International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 07 | July - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

SMART PNEUMONIA DETECTION DEEP LEARNING-BASED PNEUMONIA DETECTION USING CNN AND ResNet50 MODELS

Rakshitha Y S[1], Thanuja J C[2]

[1] Student, Department of MCA, Bangalore Institute of Technology, Karnataka, India

[2] Assistant Professor, Department of MCA, Bangalore Institute of Technology, Karnataka, India

---***---

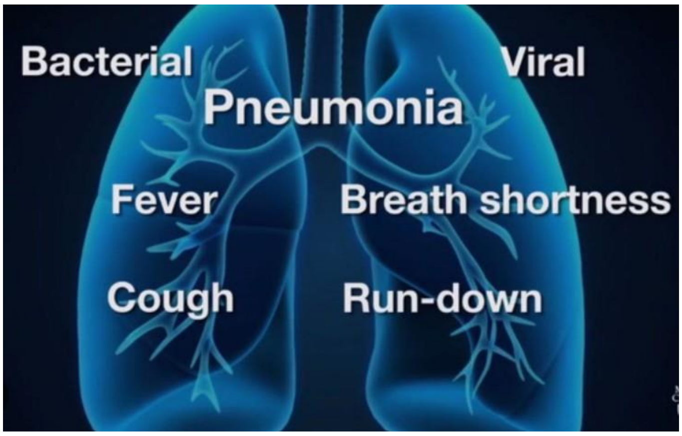
Abstract - One of the common and fatal infectious diseases around the world is pneumonia, and it is one of the main causes of death. According to the World Health Organization, one-third of total deaths is recorded as due to this infectious disease. Pneumococci are a unit, a bacterial strain belonging to the species Streptococcus pneumoniae that remains the most important causal pathogen. Swift diagnosis, especially in faraway regions, is indispensable since it is an essential condition of proper treatment. This paper will present an automated system for the detection and classification of pneumonia with chest X-ray images according to three classes: origin, Normal or viral pneumonia or bacterial pneumonia. The model applies the method of convolutional-neural-networks and a pretrained architecture design of ResNet50 in order to make its functioning. In this study, a trained ResNet50 model was used for the classification of chest X-ray images. This will aid the radiologist in making accurate medical decisions because the model will classify the specific kind of pneumonia present. Some of the performance metrics that can be used to evaluate the model's usefulness include test accuracy, F1 score, recall, precision, and support. Off this pneumonia dataset, the model depicts a very high test F1 score, which means it could label cases of pneumonia with high accuracy. The results show that the created model can be potentially applied as a useful tool in declaring pneumonia assistance for the radiologist in scenarios characterized by scarce resources. Pneumonia, CNN, X-ray images, ResNet50, convolutional neural network, precision, F1 measure, recall, accuracy.

Key Words: Smart Pneumonia Detection, Convolutional-neural-network, ResNet50, Chest X-ray Images.

1.INTRODUCTION

Since the advent of man, disease infection has been one of the most real threats to human existence. The most well-known, by far, infections are those caused by virus; pneumonia. Severe infection of the respiratory lungs is referred to as pneumonia. The lungs comprise tiny sacs called alveoli that inflate with air when a person inhales. These sacs, in a case of pneumonia, fill with discharge and fluid, which makes breathing very difficult and reduces oxygen utilization. Diseases and microorganisms pollute these, thus hurting the lungs. The most common symptoms of pneumonia are difficulty, coughing, dyspnoea, and others as secondary effects. Worldwide,

Pneumonia is the basic source of death for children. In 2017, 8,08,694 children younger than five died of pneumonia, corresponding to the WHO—nearly 15 percent of every pediatric death.when an individual unwinds. These sacs load up with release and fluid when an individual has pneumonia, which makes breathing problematic and diminishes oxygen utilization. Pollution’s achieved by diseases and microorganisms hurt the lungs. Typical signs of pneumonia consolidate trouble, hacking, dyspnoea, and different secondary effects. Around the world,



Pneumonia is a very common condition in sub-Saharan Africa and south Asia. It is a relatively reparable and preventable condition with some sensible, low-tech treatment and medication. Pneumonia typically affects 7.7 percent of the entire population regularly. The role of automated medical image classification has become increasingly significant due to the necessity of early detection for various medical conditions. This project focuses on classifying medical images into predefined categories. Recently, Deep Learning (DL) has emerged as one of the most prominent and complex approaches for generating clinical image descriptions. Moreover, DL

Models performed better compared to traditional methods on chest X-ray images taken from patients suffering from pneumonia. The constructed DL models depicted excellent perceptual capabilities of the approach that turned out to be better than human experts. Digital representation through DL models about chest X-ray images is rapidly increasing to identify pneumonia by utilizing certain portions of the image.

