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DETECTION OF COVID 19 USING CHEST X-RAY WITH VGG 16 NEURAL NETWORK

Adusumalli Harish[1], K.Prem Kumar[2]
[1]*Department of CSE, Koneru Lakshmaiah Education Foundation, Guntur, Andhra Pradesh*
[2]*Department of CSE, Koneru Lakshmaiah Education Foundation, Guntur, Andhra Pradesh*

ABSTRACT
In the present paper, an CNN algorithm is implemented to detect whether the patients are effected with Covid, a huge pandemic that tainted a big measure of the human population in the first part of the year 2020. Moreover, the investigation introduced and employed 9 popular Convolutional Neural Networks (CNNs) for the classification of images of X-ray starting from victims with COVID, pneumonia, and healthy people. Exploration evidence showed that the CNNs can possibly identify respiratory sicknesses with high accuracy, even a large number of sample pictures should be grouped. Particularly, VGG16, Scores a 95% overall accuracy. The big values related with affectability, specificity, and exactness of Corona virus strain, shows the capacity of these models to identify positive or potentially negative covid-19 cases perfectly to reduce as much as could reasonably be expected the infection to spread into the network. As the outputs show, deciding the best model for this classification task involves major exhibition measurements. Moreover, one of the empowering results is the ability of the previously mentioned CNNs to accomplish high affectability and accuracy on the healthy class along these lines guaranteeing the minimization of false positives with respect to contamination cases which can deeply help to reduce the weight on the healthcare framework.

KEYWORDS—*covid 19, neural networks, deep learning, corona virus*

I. INTRODUCTION (*HEADING 1*)

The 2020 year has been set apart by the global illness brought about by a kind of the coronavirus strain (CoV), called Coronavirus or SARS-2, which has prompted more than 4,000,000 diseases and as high as 290,000 global deaths COVID-19 is a Severe Acute Respiratory Syndrome-2 (SARS-2) that was first detected in Wuhan city of China in the 2019 December and has quickly spread universally in a couple of months, making it a profoundly infectious attack. The covid is portrayed by side effects that generally identify with the functional framework and incorporate windedness, loss of olfactory sense and taste, hack and body temperature, a scope of indications that are shared among different sorts of infections, for example, common cold.

Not at all like different infections, COVID-19 incubation period is long, going from 3 to 13 days, in spite of the fact that all things considered, the time from presentation to symptom beginning is around 5 to 6 days. The lengthy incubation duration makes COVID-19 highly infectious since individuals conveying the infection will most likely continue interfacing with others until they understand they have the infection, prompting more contaminations. Moreover, it has been accounted for that few patients conveying the sickness probably won't show any symptoms whatsoever (no symptom cases). The mix of both the prolonged development time frame and asymptomatic people puts the Covid significantly tougher to identify, follow, and has, which clarifies its fast exchange.

Since the beginning of the year 2020, a few experiments have been performed to try to develop a method to identify patients who bear the infection. Most of these software engineering studies use convolution neural networks (CNNs) to describe the Typical or non-typical CT scan images or chest X-rays, seeking to identify possible cases of Covid. The inescapable use of CNNs for tasks of image classification is due to the manner in which they have demonstrated high-exactitude execution in the image recognition field and article discovery. CNN's turned out to be more perplexing over the long term, LeNet-5, which had 5 layers, from the first CNN, to the larger ResNet-50 architecture that had 152 layers. Their prosperity lies in the way that through their various hidden layers, they can capture hidden highlights of the pictures.

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The adequacy of a few cutting edge pre-trained convolution neural networks was evaluated in this research work with regard to the programmed detection of COVID- 19 infection from chest X-Ray images. In order to train and test the CNNs, It treats and uses a variety of 200+ X- Ray scans of patients with COVID-19 disease, bacterial pneumonia, and typical events. The exchange learning technique is used due to the restricted open knowledge found with COVID-19. The key difference between our analysis and the previous studies is that this study involves an overwhelming number of CNN architectures attempting not only to recognize X-Rays between patients with COVID-19 and people without the infection, But also for the isolation of patients with pneumonia from patients with Covid as a respiratory disease classifier.

