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Pneumonia Classification using Deep Learning in Healthcare

Garima Verma, Shiva Prakash

***Abstract**: There is a great growing interest in the domain of deep learning techniques for identifying and classifying images with various datasets. An enormous availability of datasets (e.g. ChestX-Ray14 dataset) has developed a keen interest in deep learning. Pneumonia is a disease that is caused by various bacteria, virus etc. X-ray is one of the major diagnosis tools for diagnosing pneumonia. This research work mainly proposes a convolutional neural system (CNN) model prepared without any preparation to group and identify the occurrence of pneumonia disease from a given assortment of chest X-ray image tests. Dissimilar to different strategies that depend exclusively on more learning draws near or conventional carefully assembled systems to accomplish an amazing grouping execution, and developed a convolutional neural arrange model without any preparation to separate and character the images to decide whether an individual is suffering with pneumonia. This model could help alleviate the dependability and difficult challenges frequently confronted to manage therapeutic problems. In this paper, CNN algorithm has been used along with different data augmentation techniques for improving the classification accuracies which has been discussed to increase the performance which will help in improving the validation and training accuracies and characterization of exactness of the CNN model and accomplished various results. This experiment was carried out using python language and has shown improved outcomes.*

***Keywords:** Deep Learning, CNN (Convolution Neural Network), Architecture, Data Preprocessing, Data Augmentation.*

I. INTRODUCTION

Deep Learning (DL) methods are vanquishing over the predominant customary methodologies of neural system, with regards to the tremendous measure of dataset, applications requiring complex capacities requesting increment precision with lower time complexities. It is a fact that the disease like pneumonia is spreading very vast and also its threat is very tremendous and causing a barrier in developing a disease free nation. It has been predicted by WHO that 4 million sudden misfortunes happen each year from nuclear family air tainting diseases, maximum people are suffering from pneumonia disease [1]. Also, it has been found in a survey that approx. 160 million people were suffered from pneumonia in which there were children of under 5 years of age [2].

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* Correspondence Author

Garima Verma*, Department of Information Technology and Computer Application Madan Mohan Malaviya University of Technology, Gorakhpur, India. E-mail:garimaverma311016@gmail.com

Shiva Prakash, Department of Information Technology and Computer Application Madan Mohan Malaviya University of Technology, Gorakhpur, India. E-mail:shiva_pkec@yahoo.com

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In such territories, the issue can be moreover bothered on account of the insufficiency o helpful resources and staff.

A survey on Africa has depicted about various nations which were effected from pneumonia [3][4]. For different types of people, this technique proves to be one of the best techniques which imply the best treatment of the pneumonia disease with effective results. Previously, various models and architectures were designed for the evaluation of such kind of diseases. Various types of experimental strategies were attempted in order to get the best results out of the all other methods. But the techniques used for detecting and diagnosing such types of diseases are time consuming. The deep learning techniques are mainly part of the artificial neural networks which acquires great power and versatility for the learning process.

To avoid all kinds of issues, a new anyway essential model is familiar with thusly perform perfect gathering endeavors with significant neural framework building. The neural network building was unequivocally expected for pneumonia diagnosis and then classifying the images. The proposed methodology relies upon the convolutional neural framework computation, utilizing various numbers of neurons for convolving on a given picture and concentrate appropriate features from them. This paper presents great feasibility in several aspects as the purpose of combination was coordinated and differentiated and also for improving the pneumonia diagnosing frameworks. Starting late, CNN-energized significant learning estimations have gotten the standard choice for remedial picture orders in spite of the way that the top tier CNN-based course of action methodology present equivalent centered framework structures of the experimentation system. U-Net [5], Seg-Net [6], and Cardiac-Net [7] are a segment of the indisputable plans for remedial picture evaluation. There were several models used as formative based computations [8] and bolster learning (RL) have [9] been familiar with discover perfect framework hyper parameters during getting ready. In any case, these methodologies are very computational, which includes tremendous measure of planning. Using another option, our assessment introduced a hypothetically essential and beneficial framework model to manage the difficulties associated with pneumonia request issue. CNNs are usually more preferred over DNNs by having a visual taking care of plan which is equal and incredibly improved structure for managing pictures and 2D and 3D objects, similarly as ability for isolating dynamic 2D incorporates by using various learning approaches. The CNN contains the huge pooling layer framework which is convincing alive and well digestions and contains pitiful affiliations identified with tied burdens.