Besides that, DL models are also helping to eliminate time-consuming processes associated with traditional systems. These models, however, have been associated with large amounts of data, most of which is normally used for pre-training and whose labels are usually blurry. To that effect, transfer learning has been developed to handle this challenge.

Due to its ability to address the limitations of both guided and directed learning, Transfer Learning (TL) is becoming increasingly widespread. The main types of TL include: independent, inductive, transudative, and negative learning. These types have shown potential in solving issues related to DL, particularly in improving accuracy. TL plays a crucial role in providing an effective framework and focused feature extraction stage for various fields.

2. LITERATURE SURVEY

[1] Deep learning in relation to the identification of pneumonia and associated diseases has been broadly considered. In 2015, Swapnil Singh et al. studied transfer learning, multilayer perceptron's, and convolutional neural networks for the detection of pneumonia. In this research, data augmentation techniques, including image cropping, rotation, and changing brightness levels, were applied to 5,863 X-ray images to show the performance of the model. Their approach uses a specifically designed ConvNet, where the first convolutional layer uses 32 neurons, while the second and third layers used 64 neurons, the fourth layer contained 128 neurons, and finally, the last had one neuron.

[2] In a paper by Dimpy Varshini et al., the authors consider several pre-trained Convolutional-Neural-Networks models coupled with unique classifiers against 112,120 frontal chest x-ray pictures corresponding to 30,085 patients. The proposed model is structured to have three distinct architecture stages: a preprocessing step, a pattern-recognition stage, and a classification stage. The statistical results led Dimpy Varshini et al. to choose SVM for the classification stage and DensNet-169 for the feature extraction stage, even though the feature was derived from several types of pre-trained models.

[3] E. J. Palomo et al. proposed a computer-aided detection (CAD) system for identifying pneumonia in chest X-ray images using a convolutional neural network (CNN). This system fine-tuned the pre-trained CNNs, such as VGG16, Inception-v3, and ResNet50, changing their dense layer designs. From the experimental results, using the "Chest X-Ray Images (Pneumonia)" dataset yielded 96.59 percent accuracy; the best was produced by VGG-16. It surprisingly outperformed two of the models that were proposed in this paper, especially with the 6-layer CNN1. This paper compares the proposed system with existing state-of-the-art methods and claims it is more suitable and effective for the detection of pneumonia. This makes a case for using the CAD system to enhance diagnostic accuracy in the area of pneumonia detection.

[4] L. Raciˇ c et al. contributed an extensive discussion on deep ´ learning dedicated to a very detailed analysis of lung X-rays to define signs of pneumonia. They used a special model called a convolutional-neural-network and implemented it in the Python programming language. So far, preliminary tests look good at about 90 percent accuracy, always keeping in mind that with this small size of a dataset, there is always the chance of overfitting. While it is as accurate a pattern one gets, authors stress that, "a special radiographic finding does not rule out the diagnosis of pneumonia." They stress much more data is needed to improve the model. They are also looking at trying different ways of preparing the data, even different configurations of CNNs and other types of X-ray datasets, which would be representative of other health problems.

[5] It reviews the literature available on pneumonia detection from chest x-ray data, focusing on the usability, efficiency, and computational complexity of the algorithm. Traditional machine learning goes fine in resource-constrained environments but could not scale an industrial environment for pneumonia detection. This paper suggests deep learning. It can be noticed that in most of the datasets available, the biggest imbalance exists in the dataset. Therefore, in order to make pneumonia detection systems more dependable and scalable, large balanced datasets are required. It will also require large, balanced datasets to help increase the reliability and scalability of pneumonia detection systems. Large, balanced datasets are therefore required to increase the reliability and scalability of pneumonia detection systems.

3. PROPOSED MODEL

Convolutional Neural Networks is one of the deep neural network methods that are highly suitable for the task of classification of chest X-ray images to determine the kinds of pneumonia as these networks are capable of learning critical features from data. The technique of transfer learning was applied to minimize the time clinicians spend diagnosing the images and, also, to increase diagnostic accuracy. The present study is underpinned by Ensembling Learning as the new framework of the neural architecture complemented by transfer learning. This method entails the training of CNNs with the help of a RESNET50 algorithm to detect pneumonia from chest X-ray images. The authors of this paper neither have trained the CNN model from the scratch, but used appropriate methods for transfer learning and selected fine-tuning. The present ensemble learning technique that has also been proposed in this paper integrates a dropout layer as well as a batch normalization layer.

