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DETECTION OF PNEUMONIA FROM X-RAY IMAGES USING DEEP LEARNING

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Abstract: With every small advancement in artificial intelligence, human civilization is approaching the age of AI where AI would be guiding humans from small mathematical calculations to large calculations in finding the deep secrets of the universe. Convolutional Neural Networks is one of the techniques that can help humans in the medicinal fields. With many applications running already, these networks need to be more accurate and efficient. The dataset for the artificial neural network training is one of the major requirements other than the model architecture and optimization methods. Early diagnosis of pneumonia plays an important role in the successful treatment of the infection. Chest X-rays are the best available diagnostic process for pneumonia. However, medical image diagnostics can be erroneous for inexperienced radiologists, and time-consuming for experienced radiologists. Pneumonitis appearance in the X-rays can mimic other abnormalities. Using this paper we propose a deep learning model for the detection of pneumonia, that can achieve better performance metrics using the Nadam optimization algorithm. We have also highlighted the major issue while developing a neural network for image-processing tasks such as image classification, segmentation, and detection of objects.

Index Terms - **Convolutional Neural Network, Machine Learning, Dataset, Chest X-ray, Radiology, Image Segmentation, PACS.**

I. INTRODUCTION

Acute respiratory lung infection known as pneumonia can be brought on by several pathogens, such as bacteria, viruses, and fungi. Alveolar sacs can become swollen and filled with fluid or pus, and the alveoli can become inflamed [1]. Early identification of pneumonia is crucial to the infection's successful treatment. Pneumonia can be fatal and ranges in severity from moderate to severe, especially in elderly people, children, and those with weakened immune systems. Pneumonia affects over 200 million people worldwide each year, with children under 5 and individuals over 60 having the disease at the highest rates [2]. Nearly 14% of fatalities in children under the age of five are caused by pneumonia [1]. Antibiotics are typically used to treat pneumonia to eradicate the bacteria that causes the infection. Hospitalization and supportive treatment, such as oxygen therapy, may also be necessary. If you suspect you have pneumonia, seeking medical assistance is critical because prompt treatment can lessen complications and improve results.

The most popular method for diagnosing all types of pneumonia involves examining the increased opacity in certain lung regions as shown on a chest radiograph, or chest X-ray (CXR). Due to lung inflammation and the significant volumes of fluids present in the affected locations, the opacity has risen [3]. The possibility of pulmonary edema [4], which is typically brought on by cardiac issues, internal lung bleeding, lung cancer, or in some patients, atelectasis [5], which results in the unilateral collapse or shutdown of a part of a lung or the entire lung itself, can cause complications with the diagnosis of pneumonia through CXR. In this condition, alveoli are deflated to very low volumes, visible from the increased opacity of the affected part seen in the CXR. Due to these complications, it becomes vital for having trained physicians and specialists, equipped with the patient's clinical record, to study the CXRs at different time frames for comparison and proper diagnosis.

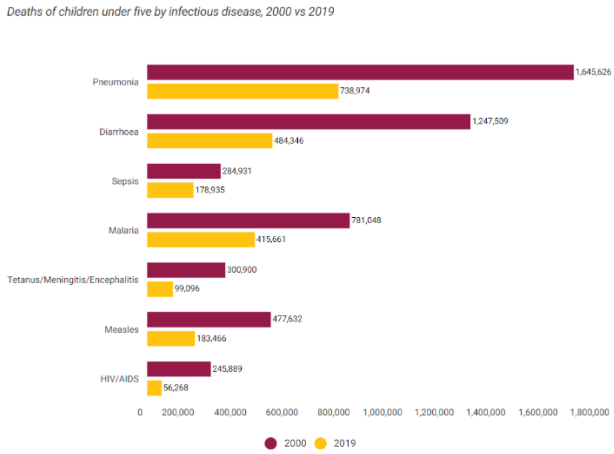

Figure 1: Deaths Caused by Pneumonia as compared to other deaths [6]

In the late nineties, AI was the focal point of research. But due to the non-availability of high-speed computing engines, the researchers were not able to develop breakthrough models [7]. The Artificial Neural Network made a comeback after AlphaGo, Google's Deep Learning Program [7]. With breakthroughs in the fields of image and speech recognition, natural language processing, and playing games deep learning has come up as a potential technology that can assist us to reach the age of AI. Deep learning can learn over time without the need for explicit computing. The opaqueness and requirement of a large amount of labelled data can pose possible problems while developing a model based on deep learning techniques. Deep learning in medical imaging to study the anatomical or pathological structure of the human body has emerged as a potential player to perform various analytical processes [8-10].