II.PREVIOUS WORK

A. Deep learning techniques for classification of images and detection of objects

Fully convolutional neural networks (CNNs) have been used by numerous examinations for the issue of image classification in writing, a significant proportion of which make up separate neural network architecture. Deep convolutional neural networks are one of deep learning's ground-breaking architectures and have been widely used in an expansive range of machine learning tasks. As indicated by CNNs, four specific activities can be addressed: training the weights without any planning in view of a huge accessible dataset, Fine-tuning the weights with more modest datasets of a current pre-trained CNN, unsupervised pre-training for weight implementation before putting inputs into CNN models and CNN as a pre-training feature extractor. The first CNN to create a standard architectural template was the LeNet-5, which uses two convolutional layers and three fully connected ones. Since the time when more architectures followed similar thinking was used to incorporate more convolutions and pooling layers, ending with at least one fully connected layer. Following the footsteps of the previous CNN, AlexNet added three additional convolutional layers, making it the perfect time for the deepest neural organization of today. Furthermore, AlexNet was the first CNN model to update Rectified Linear Units (ReLUs) as an activation function. Scientists continued to use more layers and render deeper networks before making a more minor departure from the architectures, and thus VGG-16 emerged. VGG-16 used 13 convolution layers and 3 fully connected layers, retaining the ReLUs of AlexNet as an activation feature. Essentially, further layers were added by VGG-19, a replacement for the previous organization.

In the years that followed, specialists introduced greater complexity by presenting a few techniques within the layers of the networks, apart from making the networks broader. "By using "Inception" modules in addition to the way it uses 22 layers overall, Inception-v1 uses a network within an organization "approach. The basic idea of these modules was to use equal convolution towers with different filters, each filter capturing different features, and then to group these features together. Arora et al. propelled the thought, which suggested an architecture that explores the last layer's correlation statistics and clusters them into high-correlation unit gatherings. Inception-v3, a replacement for the previous organization, was one of the first networks to use cluster standardization for the layers by sharing a common architecture. The most recent replacement of the two past networks, Inception-v4, incorporated additional Inception modules, and made several changes to increase the speed of planning. A group of other architectures, called Inception-ResNet-v2, were introduced by similar developers of the past networks, in which they moved to Residual Inception blocks over the Inception modules, generated another type of Inception modules, and introduced to the company a larger number of them, making it much deeper. Similarly, among the first networks to use ResNet-50 was standardization of clumps. In addition, It had a slightly deeper design (152 layers) and made use of missing ties or residuals. With depth wise separate convolutions, the Inception modules were supplanted by an exception. This means that it performed 1 to 1 revolutions for each channel, and then performed 3 to 3 revolutions for each yield. Like Xception, MobileNetV2 uses different depth wise convolutions, which reduce the organization's complexity and scale. In addition, a module is presented with an inverted residual structure and non-linearities are taken out in tight layers. This organization's characteristics have presented a cutting edge image classifier ideal for mobile phones. "Finally, the "war continued and resulted in a few separate CNNs for a superior organizational architecture, each of which, for example, DenseNet, NASNet, and ResNet152V2, offered an alternative alteration. Deep learning techniques focused on image recognition for COVID-19 detection.

As of now there is a different test for COVID-19 identification. Deep learning methods are commonly used on chest radiography images with the ultimate objective of identifying infected patients and the findings have been shown to be very positive in terms of accuracy. The Covid infection from chest X-beam (CXR) images is presented in a deep convolutional neural network ready to forecast. The proposed CNN depends on pre-trained transfer models to achieve high prediction accuracy from a restricted example of X-beam images (ResNet50, InceptionV3, and Inception-ResNetV2). The pictures, ordinary and COVID-19, are categorized into two groups. In addition, by using the ImageNet dataset, a transfer learning technique is introduced to defeat the inadequate knowledge and preparation time.

The results revealed the ResNet50 model's predominance in terms of precision in both the planning and testing phases. Abbas et al proposed a novel CNN architecture focused on transfer learning and class disintegration in order to enhance the display of pre-trained models for classification of X-ray images. The proposed technology is called DeTraC and consists of three phases. An ImageNet pre-trained CNN is used for nearby component extraction in the first stage. A stochastic inclination drop enhancement technique is used for

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planning in the subsequent stage and the class-arrangement layer is eventually calibrated for the final classification of the images using blunder rectification standards applied to a softmax layer. The ResNet18 pre-trained ImageNet network is used and the results indicate an accuracy of
95.12 percent on CSR images. Zhang et al presented another deep anomaly detection model for fast reliable screening of COVID-19 based on CXR images. Pictures. In particular, a spine network, a classification head, and an anomaly detection head are three components of the proposed model. The spine network extracts the highlights of images from the significant stage, which are then used as a contribution to the head of classification and anomaly detection.

