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A Study Of The Transfer Learning Algorithm For Detecting Pneumonia In Chest X-Ray Images

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Abstract: The correct diagnosis of patient's conditions and diseases is one of the most significant challenges that healthcare professionals face. A problem for both the patient and the doctor is being unable to correctly diagnose a condition. It can be very helpful, especially to increase a patient's chance of survival, to predict respiratory conditions earlier. One of the most dangerous diseases that kill a lot of people is pneumonia. The primary reason for this is that, for a variety of reasons, many people are unaware of it in its early stages, and by the time they do, it is too late. However, the likelihood of curing these conditions rises if they are discovered early on. However, because extensive screening with CT, MRI, or X-rays is not practical in many parts of the world, midsection radiology continues to be the most fundamental system. When working with medical imagery, there are frequently issues with reliability and interpretability that this model could help alleviate. For this classification task, it is difficult to obtain a large dataset of pneumonia, in contrast to other deep learning classification tasks with sufficient image repositories; As a result, we used a number of data augmentation algorithms to boost the CNN model's classification and validation accuracy, and we were able to achieve remarkable validation accuracy. For the classification of the images and the early diagnosis of pneumonia, our classification technique makes use of convolutional neural networks.

Keywords: X-rays images, transfer learning, CNN, machine learning, deep learning.

I. Introduction

Pneumonia is a serious respiratory sickness brought about by irritation of the lungs, as a rule by disease. It is one of the leading causes of death worldwide, especially among young children and the elderly. Early detection of pneumonia is important for prompt treatment and recovery. One method of detecting pneumonia is to use radiographic imaging, such as a chest X-ray. Pneumonia is a lung inflammation that mostly affects the alveoli, which are small air sacs. Common signs and symptoms include a fever, chest pain, productive or dry cough, chest pain, and difficulty breathing. Pneumonia is typically brought on by infection with viruses or bacteria, though other microorganisms are less common. It can be challenging to identify the pathogen that is to blame. Frequently, symptoms and a physical examination are used to make a diagnosis. A sputum culture, blood tests, and chest X-rays can all help confirm the diagnosis. The disease may be categorized as community, hospital, or healthcare-associated pneumonia depending on how it was acquired. Sickle cell disease, chronic obstructive pulmonary disease, asthma, diabetes, heart failure, a history of smoking, a weak immune system, and cystic fibrosis are all risk factors for pneumonia. There are vaccines available to prevent certain types of pneumonia. Other ways to prevent infection include washing hands, quitting smoking, and staying away from social situations. The person with pneumonia is typically admitted to the hospital if it is severe. If oxygen levels are low, oxygen therapy may be used. Fever, cough, and rapid or difficult breathing are typical signs and symptoms in children under five. Fever isn't very specific because it can happen with many other common illnesses and can't happen to people with severe illnesses, people who are undernourished, or the elderly. Additionally, children younger than two months often do not have a cough. Children may exhibit more severe signs and symptoms, such as blue-tinged skin, inability to drink, convulsions, persistent vomiting, extreme temperature changes, or a decreased level of consciousness. Pneumonia caused by bacteria and viruses typically share similar symptoms. Classic, but not specific, clinical characteristics are linked to some causes. The symptoms of legionella pneumonia include nausea, vomiting, and confusion. Sputum of a rusty colour is common in streptococcus pneumonia.

The World Health Organization (WHO) says that pneumonia is the leading cause of death worldwide, especially in older adults and children under the age of 5. Pneumococcal disease, which includes pneumonia, was estimated to have killed approximately 900,000 children under the age of 5 worldwide in 2019.However, the burden of pneumonia has been decreasing in recent years. For instance, pneumococcal conjugate vaccines (PCV) have reduced pneumonia cases and deaths in numerous nations. In many communities, the incidence of pneumonia has also decreased as a result of improved living conditions, improved nutrition, and expanded healthcare accessibility.

