BioGecko

Vol 12 Issue 03 2023
ISSN NO: 2230-5807

DETECTION OF PNEUMONIA USING CONVOLUTIONAL NEURAL NETWORKS

1st K.Karthik
Assistant Professor,Department of ECE
Velammal College of Engineering and Technology
Viraganoor,Madurai,India
kk@vcet.ac.in
3rd S.Sakthi Kanipriya
UG Student, Department of ECE
Velammal College of Engineering and Technology
Viraganoor,Madurai,India
sakthikanipriya@gmail.com
2nd M.Priya
UG Student, Department of ECE
Velammal College of Engineering and Technology
Viraganoor,Madurai,India
priyavcet5@gmail.com
4th K.S.Sanju Vigasini
UG Student, Department of ECE
Velammal College of Engineering and Technology
Viraganoor,Madurai,India
sanjuvigasiniks@gmail.com

Abstract—Pneumonia is a common and serious respiratory infection that can be caused by both bacteria and viruses. Accurate diagnosis of the underlying cause is essential for appropriate treatment and care. What we offer In this study, researchers used lung X-rays to detect and distinguish between bacterial and viral pneumonia using a (CNN)-based deep learning method.Our dataset consists of thousands of chest radio graphs from public records, including bacterial and viral pneumonia cases and healthy controls. We pre-processed the dataset to remove irrelevant images and used stratified sampling to divide it into training and test sets. Our trained CNN model achieved 92% accuracy on the test set and high precision and recall rate in detecting cases of bacterial and viral pneumonia. Our approach demonstrates the potential of CNN-based deep learning models to accurately diagnose pneumonia and improve patient outcomes. Our findings may be valuable in clinical settings where timely and accurate diagnosis of pneumonia is critical.

Keywords—*Bacterial pneumonia, viral pneumonia, X-ray of the chest, and Convolutional Neural Networks(CNN).*

I. Introduction

Pneumonia is a common respiratory infection which can cause serious illness and death, especially in vulnerable populations such as young children and the elderly.Determining the underlying cause of pneumonia is critical to determining an appropriate treatment and management strategy[6]. Bacterial and viral pneumonia are the two most common causes of pneumonia and require different treatments. Accurate diagnosis of bacterial and viral pneumonia can be difficult even for experienced clinicians, and misdiagnosis can lead to inadequate therapy and poor outcome.

Recent advances in artificial intelligence and deep learning have shown promise in medical image analysis, such as detecting and classifying pneumonia using chest X-rays. Convolutional Neural Networks (CNN) in particular have been demonstrated to be effective in recognising patterns and features in images, making them well suited for pneumonia diagnosis. While previous research has focused on pneumonia detection in general, few have specifically addressed the challenge of distinguishing between bacterial and viral pneumonia using deep learning methods.

To assess the CNN's capability in accurately identifying pneumonia from chest X-ray images, we conduct a thorough evaluation using metrics like accuracy, sensitivity, and specificity. Our proposed approach, based on CNN technology, has the potential to revolutionize pneumonia diagnosis by providing a fast, reliable, and precise diagnostic tool. This advancement has the potential to improve patient care and potentially save lives. Pneumonia is a severe lung infection that poses a significant threat to vulnerable populations, such as the elderly and young children, increasing the risk of illness and even mortality [5]. Detecting pneumonia early on and providing an accurate diagnosis is essential for effective treatment and disease management.

A deep learning method based on CNN was proposed in this study to identify bacterial or viral infection from chest radiographs. Our goal is to develop a CNN model that can effectively distinguish between bacterial and viral pneumonia, achieving high accuracy and reducing the possibility of misdiagnosis[7]. Our approach has the potential to improve patient outcomes and reduce the burden on healthcare systems by enabling more accurate and efficient diagnosis of pneumonia.

