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Classification of Pneumonia using a Combined Approach of Image Processing and Deep Learning Algorithms

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Abstract

The process of classifying and identifying pixel groupings or vectors in an image according to particular rules is referred to as image classification. With the expeditious development of science and technology and people's higher and better demand for quality of life, image automatic classification technology has been applied to numerous fields of development. When we classify the image, the normal image classification technique cannot accurately grasp the inner relationship between the identified objects, in addition to that because of the too high characteristic dimension of the data the traditional method also has the limitation of the recognition object feature expression. Also, it is necessary to choose which features are essential in each given image. Therefore the experimental results were not ideal. Considering the above mentioned content, this paper proposes an image classification technique gleaned from the convolutional neural network. The appropriate Convolutional Neural Network Model which is also called CNN is chosen for the dataset. Bacterial Pneumonia has comparable signs and symptoms to viral pneumonia. The deep learning methods/models that are proposed, distinguish Bacterial pneumonia to viral pneumonia. The images were pre-processed and trained for countless categorizations like Normal, Bacterial Pneumonia, and Viral pneumonia. The models advanced as a part of this work achieved about 98% accuracy on a test dataset which consists of three hundred images.

Keywords— Image classification, Convolutional Neural Network, Vgg 16, ResNet50

I. INTRODUCTION

Pneumonia is a respiratory infection that is caused predominantly by the germs, infecting the lungs and causing inflammation of the air sacs which occurs when the lung fills with fluid.[1][2][5][10].Throughout history, epidemics and chronic diseases have killed a large number of people and produced huge emergencies that have forced people to abandon their long-term survival efforts[2]. According to a 2015 study, pneumonia was responsible for approximately 15.6 percent of the 5.9 million deaths of children under the age of five; early diagnosis and treatment could considerably reduce this mortality rate[5]. Pneumonia can come in a variety of sizes, shapes, and locations[1][2][6][8]. Its target contour is quite hazy, which makes detection difficult, and improving detection accuracy is a big research challenge[8]. Pneumonia is particularly common in undeveloped and underdeveloped countries, where overcrowding, pollution, and unsanitary environmental circumstances aggravate the problem, and medical resources are scarce[11]. As a result, early detection and treatment can help prevent the disease from progressing to a deadly stage[19]. Researchers, specialists, and organizations all over the globe have recently begun to use CAD systems that can rapidly process hundreds of X-ray and computed tomography (CT) images to aid in the identification and containment of pneumonia.[10]. Even for the most skilled and experienced clinicians, diagnosing pneumonia with X-ray images is a difficult task, as X-ray images have similar region information for other diseases, such as lung cancer. As a result, diagnosing pneumonia using traditional methods is time and energy expensive, and diagnosing whether a patient has pneumonia using a systematic process is impossible[9].

Computer-assisted diagnosis has the potential to improve efficiency and lead to more timely treatment[5][8][4]. As the number of patients infected with pneumonia disease rises, radiologists will find it increasingly difficult to complete the diagnostic process in the limited time available[14]. Medical image analysis is one of the foremost promising analysis topics, as it allows the diagnosis and decision-making of a variety of disorders, including covid-19[10]. As a result, in order to enrich, accelerate, and produce an accurate diagnosis, the interpretation of these images requires experience and many algorithms. Imaging modalities and deep learning (DL) have recently received a lot of attention and effort in the field of pulmonary disease[14]. The input layer, convolutional layers, pooling layers, full-connection layers, and output layer are the five layers of the DL neural network[15].

Many computer vision applications are very complex and difficult to be solved by a single algorithm. This requires the development of models by combining two or more of the algorithms studied[9]. The choice of model is based on the needs and characteristics of the problem. Ensemble models combine more than a single model to solve a given task. This methodology aims to overcome the weaknesses of the individual models and reinforce their strengths[20]. In the medical science field, ensemble models are currently used to perform prediction tasks (e.g., regression and classification). The single models that make up the set are trained independently to solve the given task. The final output of the composite model is the sum of the different outputs provided by the single model[8]. Furthermore, the composite model reduces prediction variance and generalization error and greatly improves computational training, and can be used with some training data[7]. In this context, DL models have achieved better performance in detecting and classifying lung disease and exhibiting high accuracy than previous modern methods[6].