II. LITERATURE SURVEY

H. Bhattad and H. Deshmukh**, "**Detection using X-rays images and DL approach" proposed a study titled "Pneumonia detection using a chest x-ray image and DL approach." Predicting respiratory diseases in their earliest stages can be extremely beneficial, particularly for increasing the patient's survival rate. Pneumonia is one of the diseases that kills the most people. The main reason for this is that many people don't know they have it until it's too late, and some people don't know they have it until it's too late. However, the likelihood of a cure increases if these diseases are discovered early. However, since CT, MRI, or X-rays are not practical in many parts of the world, midsection radiology continues to be the most fundamental system. The goal of image processing is to convert an image into digital form and perform a process on it to produce a better image or extract useful information. A new technique has been developed to transform an image into digital form and carry out a few operations in order to obtain particular models. Suppressing any image distortions or unwanted information is the primary goal of image processing. Gray scaling is the process of transforming an image with continuous tones into one that can be manipulated by a computer. To change over a variety picture into grayscale we take a RGB worth of the expected pixel, find the mean RGB worth of the pixel ((R+G+B)/3) and afterward supplant the R, G and B worth of the pixel with the mean. The image is gray in shades after gray scaling. It was utilizing dark scaling to lessen variety commotion. This diminishes the data of the picture. Additionally, the result's accuracy is improved by gray scaling [1].

P. Rajpurkar and J. Irvin.," CheXNet 121 Layers" Propose CheXNet, rather than experienced specialists, the system got a higher F1 score. In addition, the team introduced Weighted Binary Cross-Entropy loss to reduce the impact of imbalanced classes. This loss differed from Binary Cross-Entropy losses in that the weights of imbalanced classes varied according to the number of classes. However, the proposed loss did take into account the various classes' training difficulty levels. To tackle the issue of unfortunate speculation capacity brought about by over-fitting and the issue of spatial meager condition brought about by customary convolution activity, lingering association organization and widened convolution was utilized by Liang in the spine network model. this algorithm, which outperforms a practicing radiologist in its ability to identify pneumonia from chest X-rays. CheXNet, our algorithm, is a 121-layer convolutional neural network that was trained on Chest X-rays14, the largest dataset of chest X-ray images that is currently available to the public. This dataset contains over 100,000 frontal view X-ray images of 14 different diseases. A test set is annotated by four academic radiologists, allowing users to compare CheXNet's performance to that of radiologists. On the F1 metric, it was discovered that CheXNet outperforms the performance of typical radiologists. This allows CheXNet to detect all 14 diseases in chest X-rays14 and achieves state-of-the-art results for all 14 diseases **[2].**

M. yaseliani and A. Z Hamadani," Hybrid Deep CNN Best on Parallel visual Geometry" proposed a hybrid CNN that used ML classifiers and parallel visual geometry group architecture. Pneumonia is a serious, acute respiratory infection that has killed a lot of people all over the world. People over the age of 65 and children under the age of five are more likely to suffer from this lung disease. Albeit the treatment of pneumonia can be testing, it tends to be forestalled by early finding utilizing computer aided design frameworks. Radiologists use CXR a lot as the primary imaging tool for detecting pneumonia at the moment. Various DL methods have been developed for the detection of pneumonia with the CAD system in mind, whereas the standard method is based on clinician decisions. A novel hybrid CNN model employing three classification methods is proposed in this regard. CXR images are classified using fully connected layers in the first classification method. The weights with the highest classification accuracy are saved after this model is trained for a number of epochs. The most representative CXR image features are extracted using trained optimized weights in the second classification method, and ML classifiers are used to classify the images. CXR images are classified using an ensemble of the proposed classifiers in the third classification method. The findings indicate that the proposed ensemble classifier employing SVM in conjunction with RBF and LR classifiers performs the best. In the end, this model is used to make a web-based CAD system that can help radiologists find pneumonia with a lot of accuracy [3].

Tawsifur Rahman and M. Chowdhury "Transfer Learning with Deep CNN" Pneumonia is a serious, acute respiratory infection that has killed a lot of people all over the world. People over the age of 65 and children under the age of five are more likely to suffer from this lung disease. Albeit the treatment of pneumonia can be testing, it tends to be forestalled by early finding utilizing computer aided design frameworks. Radiologists use CXR a lot as the primary imaging tool for detecting pneumonia at the moment. Various DL methods have been developed for the detection of pneumonia with the CAD system in mind, whereas the standard method is based on clinician decisions. A novel hybrid CNN model employing three classification methods is proposed in this regard. In the main arrangement approach, layers are used for the order of CXR pictures. The weights with the highest classification accuracy are saved after this model is trained for a number of epochs. The most representative CXR image features are extracted using trained optimized weights in the second classification method, and ML classifiers are used to classify the images. CXR images are classified using an ensemble of the proposed classifiers in the third classification method. The findings indicate that the proposed ensemble classifier employing SVM in conjunction with RBF and LR classifiers performs the best. In the end, this model is used to make a web-based CAD system that can help radiologists find pneumonia with a lot of accuracy[4].

