ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

# CONVOLUTIONAL-NEURAL-NETWORKS BASED DETECTION OF THE PNEUMONIA DISEASE –AN EMPIRICAL INVESTIGATION

**[1]PRADEEP M , [2]CH VENKANNA, [3]V.RAVI SEKHARA REDDY, [4]DR.G.SUDHAVANI, [5]B KEERTHI SAMHITHA, [6]KURRA UPENDRA CHOWDARY,**

[1]Department of ECE, Shri Vishnu Engineering College for Women, Bhimavaram, A.P, India
[2]Dept. of EIE, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, Telangana
[3]Department of ECE, Lakireddy Bali Reddy College of Engineering, Mylavaram, A.P, India
[4]Department of ECE , R.V.R & J.C College of Engineering, Guntur, Andhra Pradesh, India
[5]Dept. of CSE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, A.P,
[6]Department of ECE , R.V.R & J.C College of Engineering, Guntur, Andhra Pradesh, India

Email: pradeepm999@gmail.com , chvenkanna@gmail.com , ravisekharreddy.4@gmail.com, gsudhavani@gmail.com , bksamhitha@gmail.com kurraupendra@gmail.com

**Abstract**

Pneumonia is a fatal illness that primarily affects the developed and can occasionally prove to be life-threatening. Early diagnosis of pneumonia has a significant impact on saving many living things. The main focus of this report is the identification and compilation of pneumonia patients based on their chest X-rays. Without any preparation, a convolutional cerebrum network is employed to arrive at the aforementioned conclusion and maintain a remarkable level of precision. When used with X-light emissions, significant learning models automate the framework and guarantee quick, accurate, and comprehensive results. After the image has been processed through a series of convolutional and most limit pooling layers activated by the ReLU incitation work, the class takes place. The neurons in the thick layers are then processed, and finally, the sigmoidal limit activates the final neuron. As the model trains, the precision improves and the adversity decreases. Applying data development prior to model fitting eliminates overfitting. Accordingly, the suggested important learning models to organize the chest X-radiates for the differentiating evidence of pneumonia achieve successful and robust results.

**Keywords:** *CNN, Pneumonia, ReLU, Empirical Investigation*

## 1. INTRODUCTION

Pneumonia is perceived as one of the most compromising contamination by the WHO of late surveying more than 1,000,000 early passing's across the world. The WHO estimates that pneumonia accounts for 15% of all deaths in children under the age of five. In terms of those who signed up for the year 2017, this is almost youth. Generally speaking, it regularly affects about 450 million individuals. In 2016, it was the fourth major explanation of death.

Pneumonia is becoming more and more common in fast-paced agricultural countries. Since pneumonia can be caused by a variety of organisms and diseases, X-rays are the most important tool for diagnosing pneumonia. It's as frequently as conceivable an extreme task to choose pneumonia completely at a starting stage by taking a gander at the unique

chest X-rays. There has been a significant improvement as a result of innovation in the clinical benefits region. Regardless, Chest X-Rays are moved toward be strong, taking a gander at Chest X-bars can be decided to perceive pneumonia just like a cardiovascular breakdown or different cell breakdowns in the lungs can be frustrated. Due to their requirements, several machine learning models fail to detect similar types of illnesses, which motivates us to employ more sophisticated and cautious deep learning models—unquestionably a closely comparable CNN that aids in the process of brand name departure. Pre-training the models can improve their accuracy and usefulness. [1]
The essential test is to make a strong estimation that perceives whether or not a particular case is

encountering pneumonia, by reviewing his chest X-pillar. As the presences of people are being referred to, most outrageous second ought to be given so the estimation is unbelievably exact. One of the most popular significant learning cerebrum associations is CNN, which employs a number of layers around the optimal pooling layer.
The layers help in modified picture affirmation of the X-radiates. It in like manner contains the cured Linear Unit called ReLU layer which help to better non-linearity. It's a smoothed out plan to manage 2D as well as 3D pictures as a matter of fact. It sets an equivalence to the appropriate association of trial and error structure. The goal of the document is to identify numbers for individuals and groups who may or may not have pneumonia. [2]

As time goes on, the record is coordinated. Section 1 presents the suggested approach, while Section 2 provides a comprehensive report on the dataset utilized and chest X-ray pictures of patients with and without pneumonia. Additionally, the dataset was expanded to include the show. We've made great progress in area 3 in creating models such as CNN Network and examining the layers that are employed in their implementation. Section 4 explains how each image looks after it has been processed by the CNN layers. Fragment 5 uses graphical and quantitative representation to provide a visual grasp of the facts. Section 6 shows the final results of implementing the plan computations, together with a close-by assessment across all age groups. The work has finally addressed the conclusion and future degree.

