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Comparison of Deep Learning Algorithms for Pneumonia Detection

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Abstract:- Pneumonia is a very dangerous disease that affects the lungs of human beings and can even cause death. It is caused by a bacteria called Streptococcus pneumoniae. There are different types of pneumonia like bacterial, viral, and covid 19 pneumonia. This mainly affects children below five years and elderly people. Chest X-rays are used to diagnose pneumonia and this needs expert radiotherapists for evaluation. This may cause a delay in detecting pneumonia which can be life-threatening. Here comes the need for deep learning algorithms for analyzing medical images. In this paper, we use deep learning algorithms like CNN, transfer learning and ANN in detecting pneumonia and compare their accuracies to determine which algorithm is better. Chest X-ray dataset from Guangzhou Women and Children's Medical Center is used.

I. INTRODUCTION

A lung infection known as pneumonia is brought on by bacteria, viruses, or fungi. The infection causes inflammation in the lungs' alveoli, which are small air sacs. As the alveoli swell with liquid or pus, breathing becomes challenging.[1]Pneumonia causes the death of around 700,000 children every year and affects 7 percentage of the global population. In the present scenario where Covid19, which was found as a cluster of pneumonia, is pertaining the estimate of people affected by lung diseases is doubled. In the beginning, doctors used a clinical examination, a patient's medical history, and chest X-rays to diagnose pneumonia. Different computer-aided diagnosis methods can be used to solve the issue of a lack of experts. Deep learning is mostly used for pneumonia detection that occurs more quickly. In order to determine which deep learning algorithm provides higher accuracy at a faster rate, we are analysing the accuracy of various deep learning algorithms in this study. The compared algorithms include CNN, ANN, and transfer learning. Each year, pneumonia affects over 450 million people worldwide. The majority of children under 5 who develop pneumonia. This age group of kids has the highest prevalence of pneumonia-related deaths. Among the models compared and studied, CNN was found to have higher accuracy than other models.

II. RELATED WORKS

➢ *CheXNet: Radiologist-Level Pneumonia Detection on Chest X-Rays with Deep Learning (2017)*

Pranav Rajpurkar, Jeremy Irvin, et al. (2017) developed an algorithm that could detect 4,444 types of pneumonia from chest X-rays at a level that far exceeds the practice of radiology. The CheXNet algorithm is a 121-layer convolutional neural network trained on ChestX-ray14. Four practice radiologists described tests in which they compared CheXNet's performance to that of radiologists. They found that the CheXNet outperformed the average radiologist's F1 metric.

➢ *Pneumonia detection using CNN-based feature extraction(2019)*

In the work of Dimpy Varshni; Kartik Thakral; Lucky Agarwal; Rahul Ni-jawan; Ankush Mittal (2019),evaluated the ability of pre-trained CNN models to be used as feature extractors and then used different classifiers for the classification of abnormal and normal chest X-rays. To do this, they determine the best CNN model through analysis. The obtained results show that the proposed CNN model used in conjunction with the observer algorithm is much more useful in the analysis of chest X-ray images, especially in the diagnosis of lung disease.

➢ *Pneumonia detection in chest X-ray images using convolutional neural networks and transfer learning(2020)*

A paper by Rachna Jain, Preeti Nagrath et al (2020), presents a convolutional neural network model for lung cancer diagnosis using X-ray images. Several convolutional neural networks were trained to classify X-ray images into two classes, pneumonia and non-pneumonia, by varying the parameters, hyper-parameters, and number of layers. Six models are mentioned in the article. The first and second models have two and three convolution layers, respectively. The other four models are pre-trained models which are VGG16, VGG19, ResNet50, Inception-v3.

➢ *Prediction of Community-Acquired Pneumonia Using Artificial Neural Networks(2003)*

Paul S.Heckerling, MD, Ben S.Gerber et al wrote a paper in which ANN was trained on health, symptoms, signs, symptoms, and recommendation data from 1044 patients at the University of Illinois (training group) and applied to 116 patients at the University of Nebraska. patients (test cohort). ANNs trained with different strategies were compared among themselves and the main effects were compared with logistic regression. Calibration accuracy was measured as the square of the error and discrimination accuracy was measured as the area under the receiver operating characteristic (ROC) curve.