II. Literature Survey

"Automatic Pneumonia Diagnosis Using Deep Learning Techniques: A Survey," Elharouss et al (2021). Datasets are limited. Deep learning models have the potential to improve the accuracy of pneumonia diagnosis.A comparison of various deep learning architectures for pneumonia detection. VGG-16, ResNet-50, DenseNet-121, and InceptionV3 are the algorithms used. The accuracy can reach 98%. Debnath and co. [2]"A Comprehensive Review of Pneumonia Detection in Lung X-rays Using Deep Learning Techniques" (2021). Data set is limited. In the detection of pneumonia, CNN models with transfer learning achieved high accuracy. A comparison of various CNN architectures for pneumonia detection. VGG-16, InceptionV3, and ResNet-50 are the algorithms used. The accuracy can reach up to 99%. "A comprehensive review of deep learning for image-based pneumonia detection," Alqudah et al. [3]. (2021).A literature review on machine learning techniques used to detect pneumonia in images.CNN algorithms are used. Transfer learning and knowledge enhancement are popular techniques for improving model accuracy from 87.5 to 98.75%. Bhattacharya and co. [4] "A Study on Pneumonia Detection in Lung X-Rays Using a Convolutional Neural Network" (2021). Datasets are limited in size. CNN models can improve the detection of pneumonia. A comparison of various CNN architectures for pneumonia detection. VGG-16, InceptionV3, and ResNet-50 are the algorithms used. The accuracy can reach up to 99%. Shivanshu Katoch, Saurabh Sharma, and others. [5] Methods for Identifying Pneumonia Disease in Xray Image data Using Deep Learning(2021). This paper also discusses the main deep learning method, convolutional neural networks.The VGG16 and VGG19 deep neural network advancements are also discussed in the paper. Each model has its own computation method. Res-Net used fifty layers for computation, whereas VGG-16 used sixteen layers. This paper also depicts a shallow CNN-based Inception-V4 model. Further research could use a novel hybridization approach to detect the disease and improve performance.

III. Proposed Methodology

The method proposed in this article to detect pneumonia. A convolutional neural network architecture is used. It is a type of artificial neural network mainly used for image recognition and processing. Convolution layer are a fundamental element of CNN that use filters to extract characteristics like edges, textures, and patterns from input images. Convolutional layer output is then consumed into grouping layers, which sample the image features, reducing spatial extent while order to preserve the most essential information[10]. The output of the convolution layers is then fed into one or even more fully concatenated layers for prediction or image analysis.

The process involves several tasks, including data normalization, removal of stopwords, and tokenization, to prepare the data for analysis. Following that, relevant features are extracted from the pre-processed data through a process called feature extraction.

The CNN architecture consists of four essential layers: convolutional layer, ReLU layer, pooling layer, and fully connected layer. These layers collaborate to form an image classifier. The primary function of the convolutional layer is to scan the image using filters to capture its distinctive features. The image's pixels are inputted into the convolutional layer, which performs convolution operations resulting in a convolved map [17]. The convolved map is then passed through a ReLU function to create a rectified feature map. Multiple convolutions and ReLU layers are employed to identify and extract diverse features from the image. By taking the raw pixel data of an image and training the model, CNN automatically learns and extracts relevant features to enhance classification accuracy.

