

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ResNet50:

ResNet50 is a popular convolutional neural network (CNN) architecture that introduces residual connections to help mitigate the problem of vanishing gradients. It has 50 layers and performs well on a wide range of computer vision tasks. ResNet50 is known for its ability to capture both low-level and high-level image features effectively.

A convolutional neural network (CNN) architecture called ResNet50 came to light in 2015 by Microsoft Research Asia. "ResNet" refers to "Residual Network," and the design is based on the concept of employing leftover blocks to make it possible to train far more complex neural networks. ResNet50, a modification of the original ResNet architecture, has 50 layers total, comprising convolutional, pooling, and levels that are fully connected, as well as shortcut connections that let the network pass over some layers.

The usage of skip connections, which permits the gradient descent, is one of ResNet's major contributions to be propagated more easily through the network during training. This makes it possible to train much deeper neural networks, which may lead to improved efficiency on a number of tasks involving computer vision.

For a variety of recognition of pictures tasks, including recognising objects, scene recognition, and segmentation of images, ResNet50 has been proven to be quite effective. On a number of benchmark datasets, such as ImageNet, it has attained state-of-the-art performance, which contains over a million labelled images.

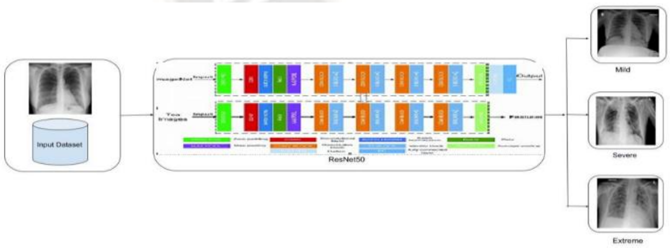

Fig6: System architecture of deep learning technique ResNet-50 to identify COVID Severity

As a non-trainable model, we employed the ResNet50 algorithm in our project. The output of the ResNet50 model was then given a flatten layer. Next, we added three dense layers to the flatten layer's output. In the dense layer, we applied the softmax function. The softmax function converts a vector of K real values into a vector of K real values that add up to 1. The softmax transforms the input values into values between 0 and 1, which makes them understandable as probabilities even though they could be positive, negative, zero, or more than one. If an input is little or negative, the softmax converts it to a tiny probability; if it is large, it converts it to a high probability. However, the softmax always converts inputs between 0 and 1.

The compile procedure requires a number of parameters. The "categorical_crossentropy" type of the loss parameter is defined. Using the Adam optimizer, our network is trained once the metrics option is set to "accuracy." Categorical crossentropy is used as a loss function in multi-class classification models with two or more output labels. Based on an adaptive estimation of first- and second-order moments, Adam optimisation is a stochastically gradient descent technique.

The ResNet50 model's accuracy on the test dataset was **92.62%**. This implies that it is highly accurate in correctly classifying objects in images.

VGG19:

VGG19 is a deep CNN architecture that consists of 19 layers. It has a simple and uniform structure, comprising multiple convolutional layers followed by fully connected layers. VGG19 is known for its ease of implementation and interpretability. However, it has a large number of parameters and can be computationally expensive compared to other models

In 2014, the VGG19 convolutional neural network (CNN) architecture was created by the Visual Geometry Group (VGG) at the University of Oxford. The term "VGG16" refers to the "VGG Convolutional Network 16," which denotes the network's number of layers. VGG19 is a variant of VGG model which in short consists of 19 layers (16 convolution layers, 3 Fully connected layer, 5 MaxPool layers and 1 SoftMax layer).

The architecture of VGG19 is straightforward and uniform, which is one of its primary characteristics. All of the convolutional layers use the same filter size and the same padding, which makes the network easier to understand and implement.

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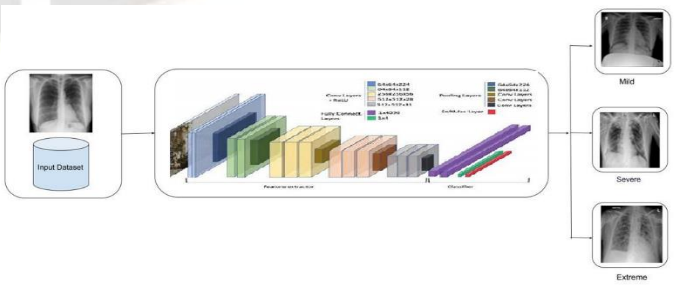


Fig7: System architecture of deep learning technique VGG-19 in identify COVID Severity

In our project we used VGG19 model with base layers as not trainable. Then we added flatten layer to the output of VGG19 model. Then we added three dense layers to the output of flatten layer. Inside of the dense layer, we employed the softmax function. Using the softmax function, K real elements in a vector are changed into K real values that sum up to 1. Despite the fact that the input values could be positive, negative, zero, or higher than one, the softmax transforms them into values between 0 and 1, making them understandable as probabilities. The softmax changes an input into a tiny probability if it is little or negative, and into a high probability if it is large, but it will always fall between 0 and 1.