- *A Novel COVID-19 Diagnosis Support System Using the Stacking Approach and Transfer Learning Technique on Chest X-Ray Images (2021)*

Soufiane Hamida et al. wrote an article in 2021 in a similar domain. The purpose of this article is to improve the rapid and accurate diagnosis of COVID-19 on chest X-ray images by using the stacking technique combined with transfer learning and KNN algorithm to select the best model. This approach can store and use the knowledge gained by pre-trained convolutional neural networks to solve new problems. To ensure the robustness of the proposed system for diagnosing COVID-19 patients using X-ray images, we use a machine learning technique called stacking to combine the performances of the many transfer learning based models. The model was trained on data that included four categories such as COVID-19, tuberculosis, pneumonia, and common diseases. Validation data was collected from a 6-domain dataset of X-ray images. They use different general measures to evaluate the effectiveness of the proposal. The proposed method achieved a very high accuracy of 99.23

- *Pneumonia Detection Using Deep Learning Based on Convolutional Neural Network(2021)*

Luka Raˇci´c; Tomo Popovi´c; Stevan ˇcaki´c; Stevan Sandi together did their research using deep learning based on cnn in 2021 itself. Their article describes the use of machine learning algorithms to process chest X-ray images to support decision making. In particular, the research focuses on the development of models using deep learning algorithms based on neural networks. The role of the model is to help solve the classification problem of detecting whether the chest X-ray varies according to the lung disease and dividing the X-ray images into two groups according to the diagnosis.

- *Deep Learning on Chest X-ray Images to Detect and Evaluate Pneumonia Cases at the Era of COVID-19(2021)*

As COVID-19 hit, faster detection of pneumonia became more necessary. During that period, Karim Hammoudi , Halim Benhabiles wrote a paper regarding this. Because lung diseases can be detected by X-rays, this article explores the deep learning process for the evaluation and interrogation of chest X-rays, hoping to provide patient doctors with equipment that has been tested for and identifies patients for COVID-19. In this context, training datasets, deep learning and analysis techniques from the data contained in chest X-ray images were tested. There is a different learning process from the learning model to learn about pneumonia, especially infectious diseases. It is assumed that cases of pneumonia diagnosed in the context of the spread of COVID-19 disease are most likely to be considered a disease of COVID-19 disease. In addition, simple sanitation measures have been proposed to predict the spread of disease and predict patient status from lung disease tests. Experimental results show the possibility of training deep learning models on published data on chest X-ray images to diagnose lung diseases. The efficacy of chest X-rays of COVID-19 patients has been confirmed by a special diagnostic model.

III. METHODOLOGY

- *Dataset description*

The dataset has three folders: train, test, and valuation, with a subfolder for each type of image (pneumonia/normal). 5,863 X-ray images (JPEG) are included, with 2 classifications (pneumonia/normal). At the Guangzhou Women and Children's Medical Centre, chest X-ray images (anterior-posterior view) were chosen from a retrospective cohort of paediatric patients between the ages of one and five. The patient receives routine clinical care that includes all chest X-rays. Prior to analysis, all chest radiographs were checked for quality control to exclude any subpar or unlawful scans. In order to train the AI system, the diagnostics from the photos were first cleaned up and scored by two experienced doctors. A third expert also checked the evaluation set to rule out any scoring problems.

- *Process*

The process consists of four stages,

- Selection of appropriate dataset
- Data preprocessing
- Building the model
- Prediction based on the accuracy of deep learning algorithms

- *Data Pre-processing*

We first alter our photographs to make them better candidates for training a convolutional neural network before we begin. Then we do data preprocessing and data augmentation for this assignment using the Keras Image Data Generator function. Additionally, this class provides simple data enhancements like random image horizontal flipping. Additionally, we utilise the generator to change each batch's values to have a mean of 0 and a standard deviation of 1. By normalising the input distribution, this will facilitate model training. The generator additionally changes our grayscale x-ray images to a three-channel format by iterating over the image's values across all channels. We need to do this since the pre-trained model we will be using demands that the images be in a three-channel format.