## 2. ALLIED EXERTION

An assessment document that included the early assurance of pneumonia employing major learning steps close was offered by Deniz Yagmur Urey et al. The creators took a novel strategy by using X-shaft imaging to focus on the common elements of this fatal illness and recall it. The grouping methods used include convolutional neural networks (CNN) and residual neural networks. The Relative audit helps perceiving Pneumonia at a starting stage and as needs be, fitting therapy can be given over to fix the disorder. This assessment impacted our report, to keep a such assessment, however, on a point-by-point method of the layers of the cerebrum association to make it more powerful and generate reasonable correctness, as well as on a lot more photos and extra summary facts [3].

Using a variety of important learning models, Dimpy Varshni et al. demonstrated the progress of a changed structure for the area of pneumonia. The researchers developed a Convolutional Neural Association for disease collection and data scaling after analysing clinical images. A DenseNet-169 layer is designed for suggestive extraction as part of the strategy. For matched portrayal, the plan worked well with an SVM model. An overview is provided for something much the same, and the model's outcomes are bad down with some twists. [4]

Garima Verma et.al. tended to an assessment document which examinations and recognizes pneumonia, predicated onX-shaft pictures, using convolutional mind association. Six convolutional layers were used in the execution, with the majority of limit pooling layers coming after each. This helped us figure out how to speed up the substantial learning model's development and implementation by adding a more discrete number of convolutional layers. Based on chest X-rays, the evaluation detects pneumonia. [5]

Okeke Stephen et.al. gives a such knowledge on orchestrating multiplex-shafts to recognize pneumonia considering convolutional mind associations. The accuracy traversed their investigation helps us with evaluating our model in connection, dependent upon the hardship and precision of the cerebrum association. In order to reduce the estimations, their affiliation is given over with a (200x200x3) perspective input form, while the images are locked in and it employs (64x64x3) angles. [6]

## 3. ANTICIPATED APPROACH

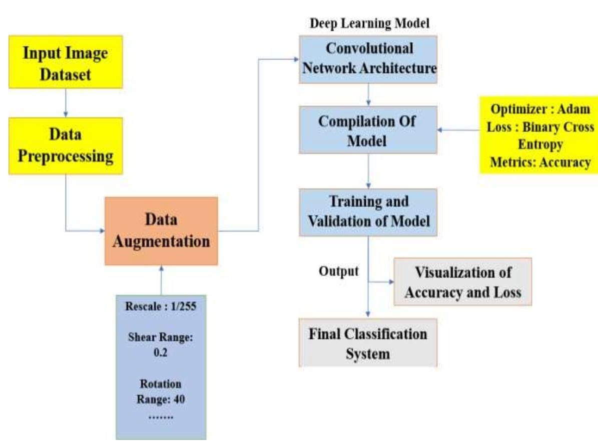


*Fig. 1 Scheme Design*

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

The image collection used in the aforementioned structure, such as the chestX-pillar photos, is pre-managed and modified using various Python programming language NumPy and Pandas libraries. Additionally, the data is stretched out at this point to provide updated and well-coordinated findings in the several important learning models. Rescale factor, sheer range, rotation range, and other attributes are taken into account in the data development phase. After that, this data is sent to the Convolutional Network, a Deep Learning Model, where it undergoes a series of movements. During the decision-making stage, an enhancer called Adam is used to measure accuracyand the setback as deceptive entropy to redesign the results. . Additionally, the convolutional network plan reveals that the model is ready. This stage's outcome aids in our ability to visualize and interact with different outlines and twists that demonstrate the dependence on certification, disaster, and other bundle elements. The Final Classification System, which breaks down whether or not the patient has pneumonia, is the result after a significant amount of work. [9] [10]

