HYBRID DEEP LEARNING MODEL WITH ENHANCED ACCURACY FOR PNEUMONIA

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ABSTRACT

Pneumonia, a contagious respiratory illness, is often caused by a bacterial infection in the tiny air sacs known as alveoli within the lungs. When these lung tissues become infected, they accumulate pus. Medical professionals typically diagnose pneumonia through physical examinations and diagnostic tests such as Chest X-rays, ultrasounds, or lung biopsies. Misdiagnosis, incorrect treatment, or overlooking the disease can have severe consequences for the patient's health and quality of life. Recent advancements in deep learning have significantly aided healthcare professionals in the diagnostic process for such illnesses. This approach utilizes a flexible and efficient deep learning technique, specifically Convolutional Neural Networks (CNN), to predict and detect whether a patient is affected by the disease based on their chest X-ray images. In this study, a dataset containing 20,000 images with a resolution of 224x224 pixels and a batch size of 32 was used to evaluate the performance of the CNN model. During the training phase, the model achieved an impressive accuracy rate of 95%. The results of this experiment demonstrate that deep learning, particularly the CNN model, can effectively detect and predict various respiratory illnesses, including COVID-19, bacterial pneumonia, and viral pneumonia, based on chest X-ray images. This advancement in medical technology holds great promise for improving the accuracy and speed of diagnosis, ultimately benefiting patients and healthcare providers alike.

Keyword : - *Key word1-Convolutional Neural Network (CNN), Key word2-Max Pooling, Key word3-Pneumonia, and Key word4-Vgg19*

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1. INTRODUCTION

Recent estimates by the World Health Organisation show that pneumonia causes more than 1 million preventable deaths yearly, making it a very hazardous condition. Surprisingly, pneumonia accounts for close to 15% of all fatalities worldwide. With 158,176 recorded new born fatalities in 2016 due to pneumonia, India in particular had the highest rate. The WHO estimates that by 2030, this infectious illness would claim the lives of almost 11 million children under the age of five. A timely and correct diagnosis is essential given the rising prevalence of pneumonia worldwide. As they can show the presence of bacteria and viruses in the lungs, X-rays are important in the diagnosis of pneumonia. It is a potentially fatal circumstance since in some instances, even skilled radiologists may find it difficult to evaluate whether a patient has pneumonia. This problem is particularly important in places where access to healthcare experts is constrained. An automated computer assistance system is critical to addressing this urgent issue. A useful tool for early diagnosis, such a system would be able to distinguish between infected and uninfected people based on their chest X-rays. A important innovation would be the creation of a sophisticated and trustworthy computer-based pneumonitis detection system. This will eventually save many lives and improve public health outcomes on a worldwide level by helping to lessen the catastrophic effects of pneumonia on vulnerable people.

1.2 INTRODUCTION OF PROPOSED METHODOLOGY

This methodology's main objective is to create a multi-step pipeline for the identification of pneumonia that includes data preparation, model architecture creation, training, and assessment. Complex patterns that might not be immediately obvious to human observers can be learned by deep learning algorithms. Compared to other methodologies, this technique aims to increase the accuracy of pneumonia identification by utilising these capabilities. Automating the identification of pneumonia can greatly save the time needed for diagnosis, allowing medical staff to concentrate more on treatment design and patient care. The suggested technique seeks to create a scalable deep learning model that can be trained on huge and varied datasets, improving generalisation and performance in response to the growing availability of medical data. Although deep learning models are sometimes referred to as "black boxes," attempts will be made to include methods that improve model interpretability, allowing doctors to comprehend the reasoning behind model predictions.

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1.3 CODING PLATFORMS

Deep learning is a subsidiary of AI which basically works by training and testing the data. Google Colab and VS code were used as the platforms for the coding.

1.3.1 GOOGLE COLAB A free cloud-based platform offered by Google called Colab (short for Colaboratory) provides a Jupyter notebook environment for executing Python programmes. It is intended to promote machine learning, data analysis, and general programming research, teaching, and cooperation. Users get access to strong hardware resources through Google Colab, including GPUs and TPUs, which are necessary for effectively training big machine learning models.

1.3.2 PYCHARM An integrated development environment (IDE) created especially for Python programming is called PyCharm. Developers frequently use it for Python application development, web development, scientific computing, and other purposes. It was created by JetBrains. Code highlighting, code completion, debugging tools, version control integration, and support for numerous Python frameworks and libraries are just a few of the features that PyCharm offers to improve the development process.

