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Diagnosis Pneumonia Using Convolution Neural Network without Maxpooling (CNNWMP) Deep Learning Model

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ABSTRACT-Pneumonia is the infection of the lower respiratory system which is caused by fungi, viral ,bacterial and nowadays covid-19.The aim of this study is to develop computer aided platform with the help of Chest X-ray images which helps to diagnosis pneumonia automatically and accurately. Chest X-rays have high contrast and different intensity values. Therefore Chest X-rays necessitate a normalization to analyzed and diagnosed accurately. This research proposed a model CNNWMP (Convolution Neural Network Without Maxpooling) for diagnosis of pneumonia.The Result of the model test Accuracy,Precision,Recall and F1-Score were 89.42%,87.67%,96.66% and 91.95 respectively with 2 convolutional without maxpooling layer, 3 dense layer and the size of input image is grayscale 128x128.
Keywords:CNNWMP, Pneumonia diagnosis, chest X-ray,Histogram.

I. INTRODUCTION

Pneumonia is a respiratory infection caused by bacterial ,viral or fungi infection [1]. pneumonia has once again taken attentionbecause it has similar symptoms like COVID-19 [4].Chest X-rays (CXR), chest MRI, and needle biopsy of the lung are available tests to diagnose pneumonia [8]. Chest X-rays is most commonly used methodin clinical care and epidemiological studies[1] [7-9].X-ray image take lesser time as compare toCT imaging and CT imaging requires high-quality scanners and these types of scanners are costly.Manual Chest radio graph analysis is the most widely used method for diagnosing pneumonia, but it is less reliable and impractical on a large scale [3]. Therefore, strong need for Computer Aided Diagnosis (CAD) tools in the diagnosis of pneumonia. Latterly, research community focus to build utterly automated tools for “reading chest radio graphs”.Deep learning technique Convolutional Neural Network (CNN) models have been developed and successfully used for diagnosing pneumonia from radio graph images [11]. There is a problem of a insufficiency of healthcare workers and radiologists for detecting and predicting pneumonia disease in many regions around the world[10, 11]. Nowadays, artificial intelligence (AI) based computers, mobile devices, cloud, and edges arethe most popular method used to diagnose pneumonia disease [12, 13]. There are several deep learning techniques used to diagnose pneumonia, like biomedical image diagnosis and convolutional neural networks (CNNs).Although CNN techniques have been proved to be effective for both image segmentation and classification by research community,There are some drawbacks of it.A Convolution neural network is significantly slower due to an operation such as maxpool[14].If the CNN has several layers then the training process takes a lot of time if the computer doesn’t consist of a good GPU[15].Due to use of Max pooling layer we loss important data[14] .suppose we use max pooling and we loss infected area features .When we use max pooling , we lost our most valuable data and that’s why we remove max pooling from CNN and create new CNNWMP .The approach consists of a 2 convolutional layer without Maxpooling and 3 Dense layer.The proposed CNNWMP consists of different blocks, which are extensively discussed in the following sections: (i)Data preprocessing and HistogramBlock :improve quality CXR images and increase the size of existing training images and reduce the overfitting problem (ii) Convolution without Maxpooling block: extract the most important features of CXR images(iii) Disease Prediction block : classifying output image into (0)normal or abnormal(1)Pneumonia.To evaluate the accuracy and efficiency of the approach, an extensive set of experiments on a public dataset is conducted.The remaining sections of the paper are arranged as follows: Section 2 presents more details of other related work and focuses on the main contribution of the suggested work. Section 3 focuses on the materials and methods of the study, including a description of the dataset used, a background and a detailed explanation of the proposed approach. The experimental results of the dataset are presented in Section 4. Section 5 presents the conclusion and considers future research.

II. RELATED WORKS

Preliminary works of diagnosis of pneumonia handled with CAD systems which gave low accuracy as compare to CNNs and DNNs, which were foundafterward. At that time Pneumo-CAD [17] had been a state-of-the-art CAD system. These methods were able to achieve low misclassification rate of 10% with kNN and HaarWavelet and~20% with kNN. Afterwards, a modified analysis of the algorithm had been organized using Pneumo-CAD with Sequential Forward Elimination (SFE), Pneumo-CAD without SFE, and Support Vector Machine (which used SFE) gave accuracies of 66%, 70%, and 77% [18], respectively.This research also conducted with the Naïve Bayes algorithm and got 68% accuracy. Aapproachingstudy performed in [19] and works performed in [20] had been done for finding the optimal model for pneumonia detection. The algorithms both have pretrained weights (from datasets such as ImageNet [21]) and are user-defined, and have been abundantly used for diagnosis pneumonia. This can be deduced from the works done by Pranav Rajpura et al. [22] and Can J Saul et al. [23]. CheXNet take advantage of 121 layer CNN which had been trained on ChestX–ray14 which provide low accuracy of approximately 76.80% for predicting pneumonia and classify 13 other diseases of chest by CXR images.In[24,25] researchers proposed a CNN architecture for detection of pneumonia early and achieved an accuracy of 78.73% withXception, VGG16, and VGG19 models [26,27] that were pretrained on the ImageNet dataset. The Xception pretrained model achieve an accuracy of 82%, VGG16 model achieve 87% and VGG19 model achieve 92%.In [28] the proposed CNN model architecture compared with algorithms such as Competitive Neural Networks (CpNN),Backpropagation Neural Networks (BPNN), and pretrained and fine-tuned networks (like VGG16 and VGG19). In[29]a user-defined CNN architecture succeeded in achieving a validation accuracy of 93.73% for similar classification. A brief analysis of all the algorithms mentioned in the literature has been conducted. This had been done in terms of the accuracy they achieved on the CXR image dataset or ChestX-ray14 dataset (used in the case of CheXNet). This analysis has been mentioned below in Figure 1.