## 4. DATASET

The Chest X-beam dataset, which is provided by the radiological division/relationship on the Kaggle site, provides the basis for all of the analyses. All of the images are X-beams modifying the RGB layout. The Convolutional Neural Network is configured and prepared using the Tensor Flow backend and the open-source Keras deep learning framework. Pneumonia and normal chest X-beams were used to separate the preparation, testing, and affirmation images in the dataset. An entire of around 6000 pictures of foremost back are available. The information is changed into the preparation and approval set to improve the framework and increment proficiency. An entire of around 5216 pictures are contained in the preparation set and similarly, to update the overall accuracy, a total of 624 images are assigned to the approval set.

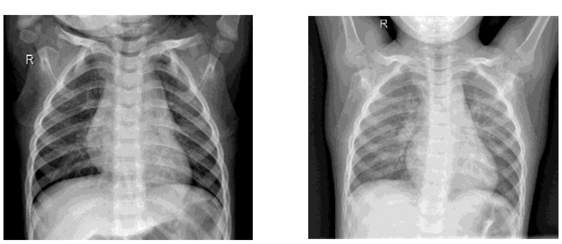

*Fig. 2 X-Ray Specimen Free Of Pneumonia*

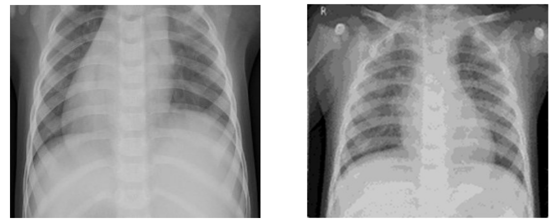

*Fig. 3 Samples Of X-Rays Containing Pneumonia*

## 5. DATA AUGMENTATION

Data improvement strategies are generally used to redesign the introduction of significant learning computations. In order to sort the chest x-radiates, the convolutional cerebrum network model is first introduced using data improvement. To increase and enhance the quality, savvy, and amount of the data, data augmentation is performed to the readiness data, which are the images for this particular situation.
.
To help the Deep Learning exhibit numerous intricacies in the arrangement photographs, a variety of assignments are completed to speed up the amount of the data. The purpose of convolutional neural networks is to help with overfitting of the data and to smooth out the model's display. At this point, when an AI or significant learning model works well on the arrangement set but yields terrible results on the testing and documentation sets, it is known as overfitting. Therefore, it is not logical to over fit the model during the achievement process. [7]

The Deep Learning and Computer Vision calculations can be made to fit the models even more successfully and skilfully by increasing the size of the readiness dataset. A variety of data enhancement techniques have been used to establish the model. This is lately conducted throughout the run time and essentially doesn't alter the core dataset. The added and modified images are stored in no unnecessary circle space.

The data improvement techniques used to erode our Deep Learning model's accuracy are:
I. Rescale Normalization - This is used to manage the picture datatype and reduce the amount of computation and handling that is expected. Any image can have pixel values ranging from 0 to 255. Every value is replicated by a rescaling factor of 1.0/255.0 to standardize this vast range and achieve the characteristics somewhere between 0 and 1.

. In this way, the required computational and it is basically lessened to manage power. This is invoked while stacking and handling the images into preparation and documentation sets using the Tensor Flow Python Library's Image Data Generator limit.

ii. Numerical Transformations - These are used to change the numerical properties of pictures and allowing the model to achieve the readiness pictures adjusted concerning these properties. It engages the model to yield and deal with pictures matching to the principal planning set, yet with slight assortments in their real characteristics. To explain this, a model may find it difficult to see a zoomed-in image if they are shown zoomed-out preparation images. Similarly, by altering the level, breadth, and zoom numerical parameters, fresh readiness images are produced that may aid the model in correctly interpreting the test image. Like the 'width_shift_range', 'height_shift_range', and 'zoom_range' defined in the Image Data Generator work, this combines a number of attributes and limitations.