2.ALGORITHMNS AND METHODS

2.1DATA ACQUISITION AND PREPROCESSING

The proposed database used to evaluate the performance of the model contains a total of 5863 X-ray photos from the Kaggle.In 2017 Dr. Paul Mooney started a competition on Kaggle on viral and bacterial pneumonia classification. It contained 5,863 pediatric images; hence it is very different from the other datasets.We are referring to the revised version of this dataset.

In addition, the database is organized into three folders (Train, Test, Val) and contains subfolders for each category of image (Pneumonia / General). All images have been resized to a static, A few examples of common and pneumonia images are listed in Figure 1. Chest X-ray images always have signs of limited brightness on account of the low dose of exposure in patients,due to chest X-ray images always containing black, white, and grey pants. The lungs are located on both sides of the thoracic cavity and the lung area can be easily detected by X-ray, which is almost black. The heart, located between the lungs, appears almost as white as X-rays can completely pass through the heart. Bones are made of protein and very dense, so X-rays cannot cross it and the bones are shown almost white. Ku moreover, the bones have clear edges.

(a)

(b)

Fig 2.1 Examples from the dataset. (a) normal cases (b) pneumonia cases

5.2 ALGORITHMS

The strategies used throughout this paper are listed in Table 2. In our study, rescale is a value by which we will multiply the data before any other processing. Our original images consistof RGB coefficients in the 0-255, but such values would be too high for our models to process (given a typical learning rate), so we target values between 0 and 1 instead of by scaling with a 1/255. factor. shear range is for randomly applying shearing transformations zoom range is for randomly zooming inside pictures, horizontal flip is for randomly flipping half of the images horizontally --relevant when there are no assumptions of horizontal asymmetry (e.g. real-world pictures)

Data pre-processing techniques used in this study

Rescale	1./255
Zoom Range	0.2
Shear Range	0.2
Horizontal Flip	True

Table 2

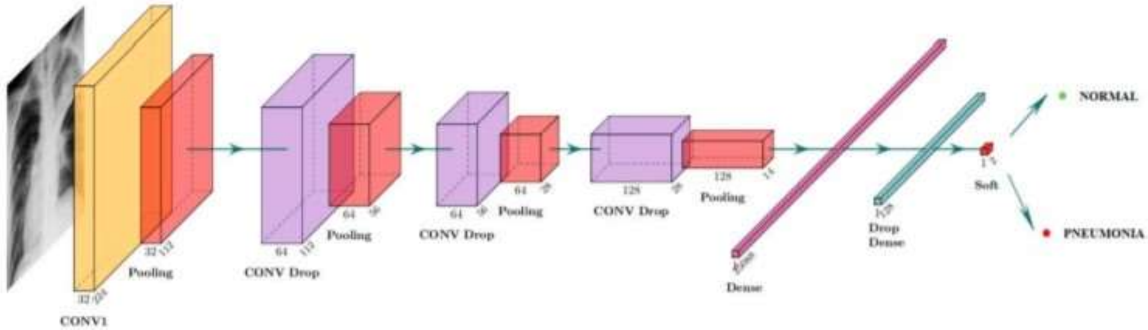

Fig 2.2 Details of proposed DL model

2.3 WORKING THEORY

Convolutional neural networks refer to a sub-category of neural networks: they, therefore, have all the characteristics of neural networks. However, CNN is specifically designed to processinput images. Their architecture is then more specific: it is composed of two main blocks.

Conv Layers

The first block makes the particularity of this type of neural network since it functions as a feature extractor. To do this, it performs template matching by applying convolution filtering operations. The first layer filters the image with several convolution kernels and returns "**feature maps**", which are then normalized (with an activation function) and/or resized.