II. RELATED WORK

Several strategies are introduced to elucidate a fast method in respiratory illness detection victimization chest X-ray pictures in recent years, particularly some deep learning methods[4].In 2021, Mahomet Farukh Hashmi, Satyarth Katiyar associated with Zong Woo Geem planned a singular approach that supported a weighted classifier is introduced, that mixes the weighted predictions from the progressive deep learning models like ResNet18, Xception, InceptionV3, DenseNet121, and MobileNetV3 in an optimal approach and so the accuracy was found to be 98%. In 2020, Md. Mehedi Hasan, Mir Md. Jahangir Kabir, Md. Rakibul Haque and Mohiuddin Ahmed proposed a Combined Approach with Image processing and Deep Learning to observe respiratory illness from Chest X-Ray pictures which Use each VGG-16 and VGG-19, variants of Deep Convolutional Neural networks for automatic detection of respiratory illness from Chest X-ray pictures and so the accuracy for VGG-16 is 95.2% AND VGG19 IS 96.4%[11]. In 2020 a project proposed focussing on Classifying respiratory illness using Transfer Learning was planned by Abdullah Irfan, Akash L. Adivishnu, Antonio Sze-To, Taher Dehkharghanian, who Investigated the employment of transfer learning to classify pneumonia[7]. 3 models, ResNet-50, Inception V3, and DensetNet121 were trained individually through transfer learning and from scratch, and conjointly the results were obtained as follows[4]

From scratch AUC ResNet50:0.46 Inception V3: 0.51 DenseNet121:0.57 Transfer learning: ResNet50:0.59

Inception V3: 0.55 Dense 121: 0.71. In 2020 Elene Firmeza Ohata, Gabriel genus Maia Bezerra, João Victor Souza das Chagas, Aloísio Vieira Lira Neto, Adriano Bessa Albuquerque, Victor-Marie Hugo C. de Albuquerque, and Pedro Pedrosa Rebouças Filho planned a title named as

Automatic Detection of COVID-19 using Chest X-Ray pictures using Transfer Learning where they applied MobileNet and Desnet201 model

15]. They applied the construct of transfer learning for this task and conjointly the accuracy and F1 score for MobileNet is 98.5% and DenseNet is 95.6%.[14]

III.BACKGROUND

In recent years, machine learning (ML) algorithms have gained experience, constantly improving accuracy and efficiency. this permits them to form better decisions[1]. As a result, these styles of algorithms shine at processing multidimensional and diverse data and is processed in dynamic or uncertain environments[2]. However, ML methods are very error-prone[1]. Choosing an algorithm in ML remains a manual task. All algorithms must run and test the information[2]. That way, we are the sole ones who can decide which algorithm must be implemented[4]. ML is often acting on data and so gets lots of knowledge for training and testing[6]. this will cause data inconsistencies.

In response to the above situation, LeCun proposed a CNN method that may automatically detect important functions without human supervision[7]. This tends to be more powerful and accurate thanks to solving classification problems[6]. This provides very high accuracy for image recognition problems[7]. The convolution layer transforms the input images and extracts features from them. With this conversion[8], the image is collapsed within the kernel (or filter). The kernel may be a small matrix that's smaller tall and width than the image to be convolved[9]. This kernel slides the peak and width of the image input and therefore the scalar product of the kernel and[8] also the image is calculated at each spatial position[10].Generally, the ReLu function is employed because of the activation function of the convolutional layer[13].

There are several approaches to pooling, but the foremost commonly used methods are Max pooling and Average Pooling[13]. With maximum pooling[14], the kernel extracts the most value of the collapsed area[14]. Max Pooling only tells the CNN to transfer information only [15]if it's the utmost information available about the amplitude within the kernel. In average pooling, layers work by selecting the common value of the weather available within the feature map kernel.[15] Basically, the whole feature map is sampled against the mean captured by the world of the feature map[16]. Therefore, maximum pooling provides the foremost prominent features of every kernel[17], and average pooling provides the common of the realm covered. Image classification automatically extracts image features because convolution[18], pooling, activation functions, and other fully connected layers are performed by continuous stacking. the photographs processed by the model then show if pneumonia is feasible by analyzing the extracted features[19]. It improves the generalizability of the model while taking full advantage of the pixel-level information within the image[19]. Over the previous few decades, with the immense development of deep learning, the subsequent CNN algorithms are proposed.