iii. Flipping - It is unlikely that the model will perceive and assess an identical representation of a readiness picture during the testing phase. Flipping is therefore used to speed up the data and transmit flipped photos of the planning data in order to guarantee a satisfactory and ideal model execution on these reflected images., without truly taking care of reflected photos of each getting ready test, onto the plate storing. Hence, a vehemently capable flipping expansion strategy helps work on the presentation of the Deep Learning with exhibiting on the chest x-shaft dataset.

iv. Shearing - In order to organize the Deep Learning model to photographs in a sheared transparency, shearing is introduced to the planning pictures, resulting in sheared pictures. It's quite possible that certain test images will resemble some readiness images in terms of sheared transparency. In order to address these test images from a real-world standpoint, the shearing transparency of explicit planning set images provides us with a common understanding.

v. Turn - Unambiguous degrees of rotation can be applied to training images to produce altered images, speed up, and build objects in the arrangement dataset. Setting the 'rotation_range' to a suitable value while displaying the Image Data Generator work fits this. In this manner, different markers from the converted images are used to enrich the data.

## 6. CONVOLUTIONAL NEURAL NETWORKS

One important class of cerebrum networks used to evaluate visual imagery is CNN. It has several layers of mystery, as well as a layer of commitment and outcome. The data is a tensor with condition of the construction ( number of pictures) * ( picture level) * ( picture width) * ( picture significance). The image becomes applied to an component map ensuing to coming to through the convolutional layer, with shape ( number of pictures) * ( feature map level) * ( incorporate guide loads) * ( incorporate guide channels). Truth be told, Every data image of the dataset is prepared and supported by CNN models, which move through layers with purifiers, concurring parts, pooling, and completely related layers. Softmax is even used to sort an item between probabilistic valuations somewhere between 0 and 1.

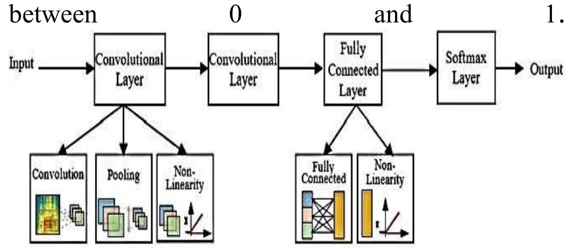


*Fig. 4 Block Diagram For CNN*

The extent of the outcome network taking in to the idea padding and step can be figured utilizing the going with formula. (10)

$nout$ =(n in+2*p-k)/s +1 ________(1)

CNN has a distinct advantage over other mind networks in that it typically detects the most malevolent presence traits with virtually little human monitoring. The main idea is that CNN exclusively uses image datasets. As anticipated, convolutional cerebrum associations can eliminate important elements from images, with the exception of the requirement to handle manual image processing techniques. When it comes to districts with greayer approximated, unshaped data, CNNs are unthinkably attractive. CNNs are similarly computationally useful and more grounded than AI guesses. CNN uses a variety of activation limitations, including as the sigmoid limit, tanh work, and the widely utilized ReLU work. [10] The accuracy of the association is greatly impacted by CNN's ambitions to increase a variety of hyper-boundaries, including combination size, target size, number of hidden layers, number of ages, and smoothing out specialist to be applied.

Journal of Theoretical and Applied Information Technology
15th November 2024. Vol.102. No. 21

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Convolutional neural networks are hence particular linkages that are intended to effectively enhance the two-layered structure.

## 7. DESIGN OF A DEEP LEARNING MODEL

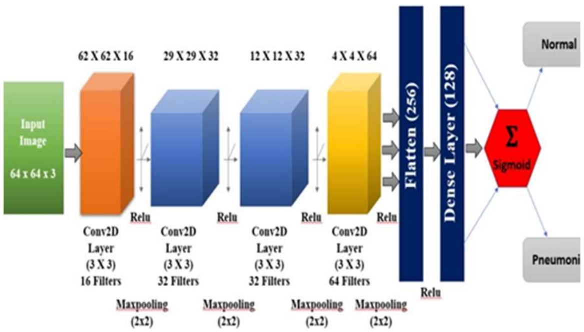


*Fig. 5 Cnn's Architecture*

A Layer Description

One method for determining whether a particular chest X-pillar image shows pneumonia or not is Deep Learning. This is accomplished by applying a Convolutional Neural Network, which consists of multiple two-layered convolutional layers, two-layered Maxpooling layers, and a thick layer with 128 neurons that handles the aftereffects of the final convolutional and Maxpooling layers. This is finally handled in a layer that was initiated with the Sigmoid Function. Since we have two different strategies, the final layer of the Deep Learning Network uses the sigmoid sanctioning work, and the outcome is the degree to which either normal or pneumonia-related contamination occurred.