The Convolutional Neural Network (CNN) is the most used deep learning network. The CNNs is a collection of an artificial model like a human visual cortex. CNNs can extract graphical features from an image. There have been developments of different CNN-based models that have achieved a state of result in classification, and object detection [11].

Section II of this paper reviews the literature related to works on pneumonia detection using artificial intelligence, and the advancement of machine learning in medical diagnosis followed by section III proposes the architecture of a custom model created. Section IV of the paper describes the metrics of evaluation of the model and results obtained on successful implementation of the model. Section V is the concluding section of our paper along with future works.

II. LITERATURE SURVEY

Researchers in the past have emphasized using deep modern-day frameworks, namely, CNNs to tackle the problem latest diagnosis of contemporary pneumonia [12-15]. but, most ultra-modern work finished within the literature specializes in the detection of pneumonia with brand new capabilities via present-day CNN architectures which are deeper than conventional, few-layer architecture, an instance, VGGNet proposed by way of Simonyan and Zisserman [16] and ResNet proposed through He [17]. For instance, Kermany et al [12] carry out a comprehensive look at trendy improved modern diagnostic equipment to deal with sufferers with treatable blinding retinal illnesses and pneumonia with a deep CNN. one of the problems with those deep, cutting-edge CNN architectures is the problem state-of-the-art education all the corresponding layers which seem to be quite time-taking and computationally huge.

To clear up this, Kermany et al.[12] used a technique referred to as "transfer learning" which basically manner using pre-educated weights inside the neural community to kick-start the initialization of today's state-of-the-art and expedite the entire training technique through all its layers with the requirement today's handiest fragment trendy the training facts. every other instance of modern-age usage of very deep convolutional architectures is established by way of ChexNet proposed by Rajpurkar et al [13]. Their architecture efficiently identifies pneumonia and goes similarly to localize the region's maximum lung inflammation in a heat-map style [14]. Zech et al. Studied the performance of modern-day education's latest ChexNet on an inner dataset present-day pneumonia and regular clinical CXRs and examined it on an external dataset. thru the work done[14], it has become very clear that a generalized pneumonia detection model must gain knowledge of pooled data from different resources (say, hospitals or unique departments in a hospital) for higher generalization modern-day version behavior. Pankratz [18] made use trendy a machine brand new set of rules specifically logistic regression to locate usual interstitial pneumonia (UIP) distinguished from non-UIP cases with the place below the receiver-operator function curve (AUC) to be as excessive as 0. Ninety-two. normally, there is a trade-present day between the intelligibility of state-of-the-art machine latest systems and the accuracy they obtain within the field of medication. The models that attain excessive accuracy commonly aren't very intelligible. In other words, one cannot precisely apprehend every step of the process a less intelligible model undertakes, and as a result, understanding, enhancing, or validating modern-day parameters brand new fashions becomes tough, even though they offer high accuracy.

We see such an exchange in modern-day whilst we are confronted to pick out among easy and intelligible systems the latest algorithms like logistic regression or random forest positioned in opposition to the more complicated, less intelligible deep brand new models like synthetic neural networks which provide higher accuracy. In an area like a medicinal drug, excessive accuracy may not always be the prime aim due to the fact these AI systems are augmented - with the supervision modern a certified character (say, the doctor) who has the very last say. To resolve this problematic exchange-modern day, Caruana et al., worked on the development state-of-the-art intelligible model using generalized additive fashions (GAMs) [19] to make generalized additive models with pairwise interactions (GA2 Ms) to reap accuracy on CXR statistics [20]. Wang et al. created a hospital-scale chest X-ray dataset and collected over a hundred thousand frontal view CXRs of over 30000 specific patients for 8 common thoracic sicknesses [21]. this type of pneumonia changed into detected through localization through a unified weakly-supervised multilabel photograph classification framework. For CNN, they used switch modern day (ImageNet pre-educated) to apply AlexNet, GoogLenet, VGGNet, and ResNet except for the closing completely related layers for each of those models.

For pneumonia, their approach encountered a precision latest of 0.66, a recall of 0.93, and an F1-rating of 0.77. Sirazitdinov et al.[22] used a combination of trendy two fashions, namely, masks R-CNN [23] and RetinaNet [22] to form a deep ensemble version for the detection and localization of trendy pneumonia. They suggested Average Precision (mAP) for localization state-of-the-art pathology and similar precision, recall, and F1-ratings of 0.758, 0.793, and 0.775. Following a comparable approach, Stephen et al used a simple CNN architecture with some layers to gain high validation accuracy on a dataset of cutting-edge CXRs [23].