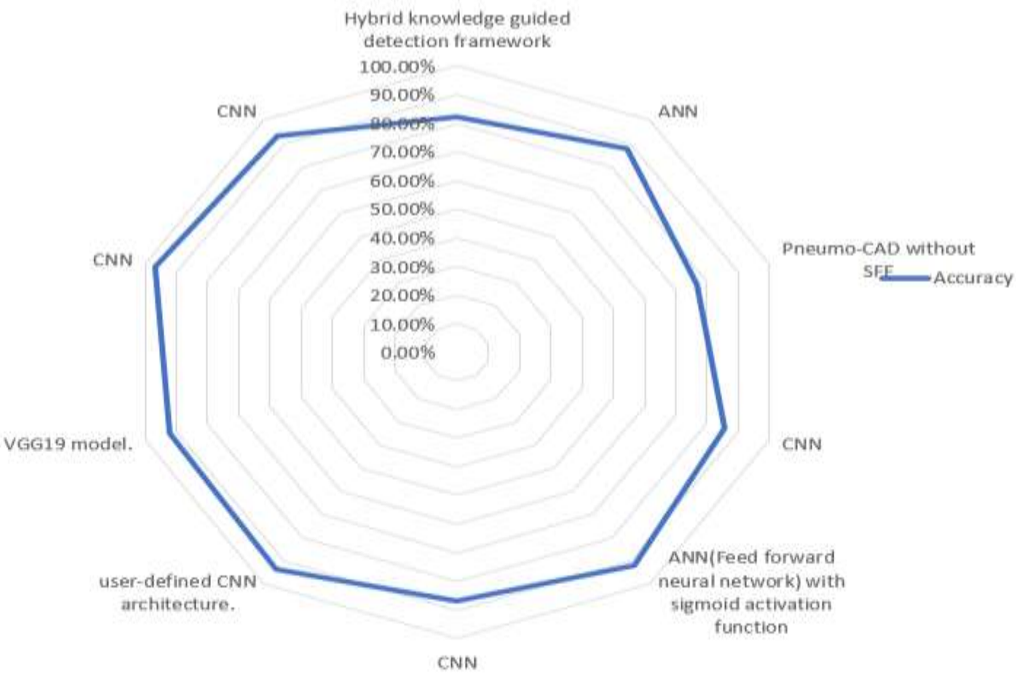

Fig 1. Comparative analysis of various deep learning models in accordance to the literature.

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III. DATA AND SOFTWARE TOOLS USED

For the purpose of coding, used Python version 3.10 with the OpenCV libraries.Dataset for pneumonia detection is taken from Kaggle.The dataset is organized into 3 folders (train, test, val) and contains subfolders for each image category (Pneumonia/Normal). There are 5,863 X-Ray images (JPEG) and 2 categories (Pneumonia/Normal).

Class	Train Set	Validation Set	Test Set
Normal	1341	8	234
Pneumonia	3875	8	390
Total	5216	16	624

IV. METHODOLOGY

The primary objective of this study is to develop a high-precision model for automated diagnosis of diseases from medical images, with an emphasis on detecting pneumonia from chest radio graph images. Realizing set objective, introduce CNNWMP, a deep learning framework for the effective identification of pneumonia from chest radio graph images.The complete block diagram of the proposed work is depicted in figure 2.The proposed CNNWMP consists of different blocks, which are extensively discussed in the following sections: Data preprocessing and Histogram block,Convolution without Maxpooling block, Disease Prediction block.