A deep convolutional neural network is presented, called COVID-Net, which from CXR images can detect COVID-19 instances. The network design involves two stages, a synergistic human-machine design framework, and a machine-driven design examination stage, and a lightweight extra projection-advancement projection-expansion (PEPX) design is used for the architecture. Additionally, for decision confirmation, a rationale-driven survey is carried out. For COVID-19 cases, the findings

demonstrated a high sensitivity (87.1 percent) and accuracy of 96.4 percent. Another study provides a CNN structure for the detection of COVID-19 from other cases of pneumonia. COVID-ResNet was considered in the structure and uses a three-adventure system to fine-tune a pre-trained ResNet-50 architecture to increase performance and decrease preparation time. Reformist resizing of input images at each stage (28x128x3-stage 1, 224x224x3-stage 2, 229x229x3-stage and fine-tuning of the network-sorts some way to achieve a prevailing theory and an extended output as a law (96.23 percent precision). With a view to classifying COVID-19 from CXR images, Hemdan et al given a system that includes seven COVIDX-Net deep learning image classifiers. As the findings showed, the best results were obtained for the classifier VGG19.

III.METHODOLOGY

A. *Dataset Explanation*

Chest X-Ray images of patients with documented COVID-19 disease, simple bacterial pneumonia, and common occurrences (no infections) are included in the data collection used in this study and are a mixture of two different datasets accessible to the public. More specifically than that,, COVID-19 cases have been collected from the Github repository of Dr. Joseph Cohen and consist of 112 Posterior-Anterior (PA) X-ray lung images. This repository includes, Photographs of patients with serious respiratory distress syndrome (ARDS), COVID-19, Middle East respiratory syndrome (MERS), pneumonia and severe acute respiratory syndrome are often taken with chest X-rays/CT (SARS). Likewise, 43 ordinary and 57 pneumonia (bacterial) chest X-Ray images were selected from Kaggle's repository. In summary, in terms of the number of instances, the dataset used for this work is equally transmitted and consists of three groups (Coronavirus, pneumonia, and typical) and is publicly available in 3 There are a few limitations that merit referencing. Initially, there are confirmed COVID-19 examples that are little contrasted with pneumonia or ordinary cases as of now. As of now, a bigger and more accurate example is certifiably not available. A similar number of tests for accuracy were selected for each class.Data Augmentation

In deep learning, data augmentation is a commonly used cycle that generates the quantity of samples availableDue to the lack of a larger number of available samples, several pre-processing procedures have been performed in this job to increase data., using Keras ImageDataGenerator during training. Arbitrary image rotation (the most extreme rotation point was 30 degrees), flat flips, shearing, zooming, cropping, and little irregular noise irritation are integrated into the transformations used. Augmentation of data increases speculation and improves the model's learning ability. In addition, by extending the measure of training data using data only in training, it is another productive technique to forestall model overfitting.

B. *Performance standards*

The adopted performance metrics are

$$Accuracy(ACC) = \frac{TP + TN}{n} \tag{1}$$

$$Precision(P) = \frac{TP}{TP + FP} \tag{2}$$

$$Recall(Sensitivity) = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - score = 2(\frac{Precision \times Recall}{Precision + Recall}) \tag{4}$$

$$Specificity = \frac{TN}{TN + FP} \tag{5}$$

Where the true positive, true negative, false positive and false negative samples for each class are referred to by TP, TN, FP, FN (covid, pneumonia, normal). At that point, the large-scale average results were calculated and used to execute the classification execution of the organizations. Accuracy is a classification metric commonly used which shows how well the classes in the test set can be distinguished by a classification measurement. Accuracy is a widely used classification metric which shows how well a classification measurement can differentiate the classes in the test set. Accuracy can be defined as the degree of the correct marks predicted to the maximum number of names (predicted and genuine), as shown in Eq 1. Accuracy refers to the overall accuracy of the model in this study in the three groups (Coronavirus, pneumonia, normal). Accuracy (Eq 2) refers to the extent of the correct names predicted to the total number of real labels, while recall (Eq 3) refers to the extent of the correct names predicted to the maximum number of names predicted. The evaluation is referred to routinely as sensitivity (likewise called true positive rate). In addition, F1-score(Eq 4) refers to the consonant mean of accuracy and recall, while specificity (also known as true negative rate) tests the

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degree of actual negatives that are correctly described accordingly (Eq 5).