Multiple parameters are needed for the compile procedure. It is defined that the loss parameter is of type 'categorical_crossentropy'. We utilise the Adam optimizer to train the network after setting the metrics parameter to "accuracy." Categorical crossentropy serves as a loss function for multi-class algorithms for classification with a minimum of two output labels. A stochastic gradient descent technique called Adam optimisation is based on adaptive estimate of first-order and second-order moments.

The VGG19 model's accuracy on the test dataset was **89.63%**. This implies that it is highly accurate in correctly classifying objects in images. We ran cross-validation studies on several datasets to judge the model's generalizability. The outcomes demonstrated consistent performance across many datasets, pointing to strong generalisation ability. We also kept an eye on the model's training and validation loss during the training phase to make sure it didn't show any overfitting symptoms.

4. ACCURACY AND EVALUATION:

Accuracy is a popular parameter for measuring deep learning model performance. In the context of deep learning, The proportion of properly categorised examples in a data set is commonly used to describe accuracy. In addition to accuracy, other metrics are often used to evaluate deep learning models, depending on the specific task. For example, for object detection, metrics such as precision, recall, and mean average precision (mAP) are frequently utilized. Metrics like Intersection over Union (IoU) and Pixel Accuracy are frequently employed for semantic segmentation.

Evaluation is an important part of the deep learning workflow, as it enables us to evaluate how well a trained model performs a certain task. The effectiveness of a deep learning model can be assessed in various ways, such as:

***1. Training and validation accuracy*:** On a validation dataset, the performance of the model is assessed during the training process that is separate from the training data. Usually, the training and validation accuracy are displayed against time to monitor the model's performance and detect overfitting.

2. Test accuracy: After the model has been trained, a separate test is used to gauge its performance. This provides us with a rough idea of how efficiently the model will extrapolate to brand-new, untested data.

3. Confusion matrix: In a classification problem, a table called a confusion matrix. The whole number of true positives, true negatives, false positives, and false negatives are listed for each class in a confusion matrix. It is capable of calculating a number of measures, including F1 score, recall, and precision.

4. Precision, recall, and F1 score: These metrics are employed to assess a model's effectiveness in a classification task, particularly when the dataset is imbalanced. The proportion of genuine positive predictions made out of all positive forecasts is measured by precision, while the proportion of true positive predictions made out of all real positive is evaluated by a recall. The harmonic average of memory and precision is the F1 score.

5. Mean Average Precision (mAP): This metric is frequently applied in jobs involving identifying objects. It gives a single value that represents the calculating the model's average precision to evaluate the effectiveness of the algorithm across various recall levels.

There are many other evaluation metrics and techniques that can be used depending on the specific task and dataset. The choice of evaluation method(s) should be carefully considered and tailored to the specific problem at hand.

$$Accuracy = \frac{tp+tn}{tp+fp+fn+tn}$$

$$Precision = \frac{tp}{tp+fp}$$

$$Recall = \frac{tp}{tp+fn}$$

$$F-measure = \frac{2 \times (recall \times precision)}{recall + precision}$$

Model	Severity Classes	Mean Accuracy	Precision	Recall
DenseNet201	Mild, Severe, Extreme	1 96.4%	1 0.9640	1 0.9564
ResNet50	Mild, Severe, Extreme	1 86.72%	1 0.8672	1 0.8672
VGG19	Mild, Severe, Extreme	1 83.57%	1 0.8357	1 0.8345

Table1: Overall performance of Dense-201, ResNet-50, VGG19 models to identify COVID-19 disease severity classification results

5. RESULTS AND DISCUSSION:

The dataset Covid-19 Xray Severity Scoring consisting of 4695 X-ray images. These images are classified into 3 classes based on Brixia score global value, labelled as Mild, Severe and Extreme cases. The dataset broadly categorized Mild with 1,312 images, Serious with 2526 images and Extreme 857 images. We employed Deep learning techniques VGG19, ResNet 50 and DenseNet201. Trained all the proposed methods for 30 epoch's. Models that was constructed with an average accuracy of VGG19-89.63%, ResNet-50 with 92.62% and DenseNet201 with 96.4% with the input of chest X-ray pictures.