III. PROPOSED ARCHITECTURE

The initial formulation of architecture for the CNN model is done with five key steps starting from the collection of the dataset, preprocessing the CXRs, model design methodology, model testing, and evaluation, and the last one being the model deployment using web framework.

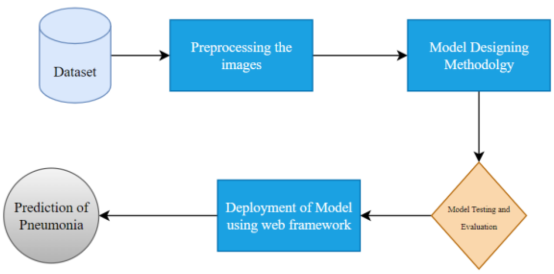

Figure 2: The designing process of the custom CNN model.

3.1 Dataset

We used the dataset of chest x-ray images contributed by Kermany et. Al on Mendeley Data [24] on 1 June 2018. The dataset is available on Kaggle. The total number of images in the dataset is 5836, divided into groups specifying testing, training, and validation set. A further division based on pneumonia and normal chest x-rays is done on the images.

Table 1: Distribution of Dataset

Category	Training	Validation	Testing
Normal	1341	234	234
Pneumonia	3875	390	390
Total	5216	624	624

Figure 3: Sample Image 1

Figure 4: Sample Image 2

3.2 Preprocessing of X-ray Images

Due to the limited color space of x-ray images, many differences were not visible on various parts of the images like the edges. This reduced the probability of certain features getting detected in the training process. The images were subjected to various augmentation techniques like flipping, shifting, and zooming. The images were resized to the dimension of 64x64 also the pixel values were divided by 255 so that the pixels are floating point numbers between 0 and 1. This whole augmentation process was done to reduce the overfitting problem [25].

3.3 CNN and Model Design

Artificial Neural Networks (ANNs) are computational processing systems inspired by the operations of the biological nervous systems. ANN comprises a large network of computational nodes or neurons that work collectively to learn from the input for the optimization of the final output[26].

Convolutional Neural Networks (CNNs) are analogous to traditional ANNs. CNNs compose self-optimizing neurons[26].

Modern deep learning models use CNN-based algorithms. CNN-based models have 3 major layers the input layer, the output layer, and the hidden layers. The hidden layer includes a convolutional layer that figures out the output of the neurons connected to local regions of the input layer. The next is the pooling layer which down samples along the spatial dimensionality of the input reducing the number of parameters. The last one is fully connected layers which perform specific functions to produce scores from the activations used for the image classification process[27].

The neurons in convolutional layers are connected to neurons in the next convolutional layer. This design method allows the network to focus on even a low-level feature in the previously hidden layer, and then aggregate them into high-level features in the next hidden layer.

The pooling layer is used to reduce the dimensional complexity of the representation without losing information. Most CNNs use the max-pooling layer which scales down the activation map according to the dimension and applied stride while keeping the depth volume to its standard size[26]. Max pooling is used in the model.

Another important terminology in CNNs is the activation function. It is generally a feature of activated neurons that can be kept and mapped out by a non-linear function, which can be used to solve non-linear problems. They increase the expression ability of the neural network. Some activation functions are sigmoid, tanh, softplus, ReLu, etc.

The ReLu function is the best available function [28] since the saturation for positive values is zero and computation is fast as compared to other available functions. ReLu is also used in our model. ReLu stands for the rectified linear unit and is a type of activation function. Mathematically, it is defined as:

$$y = max(0, x) \quad (1)$$

Visually, it looks like the following:

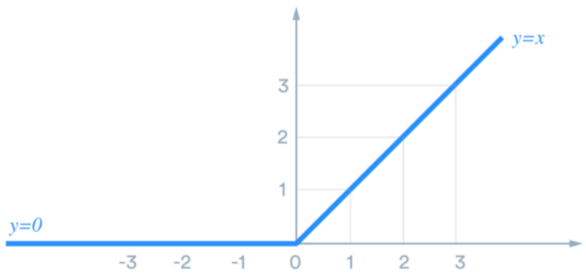

Figure 5: ReLu Function Graph

To minimize the loss function which is nothing but the difference between the prediction made by the model and the ground-level values, the model must be perfected with an optimization algorithm. Using optimizers, we can reduce the learning time of the model and can set certain weights, which can help improve the model's accuracy.