IV. METHODOLOGY OF PROPOSED MODEL

A. Data Collection:

Data can be an important input in deep learning problems. We have collected data primarily from two different and prominent online sources. We have collected pneumonia dataset from Kaggle contest. The dataset consists of three folders (Train, Test, Validation) and contains subfolders for each image category . There are 2930 X-rays (JPEG) and several categories (Bacterial pneumonia & Viral pneumonia). All chest x-rays were performed as part of the patient's routine clinical care. In the chest x-ray analysis, all chest x-rays were first screened for internal control by removing calibrated or unreadable scans. The diagnosis of the scanned image was evaluated by two experienced doctors before the AI system was trained.The scoring errors are rectified by third expert.

B. Image Preprocessing:

In most image classification tasks, the foremost purpose of employing a Convolutional Neural Network is to cut back the complexity of the model. the primary three-channel system The photos were shrunk pixels so as to suit the page. reducing the quantity of heavy calculation and with speedier processing everywhere, spread of other strategies are used. photos that are reduced in size.

C. Data Augmentation:

Data augmentation is an effective regularization approaches for preventing network overfitting and improving generalization performance. the info augmentation approaches generate more rich training data that has been changed from the first, allowing the trained network to generalize better to unknown test data.

D. Feature extraction:

Dimensional reduction process that breaks down oversized datasets into smaller groups. This makes the process easier. The fact that these huge datasets have so many variables is their best feature. Because there are various models such as VGG and ResNet. Let's explain the feature extraction of each model.

E. VGG16 Architecture:

First, the TensorFlowKerasVGG16 model is imported. The preprocessing input module is imported to properly scale the pixel values of the VGG16 model, and the image module is also imported to preprocess the image object. The NumPy module is used to process multidimensional array. The VGG16 is exclusive in this regard, focusing on the 3x3 filter convolution layer with step size 1 and always using the same padding and 2x2 filter step size 2 maximum pool layer instead of using a huge number of hyperparameters. Use the. Throughout the architecture, the convolution layer and the maximum pool layer are arranged in the same way. At the top are two fully connected layers followed by a softmax of the output. The 16 on the VGG16 hints at the fact that it has 16 layers of weight.

Model Architectures

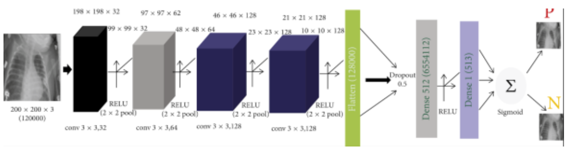

Figure 1.1: Proposed Methodology Architecture

The corridor is supplied with a fixed size 224 x 224 RGB image during training. The only pre-processing done here is to subtract the average RGB values derived from each pixel in the training set. The image is 3 x 3 (minimum size to capture the concept of left / right, top / bottom, center, 7x7 with the same effective receptive field combination). It is more complex, with more non-linearity and less parameters. The convolution filter can be thought of as a linear transformation of the input channel and is also used in one of each configuration. For 3 x 3 layer convolution, convolution steps and convolutional spatial padding. Both layer inputs are set to 1 pixel so that spatial resolution is maintained after convolution.Five max pooling layers follow part of the convolution layer to support spatial pooling. In step 2, a 22 pixel window is used to accomplish max pooling.

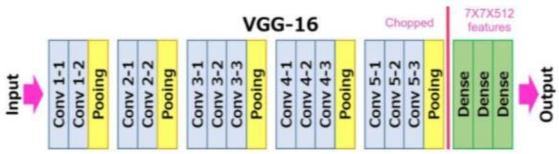

Figure 1.2: Architecture of VGG-16 Model.