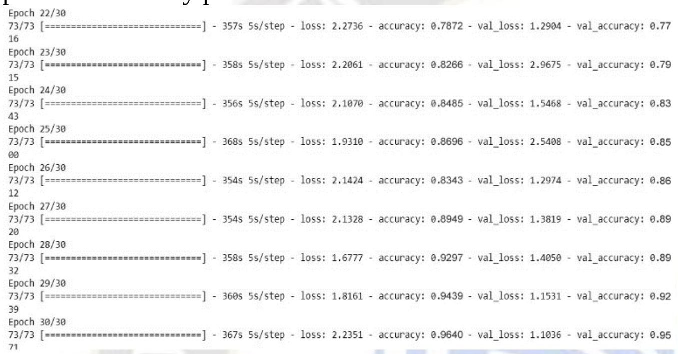
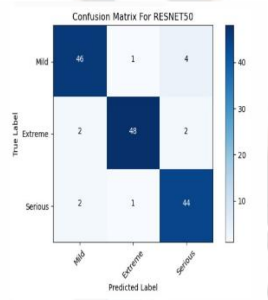
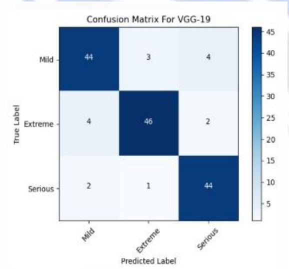


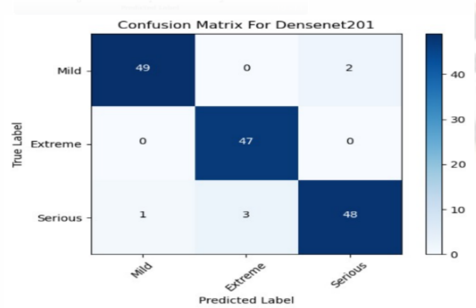
Fig:8: Results with Training DenseNet201



(a)



(b)



(c)

Fig10: Confusion matrix for (a) ResNet-50 (b)VGG-19 (c) DenseNet-201

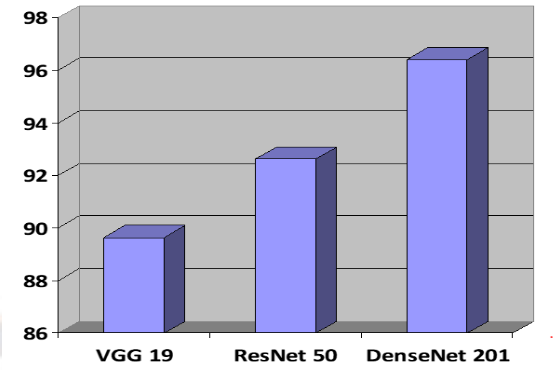


Fig 11: Indication of accuracy for VGG19, ResNet50 and Dense201

To the best of the author's knowledge and after thorough consideration of the literature, the following are the primary benefits and contributions of the methodology suggested in this paper:

1. Several other authors have recently employed CNN to detect the COVID-19 disease, however the number of images used in this proposed study to train and evaluate the CNN is higher than the number of images used in other studies.
2. The proposed study further varies from other illness detection studies in that it not only detects COVID-19 disease but also determines the severity of the COVID-19 disease.
3. This study uses CNN based deep learning models: VGG19, ResNet50 and DenseNet201, automatically set to classify COVID-19 disease severity into three categories: mild, severe, and extreme.

6. Conclusion:

Global pandemic COVID-19 has killed millions of people and spread around the world. The current COVID-19 screening procedures are pricy, tedious, and pricey. In this paper, we presented three brand-new CNN models for deep learning: Dense201, ResNet-50, and VGG19 models. These techniques were created and validated to categorize COVID-19-infected individuals according to their severity levels as mild, severe, or extreme. that was constructed with an average accuracy of VGG19-89.63%, ResNet-50 with 92.62% and DenseNet201 with 96.4% with the input of chest X-ray pictures. It is believed that this study helps frontline radiologist.

This study can be expanded upon by utilizing additional signs of organ infections to recognize COVID-19 severity. Additionally, in addition to chest X-rays, we can estimate COVID-19 disease severity using additional characteristics such as age, gender, medical history, genetic history, location information, etc. Research in the future can also take into account different respiratory characteristics.

Several more illnesses can be investigated utilizing methods based on computer vision

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