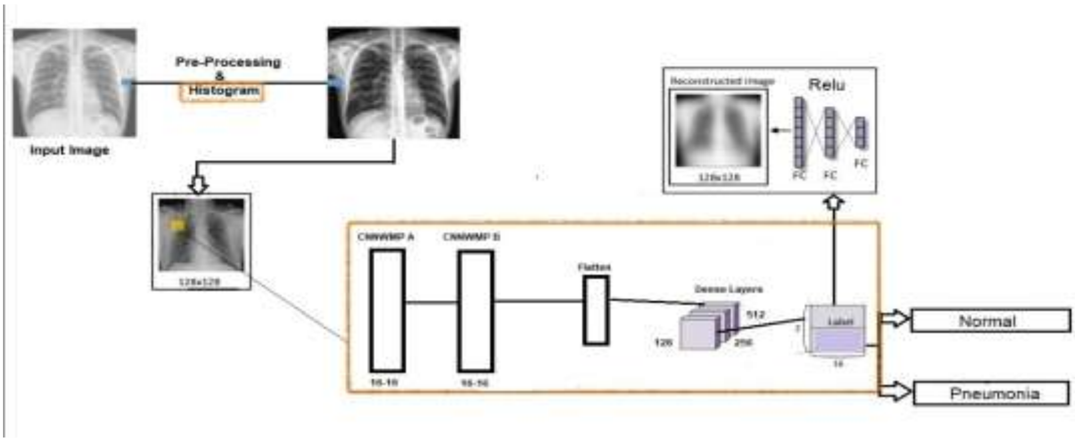

Fig.2 The proposed CNNWMP Model Architecture

1.1 Data preprocessing and Histogram block

1.1.1 Rescaling of the images is done by dividing each image by 255.

Typically, RGB values are encoded as 8-bit integers, which range from 0 to 255.It's an industry standard to think of 0.0f as black and 1.0f as white(max brightness).To convert[0,255] to [0.0f,1.0f] all you have to do is divide by 255.

1.1.2 Images are resized to 128 by 128 pixels.

The input size for the proposed model is 128 × 128. Yet, since the lengths and widths of the images in the data set are not the same size, all images were resized to 128 × 128 pixels.Downsampling the image to default size works well in most of the cases for standard architectures. To achieve higher accuracy, find an optimal image size between default size and 512. Do not use higher image size greater than 512 in which case the model may underfit and may provide low accuracy[30]. When image size increases the receptive field decreases for standard architecture which contributes to decrease in accuracy[30].

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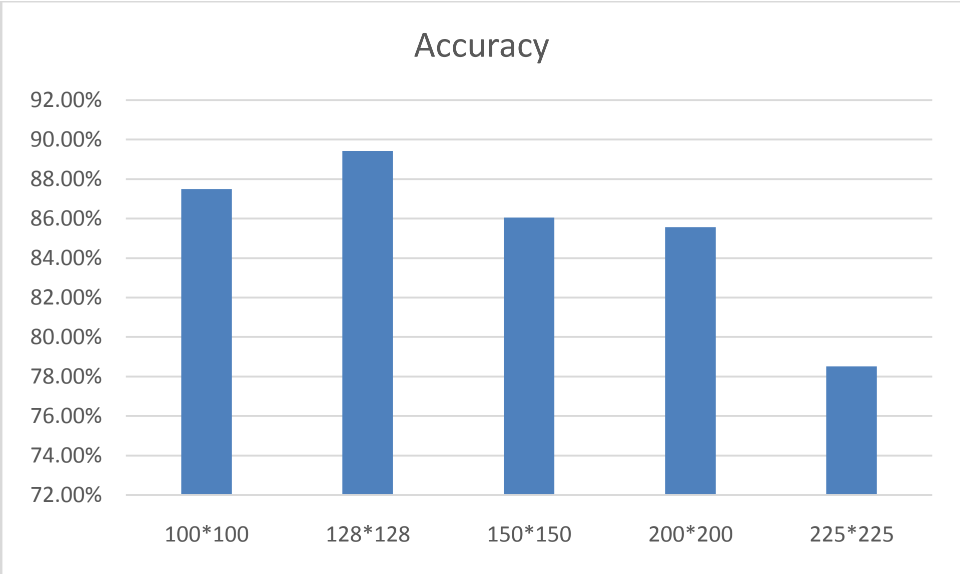
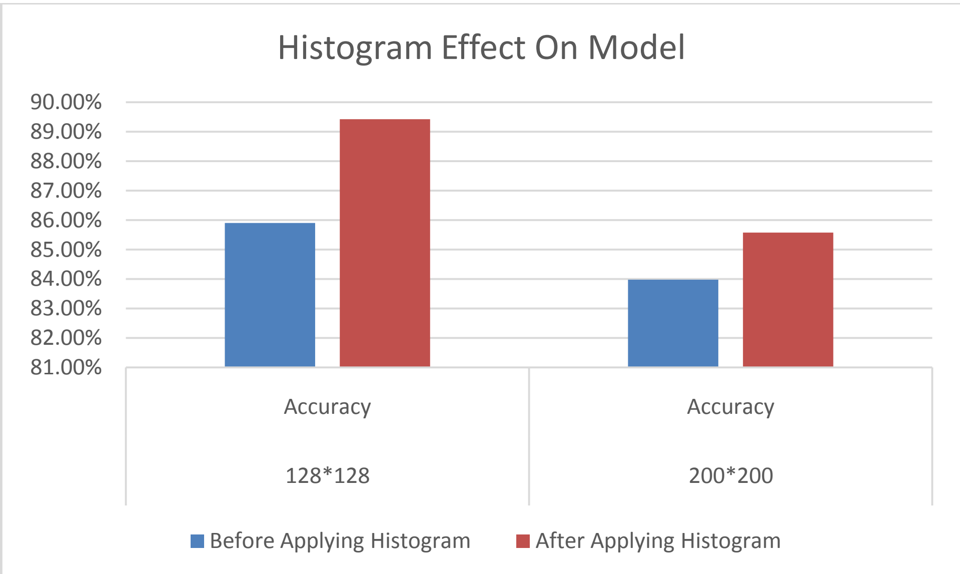