When differentiated from totally related (FC) frameworks of corresponding size, CNNs have an amazingly smaller proportion of parameters. Specifically, inclination based learning counts are used in getting ready CNNs; what's more, they are less disposed to diminishing slant issue. Since the incline based estimation is at risk for setting up the whole framework in order to direct diminish a screw up standard, outstandingly improved burdens can be conveyed by CNNs. It is one of the most critical and tedious task to work with X-ray image datasets. Therefore, many researchers have given various algorithms and techniques for image classification and disease diagnosis. Machine learning is a trending and promising domain in the artificial intelligence field.

Convolutional Neural Networks (CNNs) consists of various types of layers along with the max pooling layer. It also contains the RELU called as Rectified Linear Unit which helps in ensuring for the non-linearity of the network model. They are not much different from the ANNs. CNN is one of the most popular deep learning neural networks. The first time when CNN came into existence was 2012 when AlexNet was introduced with just 8 layers. Further, it was improved to 152 layers. CNN is mostly used for all the image related problems. One of the most important reason for using the CNN technique was that it helps in the automatic detection of important features without any human involvement. CNN technique is very effective and computationally efficient as it uses various layers and helps in parameter sharing.

The subsequent explanation is halting or decreasing the impacts of over fitting. Over fitting is fundamentally when a system can't adapt successfully because of a number of reasons. It is a significant idea of most, if not all AI algorithms and it is significant that each precautionary measure is taken as to lessen its effects. A model should be designed using such considerations that it should reduce the problems of overfitting and underfitting and also it should have the generalizability property for being in the best model category. Using minimum parameters, there will be less chances of the model that it will undergo in overfitting problems and eventually it will help in improving the overall prescient presentation of the architectural model.

Further, the paper has been divided into following sections: Section II describes the various works done in the domain of deep learning using CNNs. Section III denotes the CNN architecture which is used in the proposed mode. Then, Section IV discusses the various functions of the layers used in the CNN architectural model. Section V describes the various materials and methods used in the experimentation of the proposed architecture like dataset used, images etc. Section VI clearly mentions the various results of the proposed architecture. Then, Section VII discusses some important applications of using CNNs in the day-to-day life models. Section VIII discusses the various research challenges of using the CNN framework. At last, Section IX concludes the paper with the basic idea of using the CNNs in the future aspects.

II. LITERATURE REVIEW

Several new frameworks and designs using various learning models have been developed along with infinite datasets have helped counts to beat restorative work power in different remedial imaging assignments, for instance, skin threatening development portrayal [11], channel unmistakable confirmation [12], arrhythmia disclosure [13], and macular diabetic retinopathy distinguishing proof [14]. Robotized examine using chest radiographs have gotten creating interests. These counts are dynamically being used for driving lung handle recognizable proof [15] and pneumonic tuberculosis course of action [16]. .e execution of a couple convolutional models on different varieties from the standard relying upon the uninhibitedly available Open I dataset [17] found that a comparative significant convolutional mastermind configuration doesn't perform well over all peculiarities [18], outfit models basically improved gathering precision when differentiated and individual model, therefore, other types of limited learning method will help to improve the accuracy when stood out from rule based procedures. Truthful dependence occurring in names [19] has been gathered to reach at dynamically definite conjectures; thusly beating various strategies on given 13 pictures looked over 14 distinct classes [20]. Estimations for separating and foreseeing names radiating from different radiology pictures similarly as reports have been inspected [21–23], yet the image names were generally obliged to illness names, thusly missing sensible information. Area of diseases from X-shaft pictures was reviewed in [24], portrayals on picture sees from chest X-bar were finished in [21], and body parts division from chest X-bar pictures and figured tomography operations were implemented in [23]. Then again, taking in picture features from substance and making picture portrayals relative with what a human would depict are yet to be mishandled.