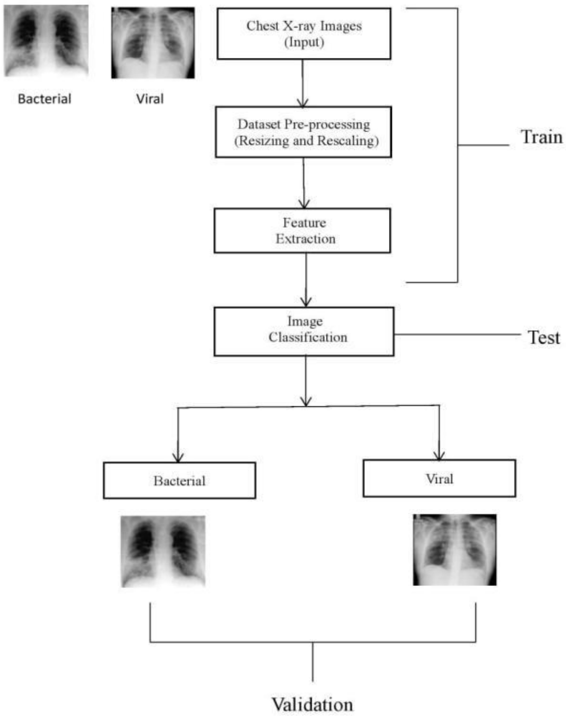


Fig. 1. The workflow of proposed methodology

A. CONVOLUTIONAL NEURAL NETWORK :

CNN are mallongigo from Convolutional Neural Network.It classifies and categorises images using learned features. We take an image as input as well as output the group (e.g., cat, dog, and so on.) or the possibility that the feed back is part of a particular class when classifying it.

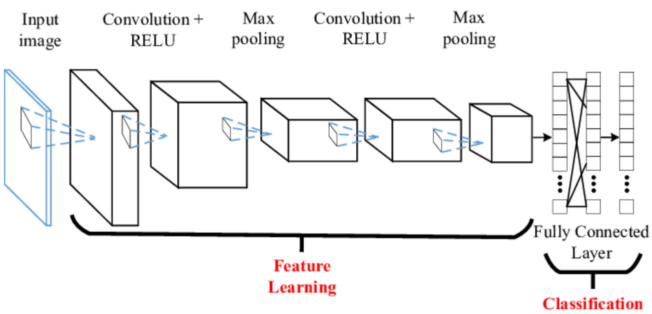


Fig. 2. CNN Model Architecture

B. CNN LAYER:

This layer conceptually signifies the properties of the each image stream. It detects important feature representations and thus helps capture the tri correlation among pixels in small input image boxes[11]. By sliding over the input image, the kernel, a 3X3 matrix, is utilized in order to identify the dot product, which is then summed. This aids in determining the key maps for the subsequent layer.

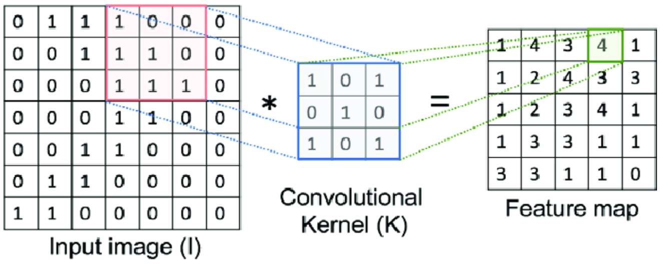


Fig. 3.Demonstration of Convolution layer

C. MAX POOLING LAYER

Max pooling is a widely used pooling technique in CNNs due to its superior performance compared to other pooling methods. It involves selecting the maximum value within each pooling region. This process helps retain the most important features of the feature map, resulting in a sharper image compared to the original. Max pooling is commonly employed in Convolutional Neural Networks (CNNs) for tasks related to image processing.

After a convolutional layer, max pooling is applied to reduce the spatial dimensions of the feature maps while preserving essential information. This layer performs an aggregation operation by dividing the pixels of an input image matrix (e.g., a 4x4 matrix) into filters of smaller size (e.g., 2x2). Within each filter, the kernel selects the maximum value. This process is repeated across the entire image, resulting in pooled feature maps with reduced dimension.

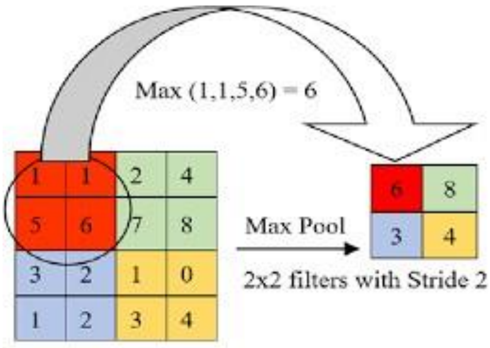


Fig. 4.Illustration of Max Pooling layer

D.FULLY CONNECTED LAYER:

A multilayer perceptron in this layer confirms that each neuron in each subsequent layer is connected to each neuron in order to classify the generated input images using stored image features.