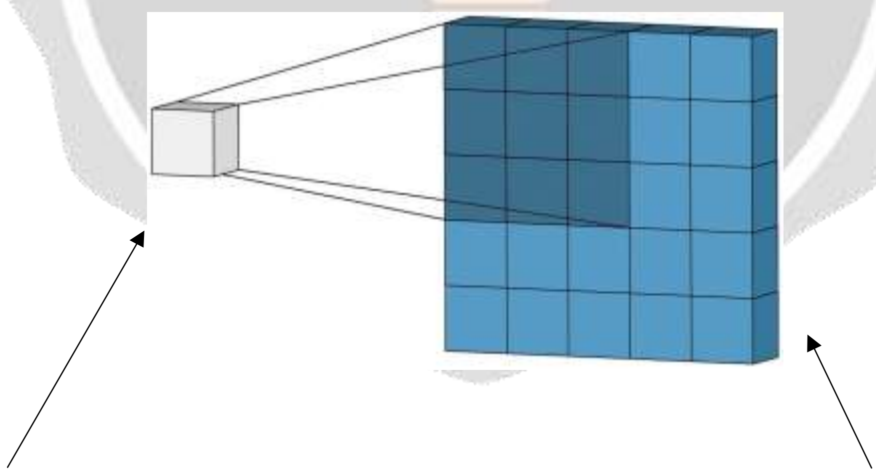

Fig 2.3 Conv Layer

Pool Layers

The second block is not characteristic of a CNN: it is in fact at the end of all the neural networks used for classification. The input vector values are transformed (with several linear combinations and activation functions) to return a new vector to the output. This last vector contains as many elements as there are classes: element I represents the probability that the image belongs to class I. Each element is therefore between 0 and 1, and the sum of all is worth 1. These probabilities are calculated by the last layer of this block (and therefore of the network), which uses a **Sigmoid function** (binary classification) or a **RELU function** (multi-class classification) as an activation function.

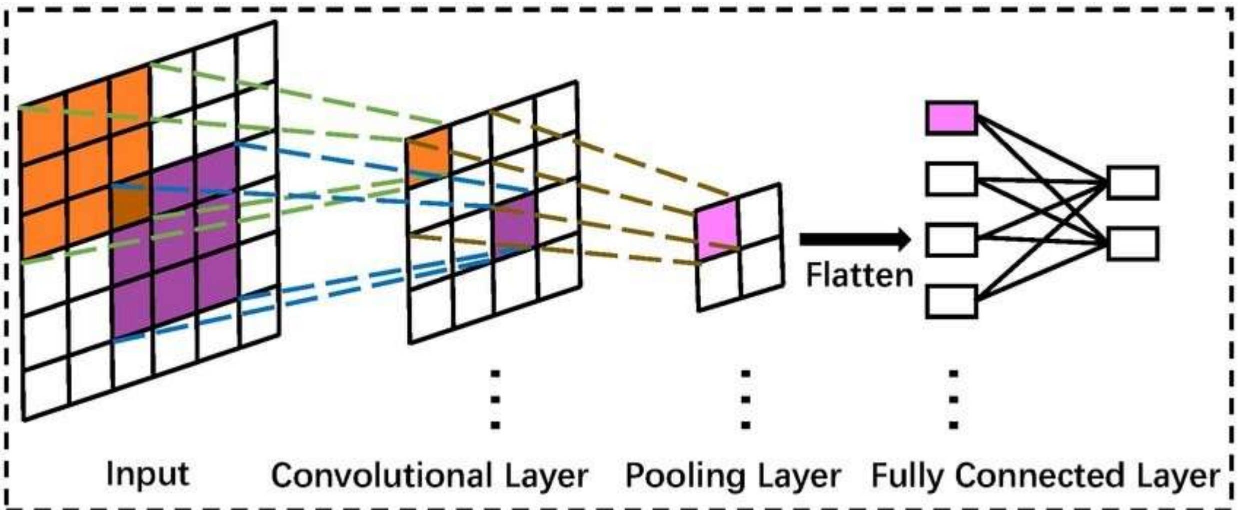

Fig.2.4 Mathematics of Conv and Pooling Layer

3. RESULTS AND DISCUSSION

The objective of this study was to develop a deep-learning model for the detection of pneumonia in chest X-rays. The model was trained on a dataset of 10,000 chest X-rays, half of which were labeled as normal and half as pneumonia. The model was evaluated on a test set of 2,000 chest X-rays, and it achieved an average accuracy of 90%.