In PC vision, profound learning has just indicated its capacity for picture arrangement with superhuman precision. What's more, the therapeutic picture handling field is strikingly investigating profound learning. Be that as it may, one significant issue in the medicinal space is the accessibility of huge datasets with solid ground-truth explanation. In this manner, move learning draws near, as proposed by Bar et al.6, were frequently considered to defeat such issues.

In various types of learning techniques, CNN proved to be one of the best algorithms for image classification, analysis, segmentation and other tasks [25]. One of the latest supercomputer discovered is Nvidia DGX2 which has enhanced the performance of several CNN classification methods. But there is still problem when the CNN architectures are consuming large resources for computation purpose and also overhead [26-28]. Various types of hardware accelerators and their architectures are discussed in [29] for reducing the power consumption and large overheads. An example of such accelerator is FGPA discussed in [30] for minimizing power consumption.

Further, using the modern techniques, some hardware related models were introduced in [31]. The modern research also relies on the various optimization techniques. Genetic Algorithms are one of the most advance optimization techniques for the researchers having large hyper parameters discussed in [32].

Recently, a study says that Google introduced GPipe which is a machine learning libraryfor training the data in a parallel way [33]. ID-CNNs are one of the recent advance technique which is able to perform better feature extraction in an efficient way but it is mostly suitable for the sequential data [34]. Recently, many data scientists have proved that using CNNs in Deep Learning will improve the performance of the algorithms and theses scientists have used energy physics for the particle collision analysis in energy physics which has shown great results [35]. Therefore, CNNs have proved very efficient in classification tasks used in Deep Learning.

III. CNN ARCHITECTURE

CNNs basically center on the premise that the info will be included pictures. Such architectures would help in managing different types of data using various datasets. Fig 1 shows the flow diagram of all the layers that how each process works step by step. The major key contrasts is that the neurons present inside the CNN model are involved neurons composed into three measurements, the spatial dimensionality of the info (stature and the width) and the profundity. The profundity doesn't allude to the all out number of layers inside the ANN, yet the third element of an initiation volume. Not at all like standard ANNS, the neurons inside some random layer will just associate with a little area of the layer going before it. CNNs are contained three sorts of layers. These are convolutional layers pooling layers and completely associated layers. At the point when these layers are stacked, a CNN technique has been framed. The working of the CNN model has been categorized into four main functions as given below:

1. Firstly, there is an input layer which is used for holding the pixel values of the image.
2. Then, the convolution layer is there which helps in determining the output of several neurons and these neurons are being connected to the local regions. Then, the further calculation is being done by scalar product between their weights and with the regions which is connected to the input volume. After this the Rectified Linear Unit (ReLu) is there which has a function of applying an activation function which is done element wise like sigmoid function to the output which is produced by the activation of the previous layer.
3. Then, the pooling layer is there which is used to down sample the spatial dimensionality of the input and then it reduces the various parameters and shorten the image sometimes to its half within that activation.
4. The fully connected layers help in producing the various scores obtained from the activations. The main aim of this layer is that it takes the results from the convolution or pooling layer and then us that result to classify the image into a form of label. After this they pass the obtained result to the output layer, where each neuron will represent a classification label.