F. ResNet Architecture:

Identity Block: Each layer in classic neural networks feeds into the following. Each layer feeds into the subsequent tier and straight into the amount 2–3 hops away in an exceedingly network with leftover blocks. that's all there's to that. But we'll consider understanding the reasoning behind why it absolutely was needed in the first place, why it is so vital, and the way it compares to other cutting-edge systems.

The ResNet-34 was the first ResNet architecture, and it involved converting an understandable network into its residual network counterpart by inserting shortcut connections inside it. Using three filters within the convolutional networks, VGG neural networks influenced the plain network in this instance. In comparison to VGGNets, ResNets are less complex and feature fewer filters. ResNets with 34 layers have 3 billion FLOPs, while ResNets with 18 layers have 1 billion

FLOPs. It also followed two simple design principles: for the same output feature map size, each layer had the same number of filters, and for the same time complexity per layer, the number of filters was doubled if the output feature map size was halved.

Resnet50: ResNet50 model is with 48 Convolutional layers, 1 MaxPooling layer, and 1 Average Pooling layer.While the Resnet50 architecture relies on the above paradigms, it does differ in one significant way because of concerns about the time required to coach the layers, the building block was redesigned into a bottleneck design during this situation.As a result, the Resnet 34 two-layer bottleneck blocks were replaced with Resnet 50 three-layer bottleneck blocks. In terms of accuracy, this model outperforms the 34-layer ResNet model.

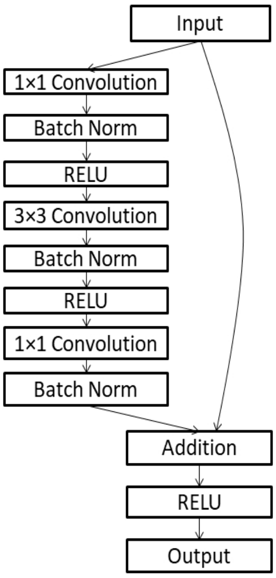

Figure 1.3: Residual Block

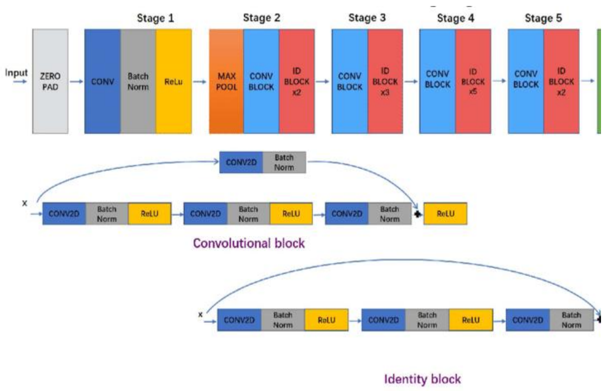

Figure 1.4: Architecture of ResNet50 Model

V. RESULTS

Parameters and hyperparameters have been significantly rotated to improve model performance. Various results have been obtained, but only the most definitive results are reported in this study. The developed model is used for detecting and categorizing pneumonia from chest X-rays taken with high verification accuracy. The algorithm starts by transforming the chest x-ray images to a size lesser than the actual size. The second step is to identify and classify the image with a convolutional neural network framework that extracts the image and classifies features from the image. The effectiveness of the trained model for the detection of respiratory disorder from chest x-rays has considerably inflated the validation accuracy of the model when compared to different approaches.To see the performance of the model, The process is repeated again and again and the same results were obtained every time. Resizing the training and validation datasets to validate the performance of the model that was trained with different x-ray image sizes yielded relatively similar results.