1.1.3 Rotation of images performed by 20 degrees horizontal rotation.

The simple method is use data augmentation. During training time ,randomly rotate the input image before feeding it to the neural network. There might need to train the neural network for more epochs. For improving the generalization ability of CNN models, there is a need for massive data during the training phase [31]. Data augmentation, which is one of this methods, improves the model's generalization ability, prevents overfitting, and increases the model accuracy [31,32]. Moreover, while training selected models, real-time data augmentation (shifting, rotating, zooming, and flipping) methods were used for avoiding overfitting.

1.1.4 Histogram Technique

Sometimes images look nicer to human eyes but when we pass those images to any Computer Vision-based model like classification and object detection results do not come up well as due to noise object which we want to find is distorted and may not match with the one on which the model was trained, so noise in an image can degrade your model's accuracy.To avoid such type of noise we apply Histogram Technique on Dataset.The proposed model is tested before applying histogram and after applying histogram and the comparative analysis is describe in following chart.



1.2 Convolution without Maxpooling block

CNNWMP Network deal with vectors instead of scalar value.There are no pooling operations in CNNWMP so we save our data from Loss.CNNWMP required less number of images for trainingCNNWMP only has 3 layers that's why it takes Minimum time for Training and Testing.The proposed CNNWMP model encompasses Five layers (Two convolutional layers three dense layers).The architecture of model and parameter used during the disease prediction will be given in Table 2.Total 134,294,993 parameters used.

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 128, 128, 3)]	0
conv2d (Conv2D)	(None, 128, 128, 16)	448
conv2d_1 (Conv2D)	(None, 128, 128, 16)	2320
flatten (Flatten)	(None, 262144)	0
dense (Dense)	(None, 512)	134218240
dense_1 (Dense)	(None, 128)	65664
dense_2(Dense)	(None, 64)	8256
dense_3 (Dense)	(None, 1)	65

1.3 Disease Prediction block.

With the help of Relu Functions We convert values less than 1 are automatically converted into 0(Zero) if more than 1 (One) then its converted into 1 .The method of directly forcing some data to be zero can create a moderate sparse characteristic to some extent. Compared with the previous two functions, the ReLu function provides a much faster computing rate[33]. The equation of this function is defined as: f(x) = max(0, x)[33].After applied RELU activation we get some values in 0 and 1 .So we label it as follows,
0==Normal
1==Pneumonia

V. RESULTS AND DISCUSSION

We trained our custom model on the training dataset using 5856 images for a total of 10 epochs (163 cycles), the results were as follows:
CONFUSION MATRIX ------------------
[[181 53]
[13 377]]
TEST METRICS ----------------------
Accuracy: 89.42307692307693%
Precision: 87.67441860465117%
Recall: 96.66666666666667%
F1-score: 91.95121951219512
TRAIN METRIC ----------------------
Train acc: 93.46

	First training model	Last training model	Testing model
Training Loss	0.4780	0.1669	
Validation accuracy	0.7007	0.8914	
Validation loss	0.7674	0.3972	
Testing model classification rate			89.42307%

VI. CONCLUSION

In this study, unlike CNN architectures, pneumonia was determined from chest X-ray images with a smaller number of layers (2 convolution layers + 3 Dense Layer). This model consists of preprocessing techniques like rescaling, resizing, rotation and histogram for improving the quality of images. There are no pooling operations in CNNWMP so we save our data from Loss.CNNWMP only has 2 convolution layers that's why it takes Minimum time for Training and Testing.Currently CNNWMP model give the testing Accuracy 89.42% and training Accuracy 93.46%.Further this model will be tested for more images and try to get more accuracy than current accuracy.

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