- *Algorithms Used*

Here the dataset is split into train, test, and validation datasets. In this study, we use deep learning algorithms like ANN, CNN, and transfer learning. Trans-fer learning makes use of different algorithms like DenseNet, VGG16, ResNet, and InceptionNet. We use these algorithms for detecting pneumonia. In this paper, we compare these algorithms and find out which one is more accurate for prediction.

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- *Deep Learning*

A subset of machine learning called "deep learning" uses neural networks. It may discover intricate links and patterns in the data. It is founded on deep neural networks (DNN), often referred to as artificial neural networks (ANN). These neural networks are built to learn from massive amounts of data, and they were inspired by the architecture and operation of organic neurons found in the human brain. An input layer is coupled to one or more primitive layers in a fully connected deep neural network. The previous group of neurons fed information to each neuron. Up until the formation of the final layer of the network, the output of one neuron becomes the input of additional neurons in the subsequent layer. The layers of the neural network transform the input data with non-linear transformations, allowing the network to learn the representation of the input data.

- *CNN Architecture*

CNNs have gained popularity as a result of their enhanced picture categorization capabilities. The network's convolutional layers and filters aid in the extraction of an image's spatial and temporal information. The weight-sharing method used by the layers aids in minimising computational work. CNNs are the best choice for tasks like image classification, object identification, and im-age segmentation because they can learn the characteristics of images. The input layer, convolutional layer, pooling layer, and fully connected layers are only a few of the layers that make up a convolutional neural network.

A set of filters (or kernels) with modest widths and the same height and depth as the volume make up the convolutional process. Each stride (for high-resolution images, its value can be 2, 3, or even 4) represents the amount of time it takes to gradually move each filter across the entire volume as we compute the dot product between the kernel weights and patch from the input volume. When we move the filters, the output is filled with filters of the same depth because we combined the 2D outputs of each filter. All the filters will be learned by the network.

This layer is placed in CNN from time to time and its main function is to reduce the size of the volume, thus speeding up computation, reducing memory and preventing overfitting. The two types of pooling layers are max pooling and average pooling. If we use 2 x 2 filters and max pooling with stride 2, the resulting volume will be 16x16x12. The results of the maps are flattened into one-dimensional vectors after the convolution and pooling layers so that they can be transmitted to a fully connected layer for classification or regression.

The results of the combined process are then put into a logistic function for classification, such as sigmoid or softmax, which transforms the output of each class into a probability score test for all classes.

- *Transfer learning*

A larger dataset often yields better results for CNNs than a smaller one does. When using CNN in applications where the dataset is small, transfer learning may be helpful. The idea behind transfer learning is straightforward: we take a big data learning model and apply its expertise to small data. We freeze the network's initial convolutional layers for object recognition in CNN and train the final few layers just for prediction. [10]tTransfer learning has recently been applied successfully in a variety of real-world settings, including manufacturing, healthcare, and baggage screening. This eliminates the need for a sizable dataset and shortens the lengthy training period that the deep learning system requires when created from scratch.

To solve the vanishing/exploding gradient problem, the architecture intro-duces a concept called residual blocks. In this network, we use a technique called skip-connections. Skip-connection links the processes of one layer to other layers by skipping some layers. This creates a residual block. Resnet is created by putting the residual block together. The benefit of adding this kind of skip-connections is that if a layer causes any problem in architectural operation it will be skipped by the normal process. The network uses a 34-layer traditional network architecture inspired by VGG-19 and then adds short links. These short links then converts the architecture to the residual network.

Each layer in DenseNet is linked to every other layer deeper in the network.[11]Compared to a conventional CNN, the DenseNet design requires less parameters. Only 12 filters and a limited number of new feature maps are used in DenseNet layers. With some essential differences, it is extremely similar to a ResNet. Due to the disappearing gradients generated by the distance between input and output processes, where data is lost before it reaches its destination, DenseNet was particularly created to improve accuracy in advanced neural networks.[11]By providing access to the gradient values from the loss function and the input image, DenseNet resolves this problem. In a DenseNet with L layers, there will be approximately L and L plus one by two connections, or L(L+1)/2. So in dense networks we have less layers than other models, so here we can easily train models with more than 100 layers using this method.