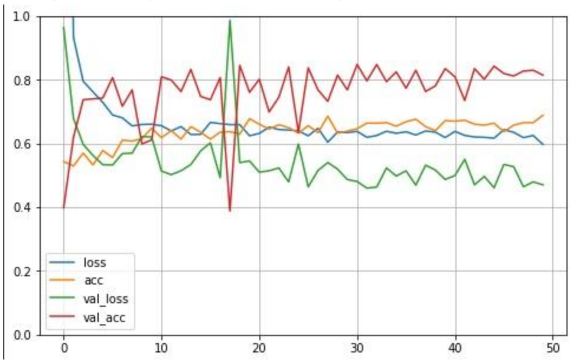

Figure 1.5: ResNet 50 Overall Result

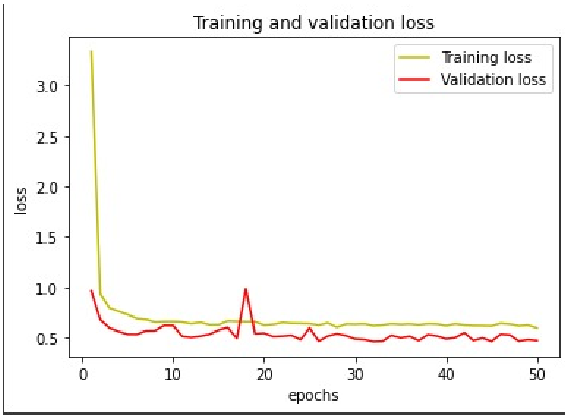

Figure 1.6: ResNet 50 Training and Validation Loss

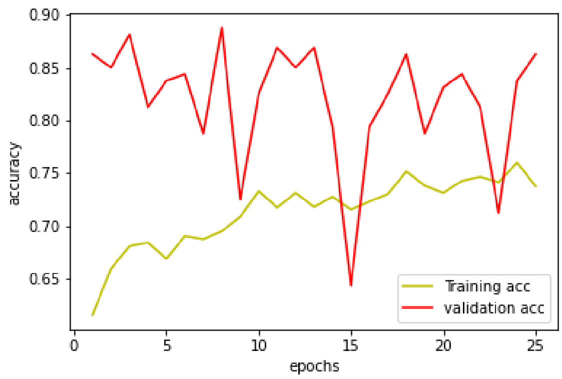

Figure 1.7: Vgg 16 Validation and Training Accuracy

Figure 1.8: Vgg 16 Training and Validation Loss

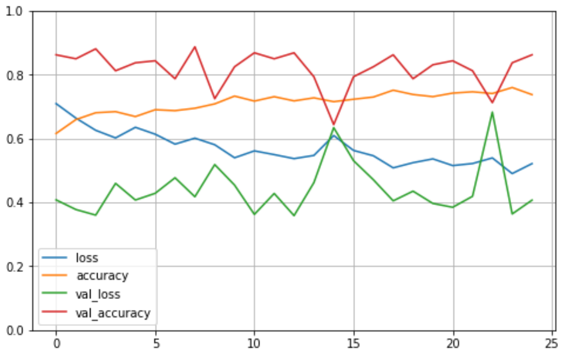

Figure 1.9: Overall VGG 16 Result

The final result obtained is training loss = 0.1289, training accuracy = 0.9541, verification loss: 0.1845, verification accuracy 0.9373. The CNN framework always requires a fixed-size image during training. X-ray photographs of 100x100x3, 150x150x3, 200x200x200x3, 250x250x3, 300x250x3 are required to show the verification performance of the model for various input data. The bigger the size of the converted image then lower the verification accuracy obtained. In contrast, the smaller the training image, the slightly better the validation accuracy. We proposed a 224x224x3 model. This is due to a minimum training loss of 0.1835, which improves verification accuracy by approximately 98%. This will greatly help improve the health of vulnerable children. Significant improvements can be made by improving data access and thereby training the model with radiation data from patients and non-patients across the globe.

VI. CONCLUSION

The presence of an experienced radiologist is the most important need for the proper diagnosis of pneumonia disease.Treatise is primarily aimed at improving medical literacy in the field of radiation therapists till it has limitations. Our study helps the early prognosis of pneumonia.Till now,a limited number of works has been done over the pneumonia dataset.Algorithms to be improved in this area have the capability to deliver large advantages to the availability of higher clinical services. We discovered the overall performance of various pre-trained CNN models and distinctive classifiers, based totally on the statistical results.hyperparameter optimization established which improves the overall performance.Comparison over existing proposed models like VGG,Resnet to validate the model Detection accuracy supposed to good if not the network would loses its functional information.future aim to provide higher classifier results over other retrained models by segmentation .Our research might result in the event of higher respiratory disease detection algorithms shortly

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