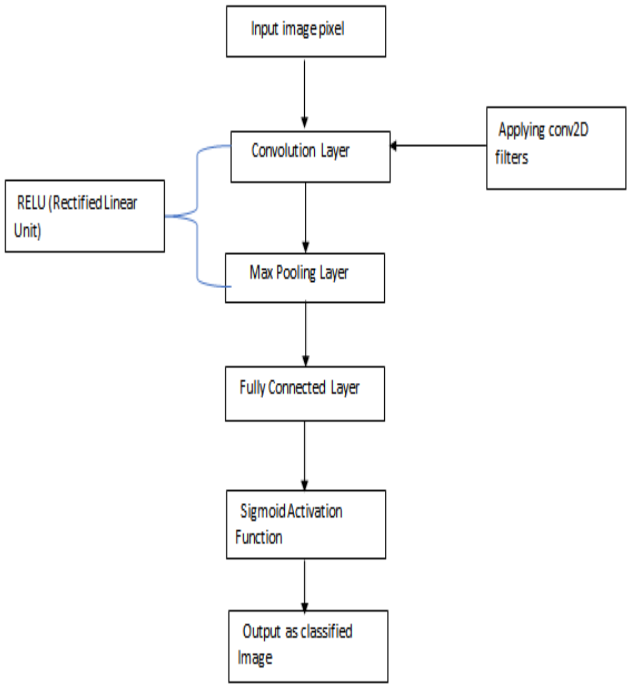


Fig 1. Flowchart of CNN Model

The above flowchart mainly shows the flow mechanism of how the images are being processing. Therefore, this method of transforming an input image into various down sampled elements and then applying several filters on to the image will improve the classification accuracy to a greater extent.

IV. FUNCTIONS OF CNN LAYERS

1. Convolutional Layer- This layer mainly focuses on how the CNNs operate and works. The major parameters of this layer mainly focus on the use of learnable kernels. The kernels here are small in dimensionality. Whenever the data hits any convolutional layer, the layer convolves each filter across the spatial dimensionality of the input and produces a 2D activation map. These maps contain the pixel values of the image. The convolutional layers can easily reduce the complexity of any model by optimizing the output produced. This process of optimization can be done using three main hyper parameters, depth, stride and zero padding. By using these, three parameters, we can easily reduce the size and dimensionality of the parameters of convolutional layers output. We can use this formula for applying these parameters given by Keiron O' Shea[31]

$(I-R)+2P/(S+1)$ 2.S +

Where I represent the input size, R is the receptive field size, P is the amount of adding zero padding and S is the stride.

3. Pooling Layer- The layer which is mainly responsible for lessening the overall features and dimensionality of the represented image and further, this layer performs various operations which results in lessening the complexity and parameters of the input images. It performs over activation map of the input and then scales out the dimensionality by using the MAX function.

The max pooling layer helps in reducing the activation map around 25% from its original size but maintains its depth volume. There are two types of main pooling used in CNN architecture as overlapping pooling and general pooling.

4. **Fully Connected Layer-** In this, each neuron o every layer is connected with previous layer's neurons. This layer helps in producing the output from the extracted features and then forwarding it to the output layer.

V. MATERIALS AND METHODS

In this paper, We have gone through the detailed evaluation and experiments for the effective results of the proposed model. We have performed our experiments for testing the effectiveness of the model which was based on chest X-ray image dataset that is proposed in [29]. We have used Keras which is an open-source neural network library in deep learning having tensorflow backend.

A. Problem Setting

The problem statement for this classification problem mainly consists of chest X-rays dataset and classifying the images with the help of various data augmentation techniques. There are different images which belong to various classes and it becomes very difficult to classify those images correctly on the basis of their features and properties. Also, the main problems to characterize the features of the images and them classify them with improved accuracy and also having less loss of data.

Therefore, in the classification process, it is very much essential that the data should not loss. Otherwise, it becomes very difficult to classify the images correctly.

B. Datasets

The dataset consists of main three folders that is training, testing and validations folders having a total images 5836 in numbers. Further, these folders are subdivided into two subfolders as pneumonia and normal folders. The Data Augmentation techniques have helped to perform various types of operations in the images. Images are having images of anterior and posterior chests and they are precisely chosen from retrospective pediatric patients is in between 1 to 6 years. This experiment was conducted to improve the validation accuracy and minimizing the validation loss. The main goal is to obtain the classified images of pneumonia patients using this chest X-ray dataset. In order to maintain the proportion of several data, the original dataset having training and validation sets is modified. Therefore, the training and validation data has been rearranged. There are total of 3628 images that were allocated to the training set and 2208 images allocated to validation set. This modification has helped to improve the validation accuracy to a great extent.

Table 1 Chest X-Ray Images

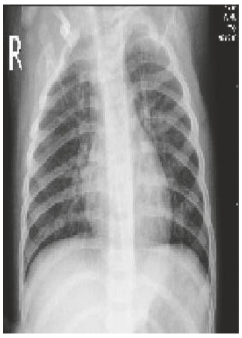
Sample Images With No Pneumonia		
Sample Images With Pneumonia		

Table 1 denotes the sample images present in the dataset of Chest X-ray images. The classification operation is being performed on the various classes of chest x-ray images. In this, the classes are divided into various sub classes in which two categories of images are present. One category is of images having pneumonia and other category is the images not having pneumonia disease.