In Fig. 4, the Convolutional Network plan is addressed. The layers provided by the Tensor Flow Python library's Keras API are used to create a progressive model. The information image has three purifiers for the assortment (RGB) and is a standard 64x64 size. After that, the data image is processed into the essential layer, which has 16 filters and 3x3 angles. Additionally, this can be written as (3x3x16).The convolutional layer then separates the image into new (62x62x16) sections. Following the basic convolutional layer, this image is similarly handled in the Maxpooling layer. The window portion of the Maxpooling layer is (2x2). As a result, the image's size is also distinct.

A further convolutional layer is then applied to the image, which is represented by Keras' successional model. 32 purifiers make up this convolutional layer, which has a 3x3 form (3x3x32). The picture achieves fresh perspectives at this time. The following image currently has the dimensions (29x29x32). Additionally, a Maxpooling layer of size 2x2 is introduced. Once more, this alters the contour of the image.
Additionally, the additional blue box in Figure 4 suggests that the altered image has undergone another convolutional layer with a comparison perspective. This convolutional layer's condition is the same as the previous one (3x3x32). To improve the nuances of the X-shaft image, the convolutional layer performs more processing on the image. The picture fulfils an additional 12x12x32 requirement. Eventually, the image is handled using a (2x2) perspective Maxpooling layer. [14]
The 64-channel two-dimensional convolutional layer is the final layer of the convolutional network. This convolutional subcase of shape (3x3x64) produces a performing image of shape (4x4x64) by improving the subtleties of the original altered image. Once more, the Maxpooling layer in advance modifies and provides better examples of the image for better handling and representation. The ReLU work stimulated all previous convolutional layers. ReLU, which stands for Rectified Linear Unit, is typically utilized when gathering is involved.

The escort is handled into the mind network layer (DNN), where the data is smoothed, after the final convolutional layer. Up until recently, this was handled into the incoming layer, which has 128 neurons to handle the key components of the image and activate the cerebrum association to organize based on the neurons' computation and discrimination. Additionally, this layer handles the data and calculates yield for that particular layer using the ReLU commencement capability. The information from this thick layer of the DNN is sent to the last thick layer, which has a single outcome neuron, to ascertain whether or not pneumonia is detected in the designated Chest X-shaft.
In matched type yield, where the result should be effectively divided into two groups, the sigmoid order work is typically utilized. Thus, an outline of the Deep Learning Model that incorporates both Convolutional and Deep Neural Networks

B. Model Summary

The Output Shape is framed by the quantity of parameters communicated at each Deep Neural

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Network subcaste in the Model Summary that is shown below. Our CNN model's layers are applied collectively since they show up in the association near each other, giving shape views and the number of restrictions. Following the level layer with zero limits and the thick layers with about 32000 limits, Four convolutional layers and roughly the same number of Maxpooling layers are present. Similarly, all of the association's feasible boundaries add up to boundaries. This model diagram provides a brief overview of Deep Neural Network data.

| Layer (type) | Output Shape | Para |
|---|---|---|
| conv2d (Conv2D) | (None, 62, 62, 16) | 448 |
| max_pooling2d (MaxPooling2D) | (None, 31, 31, 16) | 0 |
| conv2d_1 (Conv2D) | (None, 29, 29, 32) | 4640 |
| max_pooling2d_1 (MaxPooling2 | (None, 14, 14, 32) | 0 |
| conv2d_2 (Conv2D) | (None, 12, 12, 32) | 9248 |
| max_pooling2d_2 (MaxPooling2 | (None, 6, 6, 32) | 0 |
| conv2d_3 (Conv2D) | (None, 4, 4, 64) | 1849 |
| max_pooling2d_3 (MaxPooling2 | (None, 2, 2, 64) | 0 |
| flatten (Flatten) | (None, 256) | 0 |
| dense (Dense) | (None, 128) | 3289 |
| dense_1 (Dense) | (None, 1) | 129 |