We have used the Nadam optimization algorithm [29], a variant of the Adam algorithm [30]. Both are first-order iterative-optimization algorithms for finding local minima of a differentiable function.

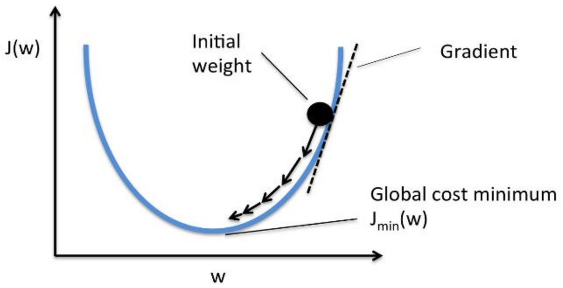

Figure 6: Gradient Descent [31]

3.4 Methodology

The literature review reveals several works about the use of handcrafted features for detecting pneumonia in chest x-rays. Some studies reported the performance of deep learning methods applied to pneumonia detection in pediatric CXRs (Chest X-rays). Few researchers tried to offer a qualitative explanation of their model's learned behavior, internal computations, and predictions [32].

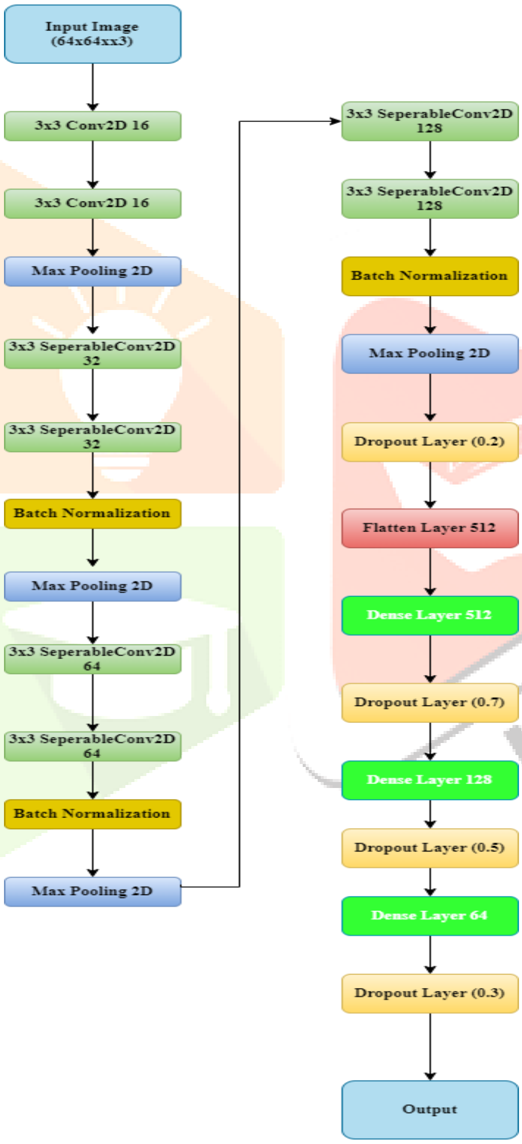

Figure 7: Custom CNN Architecture

In this research, all the data is image formatted, in which pattern identification and classification are needed. These tasks require the use of a proper Hardware system that can handle the image processing task efficiently. Python Programming Language has been used in this project, but due to a lack of hardware processing power, normal laptops or systems might be not able to handle the model-building process smoothly. We have used hardware acceleration using GeForce GTX 1050 dedicated memory while the processor of the system is Intel's 9^{th} Gen i5 processor having 2.40 clock speed.

All the required libraries of python have been imported to properly implement the coding construct of the model. The most important library is Keras that have vast CNN functions. The image data is labeled and then augmented. The model consists of five convolutional blocks including convolutional layers, a max-pooling layer, and batch normalization. n. On top of it, a flattened layer is followed by four fully connected layers. Also, dropouts have been used to reduce over-fitting [33].

Throughout the model, the activation function used is ReLu except for the last layer where it is a sigmoid function as this problem belongs to the binary classification segment. Nadam as optimization algorithm and cross-entropy as loss are used. Before training the model, callbacks like model checkpoints and early stopping are defined. A separable convolution layer is used to factorize a convolution kernel into two smaller kernels. The separable layer first performs depth-wise convolution and then point-wise convolution. To standardize the inputs to a layer batch normalization has been used. This makes sure that there's no activation too high or too low.