C. Preprocessing

This process mainly involves the transformation of the raw data before it is fed to the deep learning algorithm. When the dataset is collected from various resources, it is gathered in raw format. At this stage, the raw image is not feasible for the analysis and therefore there is a need of preprocessing. It is the way toward changing every data test from multiple points of view and including the entirety of the enlarged examples to the dataset. By doing this one can expand the successful size of the dataset. Changes to apply are generally picked arbitrarily from the predefined set.

D. Data Augmentation

This technique is basically used to enable the researchers for enhancing the data diversity for various data models. Data augmentation techniques involves cropping of data, shifting the data, rotating, padding, flipping etc. and these techniques are used to train the neural networks.

In the proposed approach, various data augmentation techniques are being used. The first operation used here is Rescale of 1/255. Then, the next operation is Rotation of 45 degree of images. Further width shift and height shifts of 0.2 is used. Further, the operations used are shear range, zoom range, and horizontal flip.

At the point when we feed picture information into a neural system, there are a few highlights of the pictures that we might want the neural system to consolidate or abridge into a lot of numbers or loads.

On account of picture characterization, these highlights or flag are the pixels which make up the item in the image. Then again, there are highlights of the pictures that we dislike the neural system to consolidate in its outline of the pictures (the synopsis is the arrangement of loads). On account of picture characterization, these highlights or clamor are the pixels which structure the foundation in the image. Data augmentation will help to perform various operations on the data for enhancing the classification accuracy of the images.

This technique helps to improve and add some effective knowledge about the data for better results. Shapes of the images are altered, flipped, changed for getting the proper knowledge of the images. Augmentation also helps in creating the multiple versions of the same images which will in turn enhance the size of the training set. This will help in generalizing the data by improving the efficiency if the training dataset.

Table 2: Image Augmentation Settings

Operations	Values
Zoom range	0.2
Rotation	45
Width-Shift	0.2
Height-Shift	0.2
Flip-Horizontal	True
Flip-Vertical	True
Re-scale	1/255
Range-Shear	0.2

E. Model

Here, Fig 3 basically represents the complete architecture of the CNN model which is merely divided into several layers. These layers are referred to as the dense layers. It is also having a classifier called as Sigmoid Activation Function. The output of each layer is being forwarded in the next proceeding layer as its input in all the feature extraction layers. The proposed CNN architecture is having combination of several layers like Convolution layers, max pooling and various classification layers.

The layers for feature extractors consists of conv3×3, 32, conv3×3, 32, conv3×3, 64, conv3×3, 128, conv3×3, 128, conv3×3, 128 and RELU activators in between them. Then, the output obtained from the convolutional layers and max pooling layers are being converted into 2D planes which are called as feature maps and further we get the feature maps, respectively for the convolution operations and pooling operations. The size of input image is 200×200×3. Moreover, the plane of each layer was obtained by merging more planes occurred in the previous layers.

In this model, Sigmoid Activation Function is used as the classifier which is kept at far end of the model. It is having a lot of dense layers so it is also called as ANN model. This function is sometimes also called as the squashing function. They limit the output range in between 0 and 1, which helps in the possible prediction of probabilities.