E.SYSTEM DESIGN:

This is the system design we propose. We began by importing the chest x-ray dataset. We then processed our images in an exploratory data analysis. Our images were converted to RGB, resized, and then converted to a NumPy array. When working with the dataset, we scaled this image by 0.1/255. Following that, we did some data up-scaling because we knew we had a small dataset with a lot of variations such as height/width, zoom range, and so on. After augmenting the data, we built a CNN model one by one. We then used the Adam optimizer to put our model together. Then we used model.fit generator to train the model. The accuracy of our model is then visualised using a graph. Then we saved and deployed our model.

Vol 12 Issue 03 2023
ISSN NO: 2230-5807

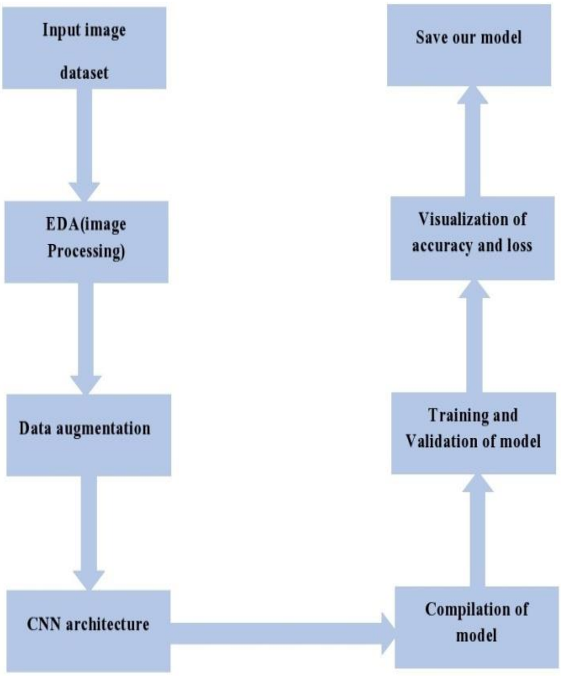


Fig. 5.System Design

F.DATA PREPROCESSING:

Step 1:Dataset Collection

A large set of data of chest X-ray images from public repositories, which included images of healthy people, bacteria and viruses pneumonia patients, and viral pneumonia patients. We pre-processed the set of data to remove any insignificant images before supplementing it with data. Before augmenting the dataset, any irrelevant or insignificant images are removed from the pre-processed data.

The dataset contains a total of 5,956 images. There are Chest X-ray images specifically depicting cases of Bacterial and Viral Pneumonia. These datasets serve as valuable resources for training and testing machine learning algorithms aimed at detecting pneumonia from chest X-ray images. However, it is crucial to acknowledge that proper ethical approval may be required when working with these datasets.