V. Kaushik and A. Nayyar," Pneumonia Detection Using CNN" Children under the age of five are most likely to die from pneumonia, an interstitial lung disease. According to a UNICEF study, it was responsible for approximately 16% of the deaths of children under the age of five in 2016, killing approximately 880,000 children. The majority of the affected children were under the age of two. If pneumonia is detected early in children, the recovery process can be expedited. The convolutional neural network models presented in this paper can be used in the real world to treat pneumonia by accurately detecting pneumonic lungs from chest X-rays. The chest X-ray images (pneumonia) dataset on Kaggle was used for the experiments. The first, second, third and fourth model comprises of one, two, three and four convolutional layers, individually [5].

III. Existing Method

This framework will give a simple way to deal with distinguishing pneumonia utilizing X-beams and a convolutional brain organization. The website allows multiple users to work simultaneously. Pneumonia will be easy to spot for both patients and doctors. Patients, medical facilities, and doctors can all use the site. The goal of pneumonia detection is to make it easier for healthcare professionals and patients to share images throughout the environment. It will cut down on time, paperwork, and costs.

IV. Proposed System

Deep Transfer Learning

In most cases, CNNs perform better in a larger dataset than in a smaller one. When the dataset for a CNN application is small, transfer learning can be useful. The idea of move learning is shown in Figure 1 where a trained model from a large dataset, like ImageNet, can be applied to a smaller dataset.

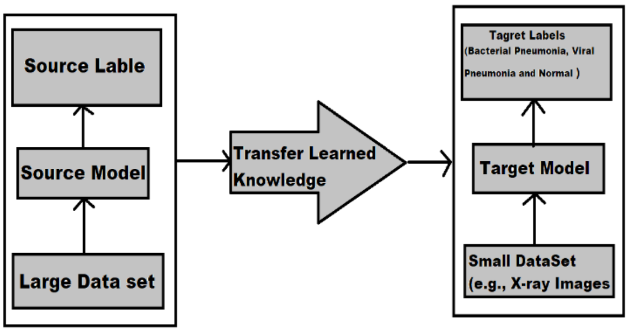

Figure 1. Transfer Leaning.

As of late, move learning has been effectively utilized in different field applications, for example, assembling, clinical and things screening. When developing a deep learning algorithm from scratch, this eliminates the need for a large dataset and shortens the amount of time spent training.

The following UML diagram depicts the process of obtaining input chest X-ray images from the dataset, followed by data pre-processing, data enhancement, and image division into a training set and a testing set using VGG16 for CNN classification. After arrangement the convolution layers with actuation capability happens. The feature images are now transformed by the flattering layer into a one-dimensional matrix that the fully connected layers with their activation function use. The model will be compiled using the Adam optimizer, categorial cross-entropy loss function, and soft-max activation following the fully connected layers stage. After this page information model will store the information and afterward load the model and grouped yield as a typical or pneumonia.

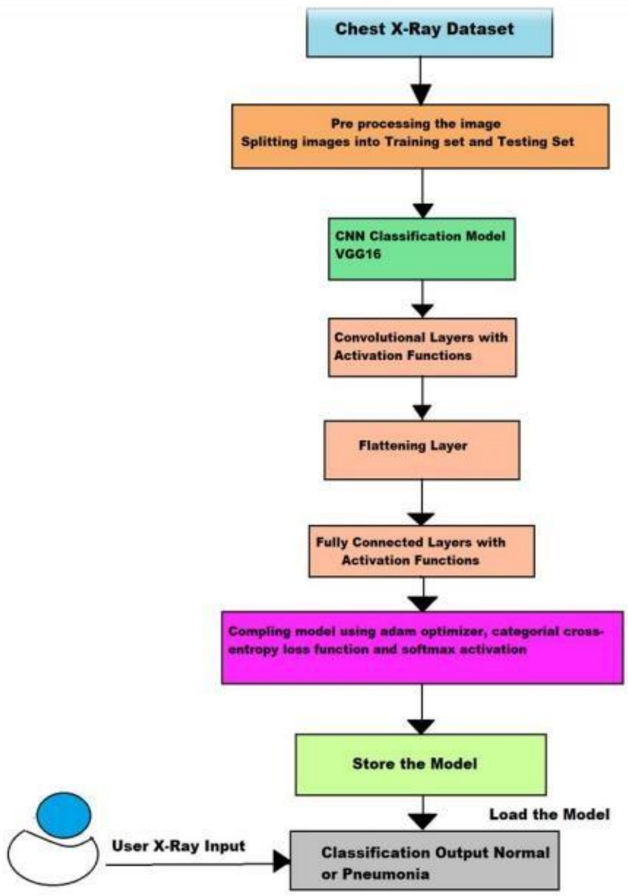

Figure 2: UML Diagram.