C. CNN using Transfer Learning

To perform precise feature extraction and classification, deep learning models require a large measure of data. With regard to data analysis particularly if the disease is at an early stage, such as in COVID-19, one significant drawback is that the dissected data has been moderately limited. Transfer learning was obtained to defeat this restriction. With less examples, the transfer learning technique achieves data preparation as the management of the knowledge separated by the pre-trained model is then transmitted to the model to be trained. A pre- trained model is a network that was previously trained, typically on a large-scale image-classification mission, on a large dataset. The instinct behind transfer learning for image classification is that this model would also function effectively as a generalized model if a model is trained on an overall broad dataset. The learned characteristics can be used to illuminate an alternative but related undertaking, including new data, which as a rule are of a more modest population to prepare a CNN without any preparation. Subsequently the need of preparing without any preparation a large model on a large dataset is killed.

IV.EXPERIMENTAL TESING

The CNN models were fine-tuned to see and request the different groups in this work (Coronavirus, pneumonia, average). On the ImageNet dataset, the weights used by all CNNs are pre-trained. ImageNet is a database of image information containing approximately 14 million images with a location for image attestation conflicts of more than 20,000 groups. A frame of the fine-tuning measure on the VGG16 network architecture is shown in figure 1. Weights pre-trained on ImageNet are dispatched to the network.
The layers of the VGG16 network have emerged as the most important explanation for the figure. VGG16 comprises 13 convolutional (CONV) and 3 fully connected (F C) layers as imparted in 2.1. The final collection of layers containing the clayers near the activation work of softmax is "head" relegated. Clayers are rejected at some point later and the final POOL layer is treated as a part extractor as shown in the figure. Finally, randomly added and placed on top of the main architecture (lower part of the figure) is another Chead layer. Advantages alluding to that the body of the network for example, the CONV layers has been "curbed" with a definite goal that solitary the Chead layer is trained The reason this lead is that the CONV layers have as of late learned discriminative filters while Chead layer is randomly instated with no arranging and subjective attributes will pound the informed highlights.

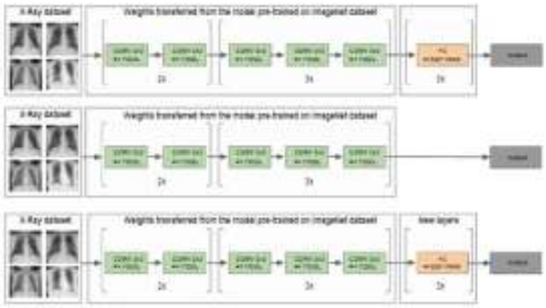

Figure 1: VGG16 network architecture Fine-tuning

A. Experimental Setup

To train the proposed deep transfer learning models, the python programming language was used, including the Keras package and a Tensor Flow backend. Keras is a library of neural networks designed on top of easy to use Theano or Tensor Flow. Keras gives the vast majority of the structure blocks required to construct sensibly advanced deep learning models. This structure was used alongside the arrangement of weights learned on ImageNet. The following configuration of the computer was known to the hidden computing base used to run the CNNs: Ubuntu 18.04 LTS 64-cycle; Intel Core i7-8550U CPU @ 1.80GHz?? 8; and 16 GB RAM..

B. Refining of Parameters

Some standard hyper-parameters are given by all the CNNs examined. All of the images were correctly scaled to a set 224 x 224 pixel size. For individual training and research, the data set used was randomly split into 80 percent and 20 percent and the planning was performed for 10 years to avoid overfitting for all pre-trained models with a learning rate of 1e-3 and a batch size of 8. CNN's were obtained using Adam's enhancement technique and the Rectified Linear Unit implements all the convolutionary layers (ReLU). In addition, a 0.5 Dropout layer is added, which means that half of the neurons are randomly set to zero at each preparation age, subsequently preventing overfitting on the dataset of preparation. A dropout is a type of regularization that powers the organization's weights to get only small characteristics that make the dissemination of weight estimates more standard. Subsequently, on small preparation models, this method will decrease overfitting. Since the problem consists of three groups, the "categorical crossentropy" is used as a loss work as seen in Eq 6, where p model[yi ?? Cy I is the probability that the model predicts that it will have a position with the classification of the breakdown. "Categorical cross-entropy" contrasts with the dissemination and actual dispersion of predictions. A one-hot encoded vector is represented as the true class, and the closer the outputs of the model are to that vector, the lower the loss

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$$CE = -\frac{1}{N}\sum_{i=1}^{N}\log p_{model}[y_i \in C_{yi}] \quad (6)$$