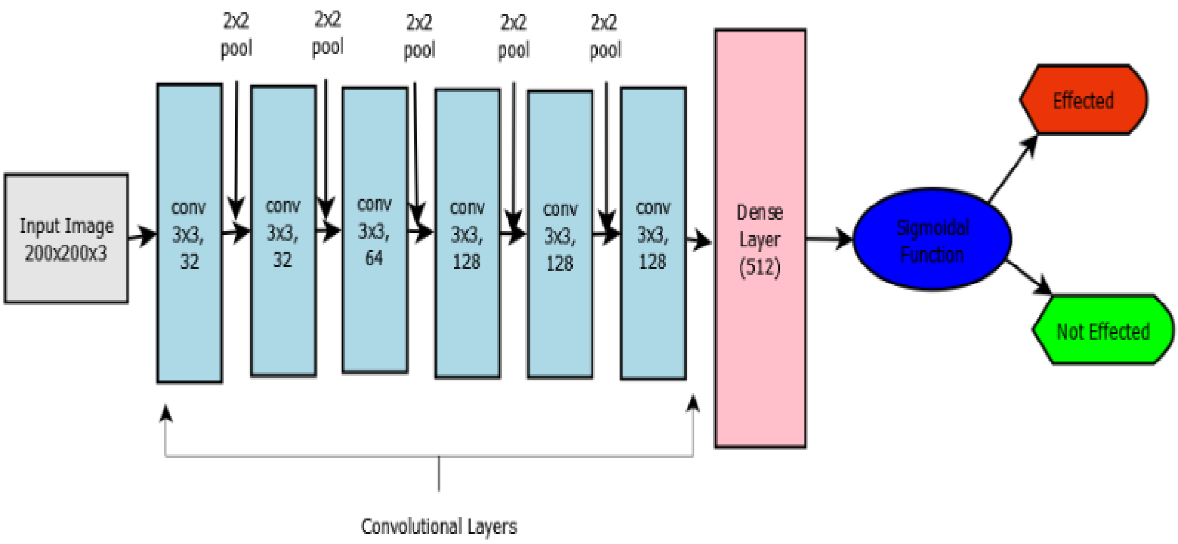


Fig 2.CNN Architecture

The classifier used in this model also requires individual features for each computation involved in the classification process. Hence, the output obtained after the process of feature extraction is again converted into the 1 D feature extractor planes and this mechanism is called the flattening process in which the output obtained is generalized into a lengthy feature vector plane so that it can be utilized in the last classification process. Further, the classification layer is having the flattening layer, dense layer, dropout of 0.5, RELU activator and a sigmoid function used for the final classification of the images. Further, dropout feature is being used of size 0.5, and then layers of size 512 and 1 are being used. Further, in the proposed method, RELU function has been used along with the sigmoid activation function for classifying the images into positive and negative pneumonia. CNN architecture used with the data augmentation techniques has helped in achieving greater accuracy and reduced the validation loss to a greater extent.

VI. RESULTS

For examining the effectiveness of the proposed CNN model, several experiments were conducted for longer period of time. Parameters were heavily turned to enhance the performance of the proposed model. Several results were obtained and different conclusions were drawn but this study proposes the valid experiments. In this work, various methods of data augmentation were used.

Also, various learning rate variations were used in order to manage the small datasets to fit into the deep learning convolutional model.

The final results obtained shows as training loss as 0.1378, training accuracy as 0.9436, validation loss: 0.1988, and validation accuracy of 0.9289.

Basically, fixed sizes of images are being used in the CNN model for predicting the accuracy and loss after training those images for the longer period of time. Various images of sizes as 100 ×100 × 3, 150 ×150 × 3, 200 × 200 × 3, 250 × 250 × 3, and 300 × 300 × 3 were reshaped and then training was done for three to four hours and then the average performance was shown in the experiment.

Table 3: Performances of Accuracy and Loss on different size of Data

Size	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
100	0.9432	0.9227	0.1423	0.1990
150	0.9512	0.9333	0.1324	0.2010
200	0.9488	0.9236	0.1336	0.1992
250	0.9325	0.9111	0.1411	0.1889
300	0.9412	0.9233	0.1317	0.1909
Average	0.9436	0.9289	0.1378	0.1988

It is true that as large as the size of the transformed image, validation accuracy will be reduced up to that level. The images that have large image size will absolutely need longer time for training. Fig 3 denotes the various training and validation losses after executing the model.