Total params: 65,857
Trainable params: 65,857
Non-trainable params: 0

*Fig. 6 Model Summary*

## 8. RESULTS

A. Pictorial Representation after Each Layer

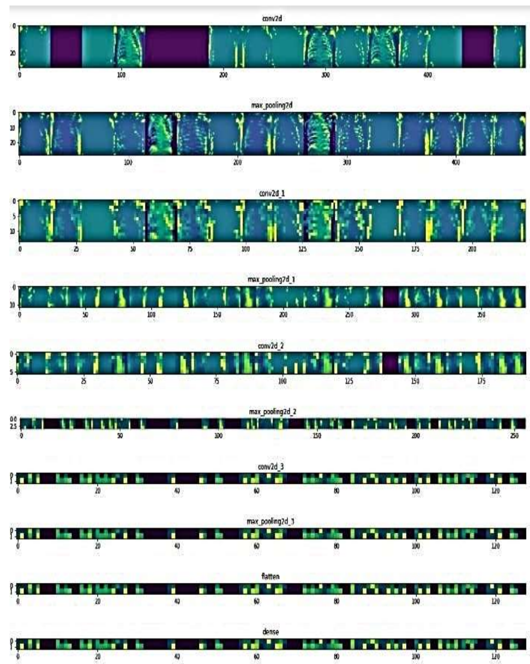


*Fig. 7 The Final Image Following Each Layer*

The aforementioned diagram illustrated how the information picture is prepared at every stage and layer of the CNN that has been used in the past. In light of the chest X-beam, it demonstrates how the image is examined at each layer for more nuanced ways to identify and assess pneumonia. This representation provides insight into how each convolutional layer and Maxpooling process the data image in a visual arrangement.

B. Training and Validation Results

The model is designed for 25 ages. For the status stage, a group size of 32 was used, which adds up to 163 stages for each age for planning, and for the testing stage, a social event size of 16 was used, which adds up to 39 stages for each age for testing. Consequently, getting ready for 25 comparable ages produced streamlined outcomes, with high exactness of96.36 and a most irrelevant misfortune of0.1020 for arranging and a corresponding91.51 accuracy and0.2705 debacle for support.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

*Table 2 Performance Of The Deep Learning MOdel*

| Stage of Epoch | Accuracy of training | Loss of Training | Validation Accuracy | Validation Loss |
|---|---|---|---|---|
| 1 | 0.8993 | 0.5478 | 0.9617 | 0.4099 |
| 5 | 0.8496 | 0.1538 | 0.9035 | 0.5789 |
| 10 | 0.8404 | 0.1357 | 0.8033 | 0.3873 |
| 15 | 0.8409 | 0.1376 | 0.8321 | 0.3088 |
| 20 | 0.8450 | 0.1148 | 0.8204 | 0.3916 |
| 25 | 0.8550 | 0.0873 | 0.9357 | 0.3380 |

This table designs the presentation yielded the CNN plan. The table gives the planning precision, getting ready hardship, ampleness accuracy and attestation incident obtained at various ages. A portrayal of the planning and endorsement credits for every five ages has been furnished.

*Table 3 Performance Metrics For C*

| Epoch | TP | TN | FP | FN |
|---|---|---|---|---|
| 1 | 462 | 292 | 64 | 49 |
| 5 | 498 | 231 | 225 | 4 |
| 10 | 496 | 289 | 64 | 6 |
| 15 | 494 | 294 | 52 | 8 |
| 20 | 496 | 294 | 62 | 6 |
| 25 | 495 | 294 | 7 | 6 |

The table above displays that the affirmation precision is about like the readiness accuracy.