C. Results and discussion

The classification efficiency for each CNN is implemented in this sectionIn order to assess the results, the following metrics were adopted for each class (Coronavirus, pneumonia, normal): precision, recall (sensitivity), F1-Score, specificity, and overall accuracy of the model as shown. The results recommend that the best classification accuracy of 95% is obtained by the VGG16. For the VGG16 model, a sensitivity of 96 percent for the Coronavirus class is noticeable. This is critical because all such cases of COVID-19 should be able to be detected by the model to mitigate the spread of the virus to the population. In other words, by using the VGG16 model as 'Coronavirus positive' 96 percent of the time, confirmed positive COVID-19 patients would be correctly identified.

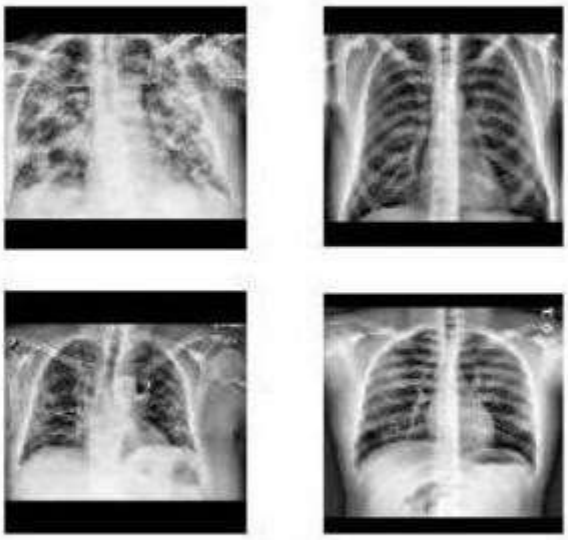

Fig 1: no covid case detected

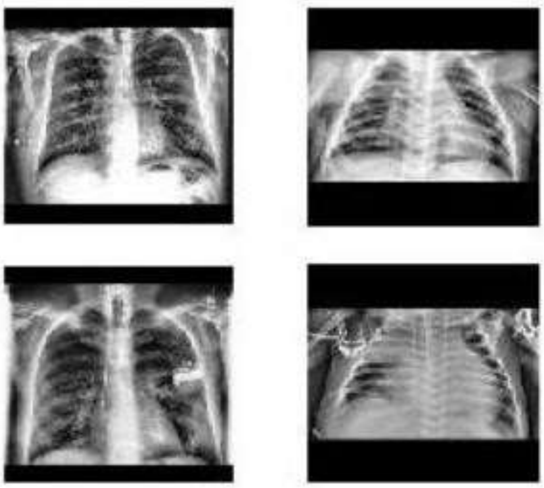

Fig 2: covid detected

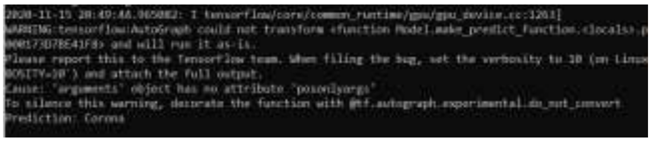

FIG3: CORONA IDENTIFIED

Fig4: Normal case detected

CONCLUSION

In this work, an investigation for the identification of patients positive for COVID-19, a pandemic that affected a significant proportion of the human population in the first half of 2020, was carried out and introduced. In particular, the study implemented and used 9 well-known Convolutional Neural Networks (CNNs) to classify X-Ray images, beginning with COVID-19 patients, pneumonia, and healthy individuals. Exploration studies have shown that CNNs might be able to highly accurately classify respiratory diseases, although a significant measure of sample images should be obtained. VGG16, in particular, achieves an overall precision of 95 percent. The high values related to the affectability, specificity, and accuracy of the class of Coronavirus, indicate the ability of these models to accurately classify positive or potentially negative void-19 cases in this way, reducing however far the infection spread to the network could reasonably be expected. As the results show, deciding the best model for this classification task involves several exhibition measurements. Moreover, one of the empowering results is the ability of the previously mentioned CNNs to accomplish high affectability and accuracy on the normal class along these lines guaranteeing the minimization of false positives with respect to contamination classes which can potentially help alleviate the weight on the healthcare framework. Finally, we want to stress that these methods cannot be used without clinical diagnosis directly. We plan to train the CNNs for future work on more details and assess more architectures, including the detection of COVID-19.

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