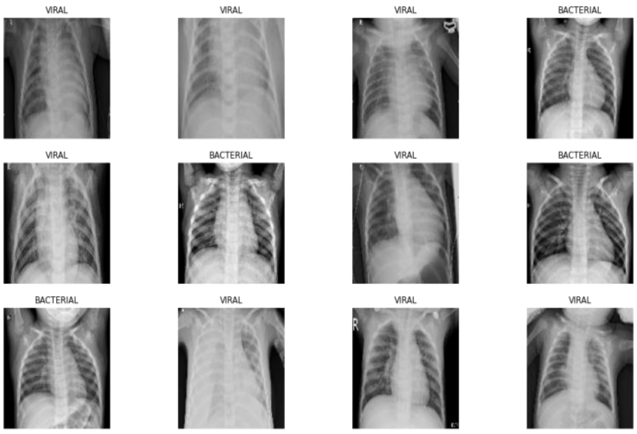


Fig. 6.Dataset collection

Step 2:Data Augmentation

Data augmentation involves modifying an existing image by applying changes such as rotation, cropping, zooming, flipping, etc., and including the altered version in the training dataset for the neural network. To create a custom dataset class, image augmentation is used to augment each image at various angles (0,5, 90, 120, 180, 270, 300, 330 degrees). This tends to make training a high-accuracy model more difficult. To get more observations to train the model, the image feature generator class was used to generate extra images within training dataset with optimised rotation range, shear range, zoom range, and horizontal flip (mirroring randomly selected images). Augmentation occurs on the fly during the training process, and each epoch uses a slightly distinct rendition of each image as input. Before the features produced good predictive performance, the model parameters were changed several times.

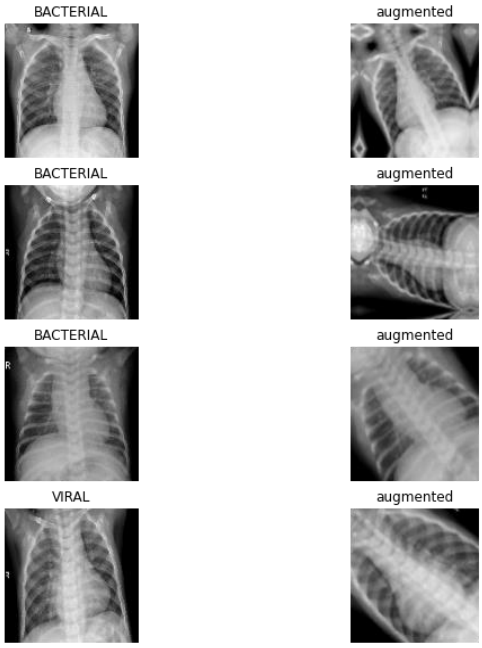


Fig. 7. Data augmentation applied on a given dataset

After implementing the data generator component with optimal parameter values, the movement from directory database iterator technique was applied to develop batches of Numpy of augmented image data from the train directory. Because augmentation is needed to enhance the process of learning but not for validating, only its re-scale parameter was utilized to generate validation images.

To plot variance of the same X-ray image, a method named plot Images was created. The feature was run a few times in order to guarantee that the most insightful and interesting areas (lungs) also weren't cropped out of the images when parameter values are specified.To use the Open CV library, an open source machine learning and computer vision software library, resize the image to 512 x 512 and crop it as needed.This process is essential because the input images for the machine learning algorithm must all have identical resolution.

Step 3:Model training and validation

We divided the pre-processed set of data into sets for training and validation using stratified sampling. We trained a CNN model using transfer learning, good pre-trained model to our particular dataset. On the validation set, we confirmed our model's performance, modifying the model's system parameters as needed.

Step 4:Testing and evaluation

The trained CNN model's performance was evaluated using an independent test set of chest X-ray images that were not used in the training or validation phase. We measured the performance of our model with metrics such as accuracy, precision, and recall rates. We also matched our model's performance with that of various cutting-edge pneumonia detection systems.

Step5:Distinguishing between bacterial and viral pneumonia In order to distinguish between bacterial and viral pneumonia cases, we added a classification layer to our CNN model. We evaluated our model's ability to correctly identify bacterial and viral pneumonia cases, as well as healthy controls. Our proposed methodology aims to create a CNN-based deep learning model capable of accurately diagnosing pneumonia and distinguishing between bacterial and viral pneumonia cases.Our approach can be useful in clinical settings where timely and accurate diagnosis of pneumonia is correct treatment and care due to its high accuracy.