The following block diagram depicts the approach formulated for the system. First of all, the user inputs an x-ray image of a particular patient into the system. The system shows that it has pre-processed the image and thereafter provides the resized HSV image. Subsequently the above mentioned pre-processed image, the system trains this image according to the company model that has been chosen. Then the following data pre-processing is done and then the model is trained on the datasets passed. They estimate the outcome depending on the training. Next there is a text output of the calculation and of the figure uploaded at the bottom of the article.

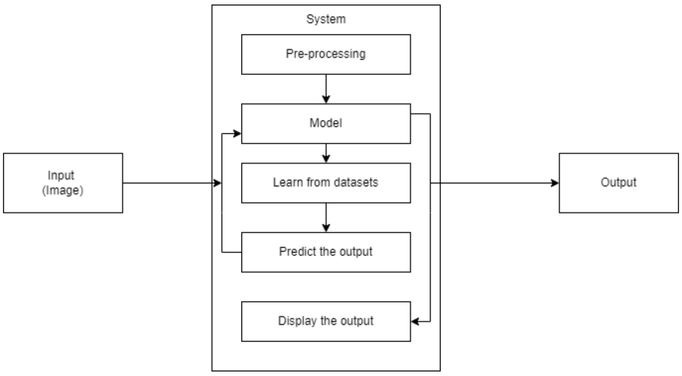


Fig. 1. Block diagram of the proposed system

CNNs are one of the deep neural networks classes that study and establish specific appearances of an image and widely used in visual media analysis. A convolutional tool that analyzes an image to form a process called feature detection where features of different types present in the image are formed. A subtractive network has many convolutional as well as pooling layers integrated in its construction. A fully connected layer uses the result of the convolution and, having gone through the above steps, classifies the image according to the features extracted from the input. The use of extracted features from a CNN is applied for minimizing the features of the dataset that is being used. This generates new functions, integrated by the primary ones of an original function.

Particularly, the researchers' aimed to find a solution by proposing a certain type of a convolutional neural network applied to the chest X-ray images to determine the presence of pneumonia. Several convolutional layers and max - pooling were followed by a few fully connected layers for feature extraction and classification. Data augmentation has been done during training using ImageDataGenerator. On the basis of five epochs of training it gives high magnitude of accuracy on the validation set therefore giving very strong results.

In this work, the proposed EL approach is formally applied to nine well-known CNN algorithms from chest X-ray pictures of pneumonia. In the training phase various TL and fine-tuning strategies were compared of which only configurations that facilitated better performance were employed at testing phase. In the document it was pointed out that the learning rate was set to 1 × 10–4 while the batch size was set to 32. Different epoch sizes were trained for the method, but it started overfitting after 20th epoch was attempted.

As a form of avoiding overfitting procedures, the method of early stopping was applied. Also, for the purpose of loss function, categorical cross entropy was reduced using the Adam optimizer. The last layer consisted of the classification layer where we used the SoftMax activation for the classifications. In this section the experiment study that was conducted is explained as follows. First, we will make some explanations about the criteria used to evaluate the execution of the algorithm and the appeared datasets and, then, we will expose the outcomes of the experiment. Last but not least, we will ascertain our proposed methodology from contemporary research on the similar topic. The model used in this work does not train a CNN from the scratch, rather is the pre-trained VGG model.

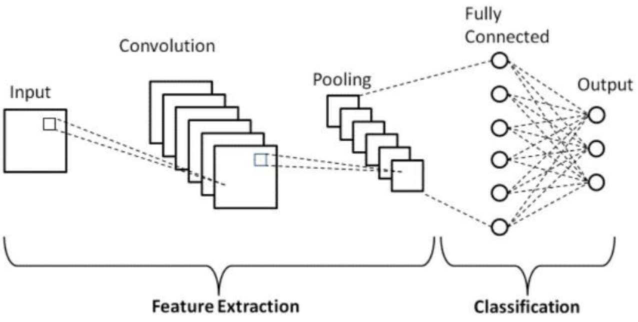


Fig. 2. Architecture of CNN

In these aspects, the model introduced in this paper based on ResNet50 was capable of identifying the type of pneumonia through lung X-ray images. As can be seen, the most frequent proposed classification methods in medical image classification at the output are precision as a recall, F1-score, and Precision measures.