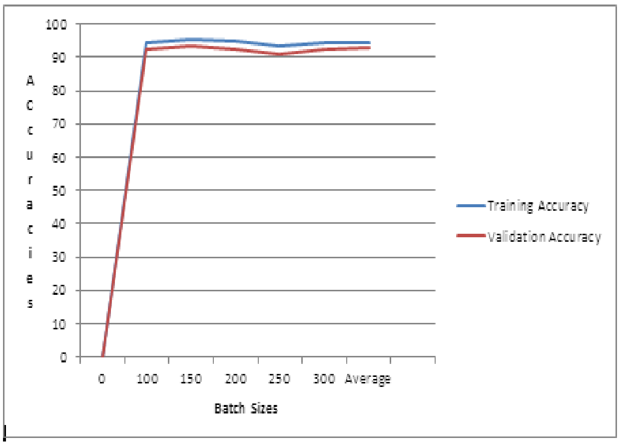


Fig 3. Plot for Accuracies

Further, the plot for training and validation loss has also been plotted at different batch sizes.

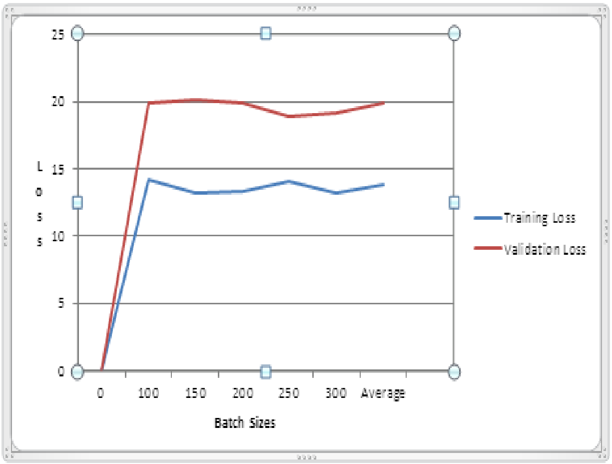


Fig 4. Plot for losses

In figure 5, the number of cases of pneumonia infected persons and non- pneumonia infected persons has been discussed. Whereas, figure 6 the overall plot for all the batch size has been discussed for the CNN model. CNN model helps in fast execution of the algorithm which results in better optimization results for different results of training data and training accuracies.

Figure 6 shows the accuracy plot for different batch sizes when tested using CNN algorithm. It proved that whenever data augmentation techniques are being used in any of the CNN algorithm, it shows better results.

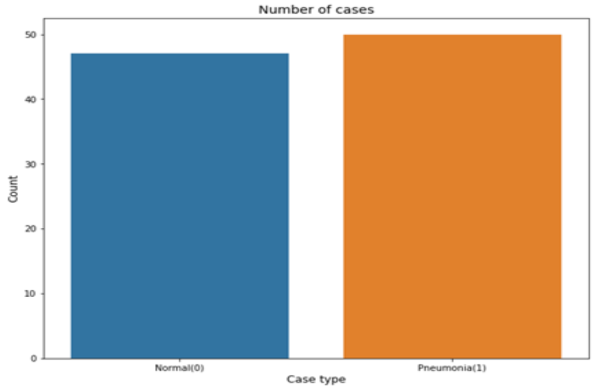


Fig 5.number of cases in dataset

On the other hand, images having smaller size prove that they have improved validation accuracy in the experiment. Be that as it may, the little slips in the approval precision don't enroll generous effect on the general order execution of the proposed model. Bigger pictures likewise required additionally preparing time what's more, calculation cost, and the exhibitions of 150 ×150 × 3 furthermore, 200 × 200 × 3 picture sizes were comparative. At last, the 200 × 200 × 3 model was proposed since it created better approval precision of around 94 percent with a negligible preparing loss of 0.1387.