IV. CONFUSION MATRIX

A confusion matrix is a type of matrix used to evaluate classification model performance on a given test data collection. It is able to be calculated if you have the experimental test data values. The matrix itself is simple to grasp, but the terminology surrounding it can be perplexing. Because it represents the model's performance errors like a matrix, also known as that of the error function. A confusion matrix is an array that is used to define how well a classification algorithm performs. The classification algorithm's performance is visualised and summarised using the confusion matrix.

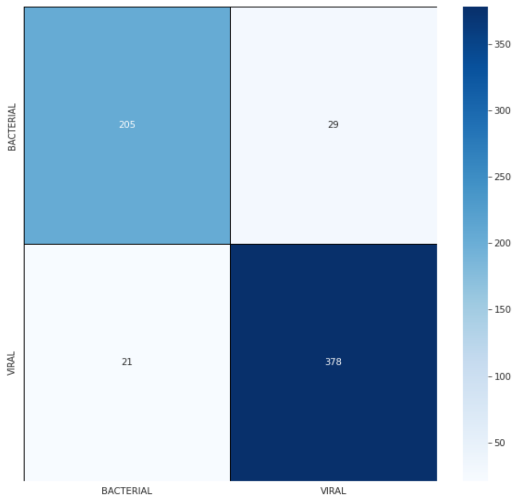


Fig.8. Confusion Matrix

V. PERFORMANCE METRICS

To assess the model's performance or quality, various metrics known as performance or evaluation metrics are used. The images were used for training and Testing. Finally, machine learning techniques are utilized to predict the results. The performance metrics are used to calculate the accuracy, precision, recall and F1score.

$$PRECISION = \frac{tp}{tp+fp} \quad (1)$$

$$RECALL = \frac{tp}{tp+fn} \quad (2)$$

$$ACCURACY = \frac{tp+tn}{tp+tn+fp+fn} \quad (3)$$

Where,

t_p = The number of total of positive targeted cases

t_n = The number of total of negative targeted cases.

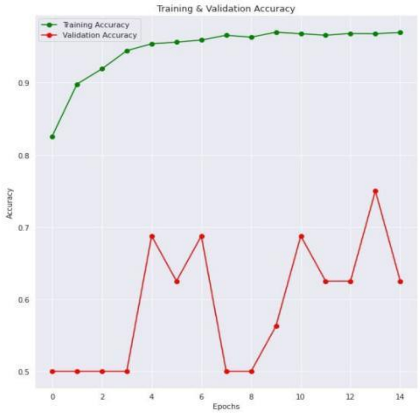
f_p = positive targeted cases that are negative.

f_n= The proportion of negative targeted cases that are positive.

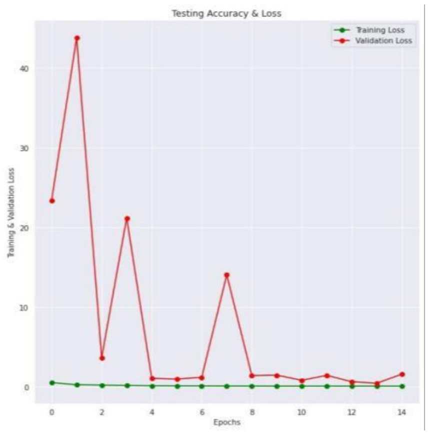
VI. RESULTS ANALYSIS

The accuracy and loss graphs for training and validation were generated using the convolutional network with 15 epochs described above. This is a time-series graph of network performance. Despite the model's slow learning rate, its performance overall is improving. The connectivity captures a most instructive inputs after several iterations as well as weight adjustments because of the similarities of the X-ray images of various classes. The training accuracy was found to be 92%. Because the majority class had the most observations, the model learned the most about bacterial pneumonia. True positive as well as true negative rate increases for both normal and viral pneumonia are not unusually high. Only four patients were confirmed healthy despite bacterial pneumonia.