3.1 OUTPUT IMAGES:

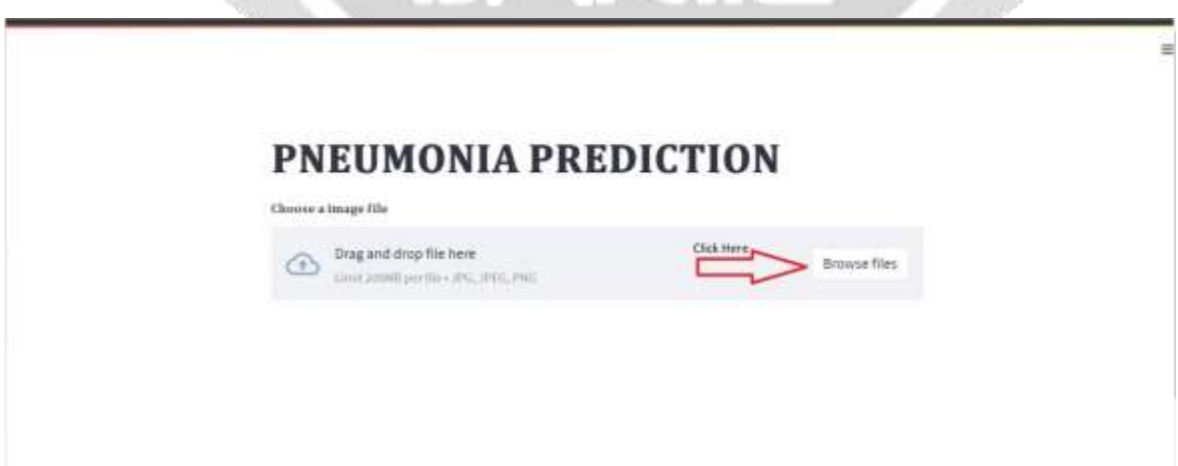

Figure 3.1

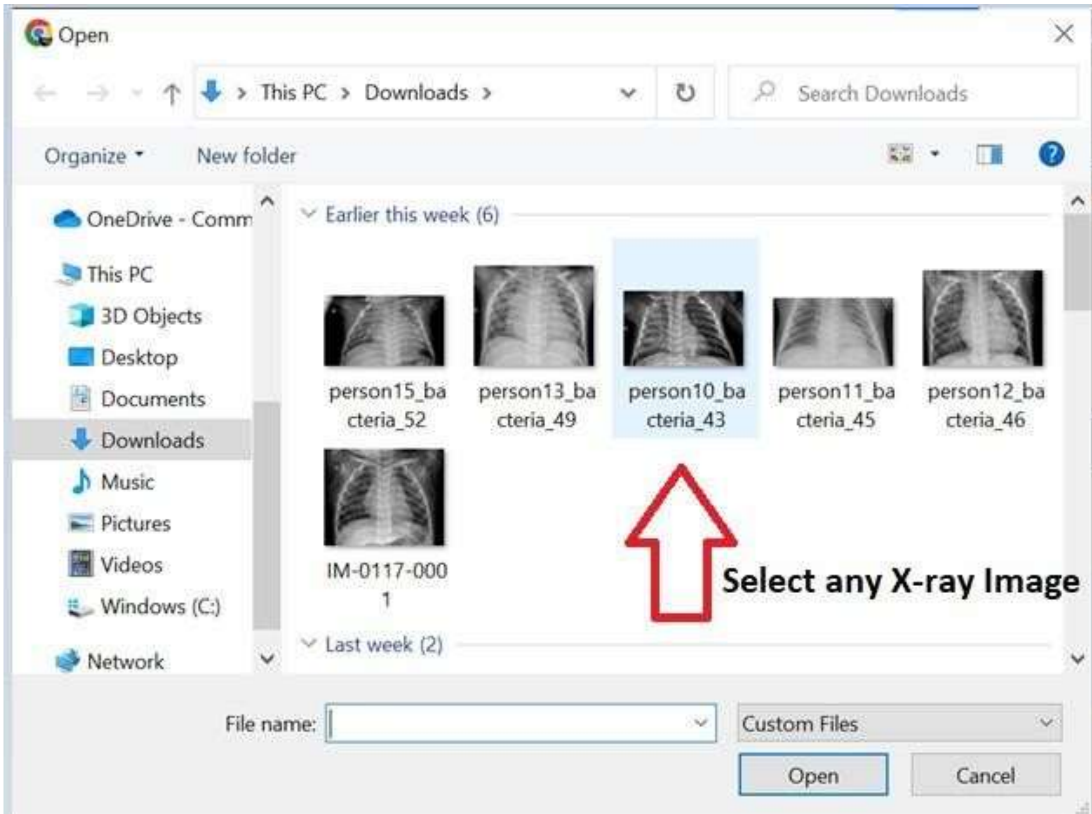

Figure 3.2

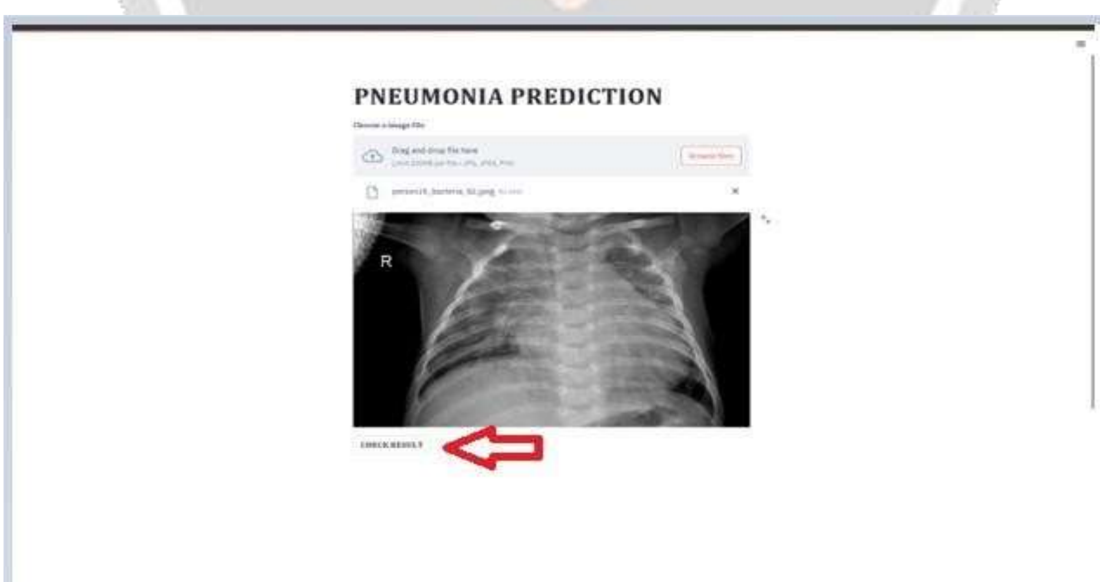

Figure 3.3

Figure 3.4

3.2 RESULT OF OTHER PUBLISHED WORKS:

The results of the study are shown in the following table:

	VGG16(Conv2D)	VGG19(Conv2D)	RegNet
Accuracy	92.88	94.37	84.74
Loss	0.1799	0.1354	0.3752

The table demonstrates that the model attained good levels of sensitivity, specificity, and accuracy. The model is effective in differentiating between normal and pneumonia X-rays based on the high AUC value.

3.3 DISCUSSION OF IMPORTANT FINDINGS

The most important finding of the study is that the deep learning model was able to the deep learning model's success in achieving high accuracy in the identification of pneumonia is the study's most significant finding. This is a noteworthy discovery because it shows that deep learning models could be utilized to create tools that are accurate and trustworthy for the diagnosis of pneumonia.The fact that the model was able to achieve high sensitivity and specificity is another crucial discovery. In other words, the model proved effective at both identifying pneumonia in people who genuinely had the illness and at minimizing false positives.

4.CONCLUSION:

In this paper, a CNN-based model for diagnosing pneumonia on a collection of chest X-ray images is described. The following is a list of the contributions to this paper. To extract the features from the original pictures or earlier feature maps, which only had six layers total and combined ReLU activation function, drop operation, and max-pooling layers, we created a CNN model. Multiple comparisons of various input shapes and loss functions were offered to demonstrate the performance of our suggested model. The CNN-based model is a potential way to identify the condition using X-rays, according the description described above.

We have an idea of combining information from several imaging modalities with X-ray pictures. Combining data from several sources may result in a more complete picture of the illness and increase the precision of the diagnostic process. To enable the network to concentrate on the most important areas of the pictures, incorporate attention methods into the model design. The model's capacity to recognize minor patterns suggestive of pneumonia may be improved as a result. It can be easier to grasp the model and help physicians make better judgements if uncertainty estimates are provided along with forecasts. Models may be trained on bigger, more varied datasets that may encompass a range of demographics, age brackets, and geographic areas. We will carry out additional study in the future to investigate more precise categorization systems for the diagnosis of two forms of pneumonia, viruses and bacteria.

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