4.1 System Architecture

Dataset assortment: A substantial set of labelled medical images that have been examined by radiologists and annotated as either normal or abnormal (i.e., displaying signs of pneumonia) is required for the model.

Pre-processing: Pre-processing is used to normalize the sizes of the medical images, adjust brightness and contrast, and get rid of noise or artifacts.

Extracting attributes: The model takes features like edges, textures, and shapes from the medical images. This is done with the help of convolutional neural networks (CNNs), which are made to process images.

Model education: The model is trained with the extracted features to classify images as normal or abnormal. This is regularly done utilizing a regulated learning approach, where the model gains from a bunch of marked models.

Evaluation of a model: A separate set of images that were not used during training are used to evaluate the model. This aids in determining the model's generalizability and accuracy.

Deployment: After the model has been trained and tested, it can be used in a clinical setting to help doctors make accurate diagnoses by analysing medical images in real time.

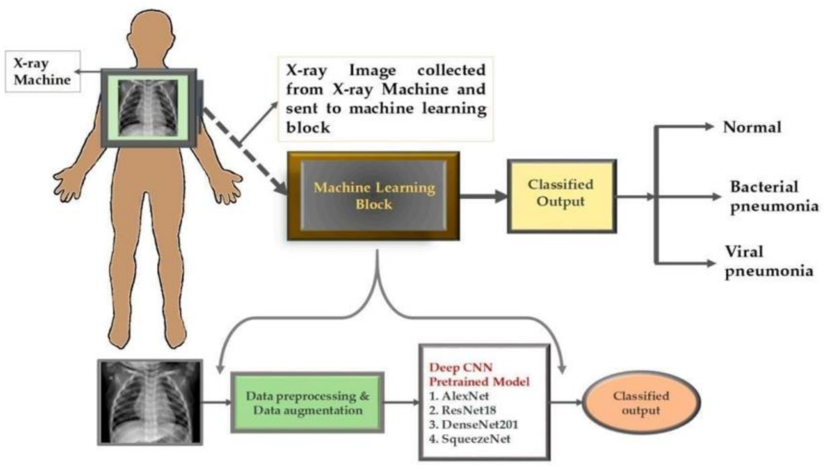

Figure 3: Overview of the Model

Data Augmentation

As examined before, CNNs work better with a huge dataset. Nonetheless, the size of the functioning data set isn't exceptionally huge. When training deep learning algorithms, it is common practice to use data augmentation techniques to expand a relatively small dataset into a large one. Deep learning algorithms' classification accuracy may rise with data augmentation, according to reports. Rather than acquiring brand-new data, it is possible to enhance the performance of deep learning models by adding to the data that is already available. The algorithms of some deep learning frameworks include a facility for data augmentation; However, as depicted in Figure 4, the authors of this study have employed three augmentation strategies to generate new training sets: translation, scaling, and rotation.

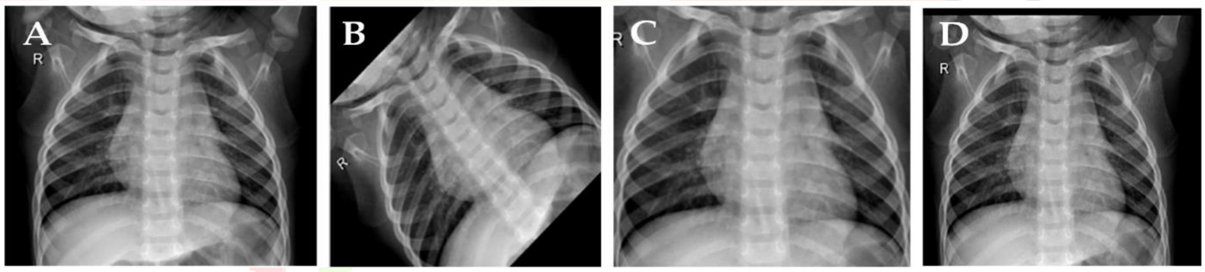

Figure 4. Original chest X-ray image (**A**), chest X-ray image after rotation (**B**), chest X-ray image after scaling (**C**), and chest-X-ray image after translation (**D**).