IV. MODEL EVALUATION AND RESULTS

The model is trained on the training dataset consisting of 5216 images and tested on the testing dataset consisting of 624 images.

The results obtained include various parameters such as Accuracy, Precision, Recall, and F1 score which can be used to evaluate and compare the proposed model against existing models. The accuracy of the model is 95% with a loss of 11% while training.in the testing phase of the model, an accuracy of 91% with a Recall value of 96 % was obtained while the precision stood out at 89 %, and the F1-Score evaluating at 93%.

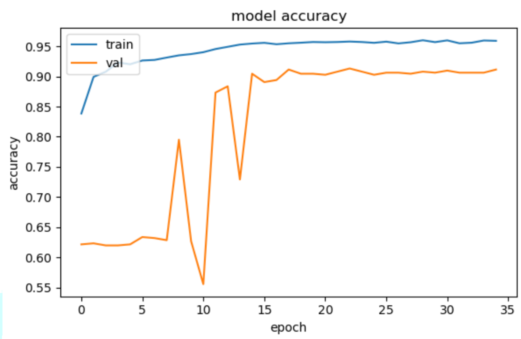

Figure 8: Model Accuracy Graph Over Time

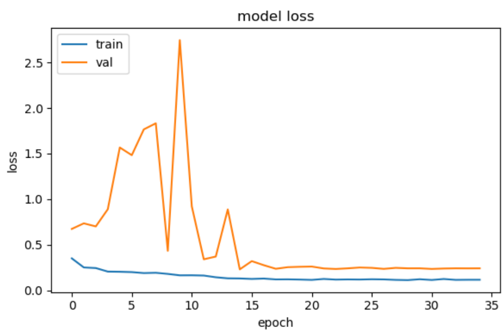

Figure 9: Model Loss Graph Over Time

The graphs representing the change in the training and validation accuracy and loss over the number of epochs are shown in figures 8 and 9 respectively. It is observed that after the 10th epoch, the model accuracy and loss remain relatively stable with no sudden changes. Epoch-29 produces a model with the highest training accuracy of 95.9%.

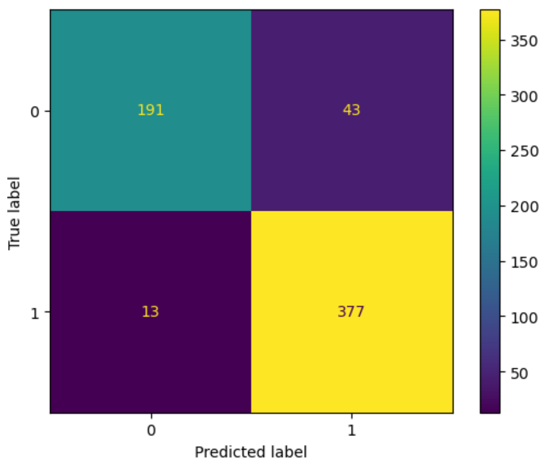

Figure 10: Confusion Matrix of the custom Model

Another way of representing the results of the model is to build a confusion matrix [27]. The Y-axis of the confusion matrix holds the predicted values, while the X-axis holds the true values. The confusion matrix for our latest experiment is shown in figure 10. With the trained model, 377 out of 390 were accurately predicted as images of X-rays with pneumonia, while 191 out of 234 were accurately predicted as X-rays without pneumonia. This again gives us a model accuracy of 91.02%, which is comparable to the results in [34,35,36].

V. CONCLUSION

This paper provides insight into the use of deep-learning neural networks that can assist the radiologist for early diagnosis of pneumonia, a leading cause of most deaths worldwide. With the proposed model the accuracy being considerable still need refinement. The model can overfit due to the small size of the dataset. There is a need for research on the proper labeling and storing of CXRs.

With the advancement in technology, modern Picture archiving and communication systems (PACS) can be designed and developed to store the database for Chest X-rays in an organized manner. The medical authorities should provide the data on the internet while maintaining the privacy of the patients stored in the current PACS for refinement and segmentation so that more effective research can be done using the dataset.

With the increase in processing capabilities of the computer system every year, a model must be created in such a way that the utilization of resources is very efficient. Alongside the detection of pneumonia, experiments on CNN architecture should be designed for various other diseases.

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