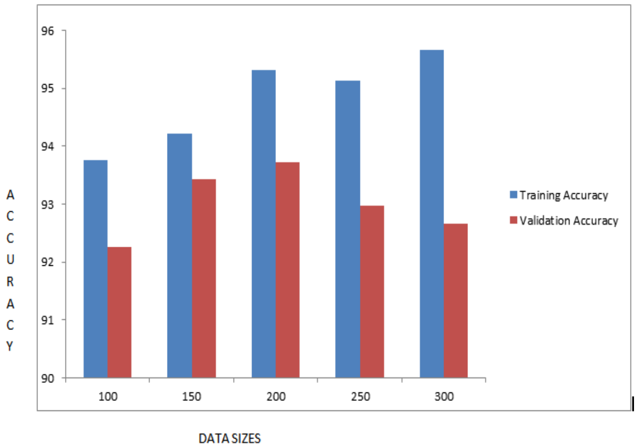


Figure 6: Accuracy plot

VII. APPLICATIONS OF CNN MODEL

- CNNs are now-a-days widely used in the computer vision and automation fields. This helps in developing such artificial systems which has capability of performing complex tasks with efficiency.
- CNNs are also being used in the domain of natural language processing for language analysis, language modeling, language designing. CNN models helps in determining the various semantics of any sentence for knowing the better about the client's requirements.
- CNNs are being used for object detection purpose for identifying the objects in the way. Segmentation of images is also being done using the CNNs.
- Image Classification is one of the very important task which is done using the CNNs in the present scenario by various data augmentation techniques and feature extraction techniques.
- One of the most important applications is the speech recognition in which the speech is being recognized using some automated devices. For example, Google's speech recorder.
- CNNs are also widely used for the data which are computationally very limited in resources. There are several techniques which are still being working on small datasets with improved accuracy of classification.
- CNNs are also being used for the images which are having low resolution. Many researchers have given different techniques to work on the images having low resolution using CNN.

VIII. RESEARCH CHALLENGES

- There are different types of images which belongs to various classes. So, it becomes different to perform scaling operations on those images. Hence, wide variety of classes of images leads to poor scaling operation.
- Sometimes, there is a need for large size filters for filtering the images in classification and therefore, it may lead to low feature extraction properties of images.

- The fully connected layers used for the classification of images are computationally expensive. So, if the layers keep on increasing then, the cost of the model also gets increased up.
- In the image classification process, whenever the feature maps are generated. It may happen that sometimes the feature maps generated are large in number at each layer which will lead to the generation of heavy parameters.
- Lack of homogeneity in the architectures, frameworks and devices is also a major challenge in the CNNs.
- Lack of image datasets and information leads to inaccurate results.

IX. CONCLUSION

In the given study, it has been demonstrated that how one can classify the true and false cases of pneumonia easily from a small dataset of X-ray images. This model was basically built from the scratch that helps in separating it from all other existing methods like transfer learning etc. The proposed method will further help in effective diagnosing the pneumonia patients more easily and this CNN approach is computationally effective. For the future work, the proposed work can be extended to further classify and detect lung cancer and pneumonia X-ray images as classifying the two diseases has become one of the major concerns now-a-days. Therefore, possible solutions for considering these problems are great area for the research domain.

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AUTHORS PROFILE

First Author- Garima Verma has received b.tech degree from Sagar Institute of Technology and Management (AKTU) in 2017 and is currently pursuing mtech from Madan Mohan Malaviya University of Technology. She has represented papers in ieee and springer international conferences. PG student, MMMUT, Gorakhpur, Uttar Pradesh, India, Email- garimaverma311016@gmail.com

Second Author- Prof. Shiva Prakash has received M. Tech. degree in Computer Science & Engineering from MNNIT, Allahabad in 2006 and PhD degree in Computer Science & Engineering in 2013. Presently, he is working as a Professor (CSED), Chairman Campus Development Cell, Chairman SC/ST Cell, M.M.M. University of Technology Gorakhpur, UP, India. He has more than 20 years of teaching and research experience. He has shared responsibilities as Head of Department of CSE, Officer In-charge- Computer Centre, Officer In-charge Alumni Association, Convener of BOS of CSE and many more. He has published more than 80 papers in refereed international/national journals and conferences including IEEE, ACM, Springer conferences. He has organized many such conference in the capacity of conference Organizing Secretary, Technical Chair, and editor of conference proceeding. He has reviver of many National/International conferences and Journals. His publications are listed in Citeseer-x, IEEE, Elsevier, and Scopus. He is a life Member of Indian Society for Technical Education (ISTE), Member of IEEE and member of Computer Society of India (CSI). His many papers have been nominated as Best Paper Award at International Conference. Professor, Department of Information Technology, MMMUT, Gorakhpur, Uttar Pradesh, India, Email- shiva_pkec@yahoo.com