V. METHODOLOGY AND ALGORITHM

Transfer Learning Algorithm

Transfer learning is a popular method in computer vision because it lets us build precise models in a faster way. With a trained model in advance:

Instead of learning from scratch, transfer learning uses patterns you've learned from solving a different problem. Instead of having to learn everything from scratch, you will be able to put what you already know into practice. The expression "standing on the shoulder of giants" from Chartres has been adapted for deep learning.

How transfer learning works in practice is as follows:

Model with pre-training: First, a large and diverse dataset for a task that is similar to the target task is used to train a pre-trained model. The target task is then started off with this pre-trained model.

Extracting attributes: High-level features from the input data for the target task are extracted with the help of the pre-trained model. A new model that is tailored to the intended task is then incorporated with these features.

Fine-tuning: The extracted features are used to train the new model on the data for the target task. The objective is to fine-tune the model to be able to accurately predict the target task. Typically, this process of fine-tuning involves adjusting the new model's weights to make them fit the intended task better.

There are a number of advantages to transfer learning:

Improved training: Because the model has already learned many of the low-level features from the model that has already been trained, transfer learning allows for faster training times.

Gained efficiency: When compared to training a model from scratch, transfer learning frequently results in better performance on the target task. This is because the pre-trained model already knows a lot of the low-level features that can be used for the target task and are useful for a wide range of tasks.

Less data is needed: When compared to training a model from scratch, transfer learning typically requires less data to achieve good performance on the target task. This is due to the fact that many of the low-level features have already been learned by the pre-trained model from a diverse and extensive dataset.

Dataset

The Kaggle chest X-ray pneumonia database, which contains 5247 chest X-ray images with resolutions ranging from 400p to 2000p, was utilized in this study. Table 1 shows that 1341 of the 5247 chest X-ray images are from normal subjects and 3906 are from patients with pneumonia. In some cases of pneumonia, there is an infection that is both viral and bacterial. However, this study's dataset does not contain any instances of viral and bacterial co-infection. The training set and the test set were separated from this dataset.

pre-processing

Resizing the X-ray images was an essential step in the data pre-processing process because the image input for various algorithms varied. The images were resized to 227 x 227 pixels for AlexNet and SqueezeNet, but they were resized to 224 x 224 pixels for ResNet18 and DenseNet201. The standards for the pre-trained model were used to normalize all of the images.

Different experiments

Five-fold cross-validation was used to train and evaluate four CNNs in this study. After the training phase is over, the performance of various networks on the testing dataset is compared using the following six performance metrics: exactness, responsiveness or review, explicitness, accuracy (PPV), the region under bend (AUC), and F1 score. Six performance metrics for various deep CNNs are presented in:

$$Accuracy = \frac{(TP+TN)}{(TP+FN)+(FP+TN)} \quad (1)$$

$$Sensitivity = \frac{(TP)}{(TP+FN)} \quad (2)$$

$$Specificity = \frac{(TN)}{(FP+TN)} \quad (3)$$

$$Precision = \frac{(TP)}{(TN+FP)} \quad (4)$$

$$F1\ Score = \frac{(2*TP)}{(2*TP+FN+FP)} \quad (5)$$

VI. CONCLUSION

The experience of working on this project has been enriching. This task has offered the chance to deal with another stage and advance totally new innovation. This system, which was made for doctors and patients, is very useful because it can catch pneumonia early. With high recall values, this model classifies pneumonia based on chest X-ray images taken from frontal views. The chest X-ray images are first resized by the algorithm so that they are smaller than the original. The convolutional neural network framework, which extracts features from the images and classifies them, is used in the subsequent step to identify and classify them. In the medical field, utilizing machine learning to identify pneumonia is a promising strategy because it can provide an accurate and efficient diagnosis with minimal human intervention. Using medical images like chest X-rays and CT scans, this method trains machine learning models to identify pneumonia-indicating patterns and features. However, it is essential to keep in mind that the quality of the data used to train machine learning models is only as good as the data itself. As a result, it is essential to make certain that the training data are varied and representative of the population being diagnosed. The application of machine learning to the detection of pneumonia is a promising strategy that has the potential to revolutionize the field of medicine. Additionally, machine learning models ought to be validated and tested on extensive and diverse datasets to guarantee their reliability. However, before these models can be widely used in clinical practice, additional research is required to further refine and validate them.

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