C. Performance Chart for the Verification Stage

The exhibition standards to determine precision based on the arrangement outcomes are displayed in the above table. The model correctly predicts a case of pneumonia, as indicated by the true positive rules. A genuine negative indicates a scenario in which it accurately forecasts when a person won't be affected by pneumonia. Misleading Negative suggests that the model incorrectly assumes that a person with pneumonia is not dangerous. Bogus Positive connotes that an individual not impacted by pneumonia is ordered to have it. In this manner, grounded on relating order, we see from the table above how different approval cases have been arranged into every measures. It serves to computation of precision of the model. For example, at the 25th age, the approval precision can be closed as follows -

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \qquad \text{\_\_\_\_\_\_\_\_\_\_}(2)$$

Where TP = True Positive; TN = True Negative;
FP = FalsePositive; FN = False Negative.

Thus, for the last epoch, we get –
Validation Accuracy =0.9866
Validation Accuracy = 0.9866*100 = 98.66 %

D) Graphical Representation:

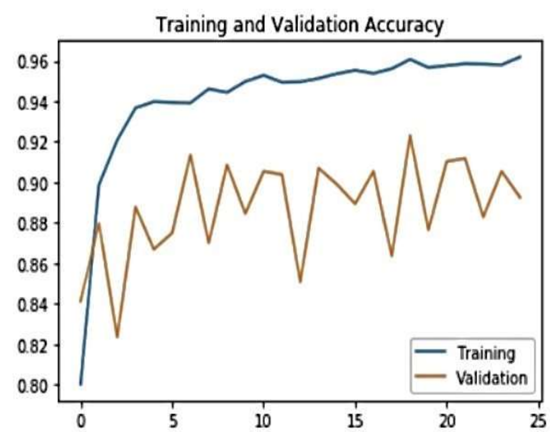


*Fig. 8 Training And Validation Accuracy*

The figure given above depicts the slanting diagram regarding how the preparation and approval exactness fluctuates with the age count. On close affirmation, the chart places that when the quantity of ages speed up there's a significant expansion in the preparation precision though there's a progressive updating and plunge in the approval exactness. Toward the finish of the 25th age the preparation exactness accomplished is similarly high as 96 in contrasted with the 92 precision put together by the approval bend. There's a ceaseless extension in the preparation exactness bend after each age as we've set around 163 stages for every age in differentiation to the 39 stages for every age in the affirmation precision bend to yield as ideal and usable outcomes.

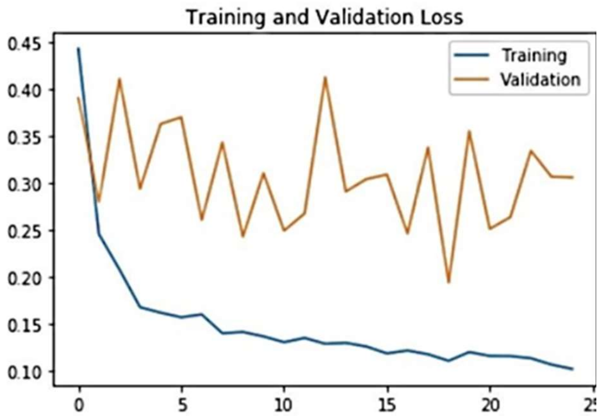


*Fig. 9 Training And Validation Loss*

The update and decline of misfortune in the organization as the number of ages increases is depicted in figure 9 above. On review, we accomplished that there's an extraordinary dunk in the preparation misfortune as the quantity of age arrive at 25. The misfortune enormously diminishes shaping the organization besides precise and effective. The preparation misfortune at end of the multitude of ages results to the 0.0962. The approval misfortune on the stage has a dynamic increment and decrement as the ages expands because of less advances per age when contrasted with the preparation bend. This shows the misfortune toward the finish of all ages gives to0.2290. In this way, these representations support the outcomes accomplished and delivers our organization effective and precise for conclusion of Pneumonia.