One of the most well-known models of convolutional neural network (CNN) architecture to date is VGG16. It begins with blocks of two or three convolutional layers, then moves on to a pooling layer, a dense network made up of two hidden layers, and finally an output layer. VGG16 employs a max pooling layer with a 2x2 filter with stride 2 and a convolutional layer with a 3x3 filter at the same padding in place of several hyperparameters. Throughout the architecture, it always adheres to the convolutional and maximum pooling layer orders. Last but not least, it has two arrays of connections, all of which are output by Softmax. The 16 in VGG16 denotes the presence of 16 weighted layers.

The GoogleNet is another name for the InceptionNet. The architecture offers inception module subnets. It enables quick training, complicated pattern computation, and parameter usage optimisation. To increase speed and precision, it employs a variety of strategies. There are 22 layers in the architecture altogether. Nine linearly fitted inception modules make up GoogleNet. There are 22 layers (27 including the outer layers). The architecture's last layer, global average pooling, which determines the average value of each feature map, replaces all previous levels. This drastically lowers the total number of parameters.

- *ANN Architecture*

Artificial neural networks are created from the structures and operations of human neurons. It is also called neural network. Artificial neurons, also called units, are found in artificial neural networks. All the artificial nueral networks made up of these artificial neurons are arranged in a single layer. A fully connected neural network has an input layer and one or more hidden layers. Each neuron receives input from the previous input processes. The output of one neuron becomes the input of other neurons in the next layer of the network, and this process continues until the last layer of the network is formed. Then, after going through one or more hidden processes, this information is converted into master information for the output process. Finally, the output process is displayed as the neural network's response to the incoming data.

IV. RESULT

The death rate from pneumonia can be lowered with early identification. various algorithms is effective in identifying pneumonia. Our goal was to identify the algorithm that serves superior. In order to do that, we contrasted a number ofdeep learning algorithms, including ANN, CNN, and transfer learning. Accuracy ratings for the models were determined. The fraction of correctly predicted outcomes is what is referred to as accuracy.

The accuracy is measured using different elements namely true positives(P), true negatives(N), false positives(p), false negatives(n),precision(x) and recall(y). It is calculated using the below equation:

$$\text{Accuracy} = (P + N)/(P + N + p + n) \qquad (1)$$

The recall score for a model is calculated as:

$$\text{Recall} = y = P/(P + n) \qquad (2)$$

Precision is defined as the number of accurate positive predictions and is calcu-lated as:

$$P\,\text{recision} = x = P/(P + p) \qquad (3)$$

F1-score measures the model's accuracy and it is calculated as:

$$F\ 1\text{Score} = (2 * x * y)/(x * y) \qquad (4)$$

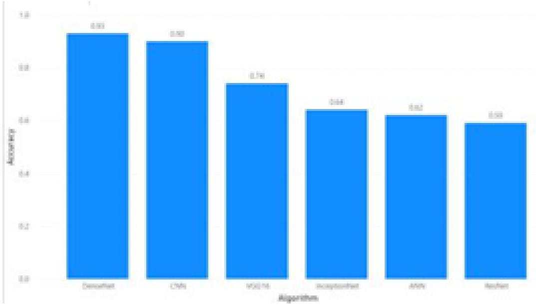

Fig 1: Accuracy Graph

The work under discussion assesses how well different deep learning algorithms, such as ANN, CNN and transfer learning, such as DenseNet, ResNet,VGG16 and InceptionNet, recognise pneumonia. We evaluate the performance of various algorithms to see which one is faster and more accurate. The best deep learning-based pneumonia detection algorithm must be selected based on the results of this test. DenseNet surpassed other methods utilised in the study, according to the computed accuracy of 93 percentage. The DenseNet model per-formed this task with great accuracy, raising the possibility that it could help identify pneumonia early even in the absence of specialised radiologists.

V. CONCLUSION

Detection of pneumonia in its early stage is necessary to reduce the death rate. Due to the lack of expert radiotherapists, this task becomes a bit difficult, this is solved using deep learning algorithms. In our study, we have used several algorithms to detect pneumonia and concluded that DenseNet is more accurate than other algorithms in the faster detection of pneumonia with a calculated accuracy of 93 percentage.

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