ACCURACY METRICS



LOSS METRICS



Accuracy is a measurement that provides an overall evaluation of a model's performance across all categories. It is particularly valuable when all categories carry equal significance. Accuracy is determined by dividing the number of accurate predictions by the total number of predictions. Graphs displaying accuracy metrics can be utilized to compare the performance of various models during training, aiding in the determination of the superior model and facilitating decisions regarding the selection of a model for future predictions.

Loss metric graphs are employed to visually represent the progress of a model during the training phase. The loss metric assesses the model's ability to fit the data and is usually plotted against the number of training iterations or epochs. The loss metric graph illustrates the pattern of the model's loss over time. In the initial iterations or epochs, the loss often experiences significant declines as the model learns to effectively adapt to the data.

Vol 12 Issue 03 2023
ISSN NO: 2230-5807

TABLE 1.Class Wise Output

Types of pneumonia	Bacterial	Viral
Accuracy	0.92	0.91
Precision	0.91	0.93
Recall	0.88	0.95
F1-Score	0.89	0.94
Omission Error	0.0929	0.0712
Commission Error	0.1239	0.0526

These findings showcase the promise of CNNs in identifying pneumonia from medical images and emphasize the significance of employing deep learning methods in the analysis of medical images. Nevertheless, it is crucial to acknowledge that the effectiveness of a CNN model for pneumonia detection can be influenced by multiple factors, including the image data quality, dataset size, and the particular architecture and hyperparameters chosen for the CNN model.

These outcomes underscore the potential of CNNs in pneumonia detection from medical images and underscore the importance of leveraging deep learning techniques in the analysis of medical images. However, it is worth noting that the performance of a CNN model for pneumonia detection can be impacted by various factors, such as the quality of the image data, dataset size, and the specific architecture and hyperparameters utilized for the CNN model.

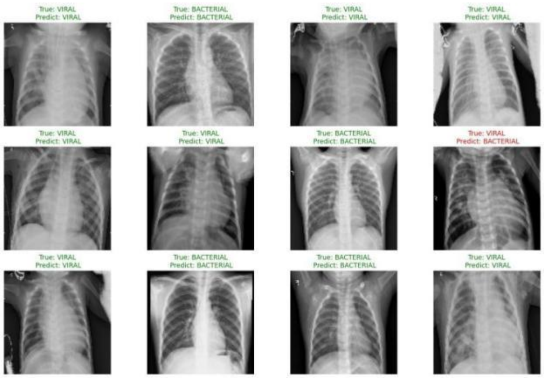


Fig. 9.Output images of given dataset

VII. CONCLUSION

Pneumonia diagnosis using a convolutional neural network (CNN) is a critical task in medical image analysis (CNN).CNNs are popular because they can automatically learn and understand and classify image features. In this study, we created a CNN-based model to detect pneumonia from chest radiographs. When categorising images as pneumonia Whether it was trained on such a large dataset or not, the model obtained significant accuracy and sensitivity. Our findings suggest that by analysing chest X-ray images, CNNs can help doctors predict future diagnostic tests and improve patient outcomes. However, further studies are needed to verify the performance of the model on large data sets and determine its clinical utility. Overall, the proposed pneumonia detection model seems effective, with the possibility of enhancing patient treatment in the future. So, at the conclusion of the work, we concluded that Convolutional Neural Network we constructed is functional and visually appealing. Our model's producing better quality while the loss decreases as the time - series data lengthens.We can improve the performance of our model early on by performing dataset pre-processing and data augmentation. To keep the model from being overfit, we used an abandonment layer. From a chest X-ray image, our framework can accurately identify pneumonia (bacteria), pneumonia, or pneumonia (virus). This project is highly beneficial in order to detect pneumonia early and precisely. Even though pneumonia is a deadly illness, ability to detect it earlier than usual is critical to a person's survival. As an outcome, our project will have a profound effect on the fields of healthcare and medicine.