## 9. CONCLUSION

Thus, it is believed that the above-mentioned substantial learning model arranges the chest X-radiates for the diagnosis of pneumonia in a genuinely authentic way. The model's shortcomings are limited throughout preparation, and its accuracy simultaneously rises across all age groups to provide distinct findings for characterizing those who have and have not contracted pneumonia. By preventing the display of convolutional cerebrum associations and important mind networks from being abused toward overfitting, the data advancement and preparation phases help to guarantee that the outcomes obtained will consistently remain normal. With fewer neural layers, the proposed model correctly identifies whether a particular chest X-pillar illustration is common or has pneumonia. In the clinical setting, this greatly aids in the early and precise diagnosis of pneumonia in patients. Finding a solution ahead of time is crucial for saving a person's life since it guarantees that the patient will receive effective treatment quickly.

## 10. FUTURE SCOPE

The familiar model can be improved further to communicate pneumonia stage-by-stage findings. This study can also be expanded to examine patients infected with the coronavirus (Covid-19), which has afflicted millions of people worldwide during the 2020 pandemic. In addition to ensuring a quick and reliable testing procedure, an X-bar-based detection of corona contamination would also reduce the risk of receptiveness to the clinical staff responsible for testing. Given a significant amount of data, the Deep Learning model can be closed for the detection of COVID-19 using move progressing as well.In like manner, the Deep Learning model can moreover be used for different clinical purposes and finding, concerning bone disguise in chest wretchedness, to investigate respiratory afflictions. Thusly, this adventure has tremendous augmentation in the field of medicine and clinical benefits, and can be happened for different contrasting wise appearances.

## REFERENCES

[1] Acharya, A. K., & Satapathy, R. (2020). A deep learning based approach towards the automatic diagnosis of pneumonia from chest radio-graphs. *Biomedical and Pharmacology Journal*, *13*(1), 449-455.

[2]Chandra, T. B., & Verma, K. (2020). Pneumonia detection on chest x-ray using machine learning paradigm. In *Proceedings of 3rd international conference on computer vision and image processing* (pp. 21-33). Springer, Singapore.

[3]Saul, C. J., Urey, D. Y., & Taktakoglu, C. D. (2019). Early diagnosis of pneumonia with deep learning. *arXiv preprint arXiv:1904.00937*.

[4]Varshni, D., Thakral, K., Agarwal, L., Nijhawan, R., & Mittal, A. (2019, February). Pneumonia detection using CNN based feature extraction. In *2019 IEEE international conference on electrical, computer and communication technologies (ICECCT)* (pp. 1-7). IEEE.

[5]Shah, S., Mehta, H., & Sonawane, P. (2020, August). Pneumonia detection using convolutional neural networks. In *2020 Third International Conference on Smart Systems and*

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

*Inventive Technology (ICSSIT)* (pp. 933-939). IEEE.

[6]Stephen, O., Sain, M., Maduh, U. J., & Jeong, D. U. (209). An efficient deep learning approah to pneumonia classification in healthcare. *Journal of healthcare engineering*, *2019*.

[7]Shanthamallu, U. S., Spanias, A., Tepedelenlioglu, C., & Stanley, M. (2017, August). A brief survey of machine learning methods and their sensor and IoT applications. In *2017 8th International Conference on Information, Intelligence, Systems & Applications (IISA)* (pp. 1-8). IEEE..

[8]Mikołajczyk, A., & Grochowski, M. (2018, May). Data augmentation for improving deep learning in image classification problem. In *2018 international interdisciplinary PhD workshop (IIPhDW)* (pp. 117-122). IEEE.

[9]Mullangi, P., Srinivasa Rao, Y., Kotipalli, P. (2018). Texture and Clustering-based Skin Disease Classification. In: Urooj, S., Virmani, J. (eds) Sensors and Image Processing. Advances in Intelligent Systems and Computing, vol 651. Springer, Singapore. https://doi.org/10.1007/978-981-10-6614-6_11

[10]Pradeep, M., Chintamaneni, V., Anantha Raman, G.R., Srividya, A., Fathima, S.S.S., Rajeswaran, N. (2023). AI-Based Smart Farming Technology Using IoT. In: Reddy, V.S., Prasad, V.K., Wang, J., Rao Dasari, N.M. (eds) Intelligent Systems and Sustainable Computing. ICISSC 2022. Smart Innovation, Systems and Technologies, vol 363. Springer, Singapore. https://doi.org/10.1007/978-981-99-4717-1_20