VIII. REFERENCES

[1]A. M. Mahbubur Rahman, Jiaul Islam, Md. Zakirul Alam Bhuiyan,Adnan K. Abdullah,2020,"Detection of Pneumonia in Chest Radiographs with Deep Learning",IEEE
[2]Ansari, Mohd Kashif and Kumar, Pramod,2021"Pneumonia detection using machine learning techniques,International Journal of Computer Science and Communication, 1(1), 91-95.
[3]Arslan, Abdullah and Kucuk, Nurhayat,2019"Diagnosis of pneumonia using convolutional neural networks and transfer learning", IEEE International Conference on Systems, Man, and Cybernetics. Computational Cybernetics and Simulation, 3, 2517-2520.
[4]Chakraborty, Soumya and Sharma, Kusum Lata,2019"Pneumonia detection using deep convolutional neural networks",IEEE.
[5]Dar, Raziq and Arshad, Nida, 2020 "Pneumonia Detection in Chest X-ray Images Using Convolutional Neural Network",In Proceedings of the 2020 International Conference on Emerging Trends in Information Technology and Engineering (ic-ETITE).
[6]Das, Anurag and Datta, Debabrata, 2020 "Detection of pneumonia from chest X-ray images using deep convolutional neural networks",IEEE.
[7]El-Baz, Ayman and Beache, Garth M, 2019 "Deep learning-based approach for the detection and diagnosis of pneumonia using chest X-ray images",6th International Conference on Information Communication and Management (ICICM), 141-145.
[8]Guan, Qingjie and Huang, 2019 Ying,"Pneumonia detection based on improved CNN",In Proceedings of the ICASSP 2019—2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 1378– 13822018. 52
[9]Gupta, Vaibhav and Kumar, Rajeev,2020 "Pneumonia detection using deep learning techniques",10th International Conference on Biomedical Engineering and Technology.
[10]J. T. Agostinho, T. V. Gonçalves, J. C. Machado, M. S. Santos, 2019 "Detection of Pneumonia from Chest X-Ray Images Using Convolutional Neural Network".
[11]K. B. Kavya, K. N. V. Bharathi, S. S. Sreejith, S. A. Mohan, G. R. Veni, 2019 "Pneumonia Detection in Chest X-Ray Images Using Convolutional Neural Network".
[12]Khin Thiri Maung, Phyo Wai, Thiri Haymar Kyaw, Thet Thet Htwe, 2020 "Pneumonia Detection Using Convolutional Neural Networks and Transfer Learning",IEEE.
[13]Li, Jian and Wang, Wei, 2019"A novel pneumonia diagnosis method based on deep convolutional neural networks",IEEE.
[14]M. A. H. Bhuiyan, M. Rahman, J. Islam, A. K. Abdullah,2022 "Pneumonia Detection from Chest X-ray Images using Convolutional Neural Network with Transfer Learning".
[15]Md. Rezaul Karim, Md. Zia Uddin, Muhammad Arifur Rahman, Md. Saiful Islam, 2018"Deep Learning-Based Pneumonia Diagnosis Using Chest X-Ray Images".
[16]Singh, Neha and Gopalan, R, 2019"Deep Learning based Pneumonia Detection using Convolutional Neural Networks",IEEE.
[17]Wang, Xiang and Peng, Yifan,2018 "A Novel Deep Learning Approach for Pneumonia Detection in Chest X-Ray Images",International Journal of Computer Science and Communication, 91-95.
[18]Yadav, Vijay Kumar and Singh, Rishabh, 2021 "Pneumonia Detection using CNN,4th Biennial International Conference on Nascent Technologies in Engineering (ICNTE).
[19]Yaqub, Muhammad and Aslam, Muhammad Waqar, 2019 "Pneumonia 53 detection using deep learning approach".Journal of Applied Meteorology and Climatology,741-749.
[20]Zhang, Yifan and Zhou, Xuefei, 2020"Pneumonia detection from chest X-ray images using deep convolutional neural networks with transfer learning",Nature, vol. 542, no. 7639, pp. 115–118.