4. CLASSIFICATION

1. Dataset description

It employed chest x-ray pictures obtained from Kaggle forum, which included 10,291 overall photos. The pictures were grouped into bacterial, viral, normal pneumonia and other. This dataset is balanced, then preprocessed into an HSV image by the following processes; all the pictures were sized 256 by 256 pixels and further grouped into their respective category. There are several data augmentation that it has namely Gaussian blur, CLAHE, and equalize.

2. Model Architecture

Therefore, many newly developed DCNN models serve to enhance the performance and efficiency of ML. In addition, since the architectures of DCNN models are scalable and features are auto-extractable, this has been one of the most researched deep learning techniques. Since the topologies of most deep learning algorithms such as MobileNet and DenseNet are adjustable, and all the algorithms can automatically extract features, most of them have combined the depthwise separable convolutions to overcome the negative

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 07 | July - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

aspects of conventional operation. Also, on that regard, the depthwise separable convolutions operate in every input unlike the conventional convolution processes. Thus, what can be taught to the algorithms include faster with fewer parameters and require fewer resources to execute as compared to rule based. That is why, recently an ensemble technique has been developed which claims to be more effective than the single network in learning the complex features of the representation. Two kinds of ensemble methods have been employed in the CNN designs. In a number of investigations, the first approach was used to extract information from the medical images with the help of various CNN algorithms. The attributes thus collected are accumulated and in conjunction with various machine learning methods are utilized for the processes of classification and clustering. Some of the limitations of this method include; this method has two learning approaches as well as complex relationships. The first method

A lot of CNN procedures are used for extracting characteristics from the medical images. Thus, all the features extracted are integrated, and the classification and categorization problem is solved with help of different machine learning techniques. The following are some of the disadvantages of this technique; two separate training methods and complex algorithms. In the second one, the computation formula brings the forecasted values together. The benefit of this strategy is that if the same thing happens with another CNN models, such data will be classified with the help of the aggregated method. Therefore, in this paper, ensemble technique is applied to enhance the performance of the classification process. When defining the architecture of the final ensemble model one of the types of a convolutional neural network is used and it is called ResNet50 or Residual Network. The term was first applied in the book; Deep Residual Learning for Image Recognition jointly authored by He Kaiming, Zhang Xiangyu, Ren Shaoqing, and Sun Jian published in the year 2015. ResNet-50 is a deep convolution neural network with 99% depth, 50 layers of which 1 is a MaxPool layer, 1 an average pool layer and 48 convolutional layers. Residual neural network can be classified as artificial neural network which creates networks through additional blocks. ResNet-34 is one of the ResNet models that have been developed to contain 34 weight layers. It offered a novel approach of how the number of convolutional layers in a CNN can be made larger with little effort without suffering from the vanishing gradient problem by the inclusion of the shortcut connections. A residual network is built up if the shortcut connection 'leaps' over a few levels in a standard network. The standard network for this scenario was the VGG-16 and VGG-19 neural networks. Moreover, each of the convolutional networks was fit a 3×3 filter. On the other hand, there is a ResNet50 which has relatively less complex and a lesser number of filters when compared to VGGNet. Where performance goes, a 34-layer ResNet50 can go 3. 6 billion FLOPs, while an 18-layer ResNet50 comes in at a small 1,220 million. 8 billion FLOPs. As opposed to a VGG-19 Network, designed to achieve 19. 6 billion FLOPs, this comes in significantly faster.

3. Detection

The accuracy, precision, recall, F1-sore, and recall are used to measure the efficiency of the suggested classification approach in this paper. Preprocessing is involved as soon as the user uploads the picture; it is resized and converted into HSV. Subsequently, the discovered ResNet50 trains on the dataset used to make a prediction. It also learns from the dataset the output to be either Viral pneumonia, bacterial pneumonia, or normal.

5. RESULTS

Experimental results for detecting Bacterial pneumonia, Viral pneumonia, and normal.

	precision	recall	f1-score	support
Bacterial_Pnemonia	0.95	0.92	0.93	914
Normal	0.86	0.97	0.91	905
Viral _Pneumonia	1.00	0.90	0.95	879
accuracy			0.93	2698
macro avg	0.94	0.93	0.93	2698
weighted avg	0.94	0.93	0.93	2698

Fig. 3. Evaluation metrics

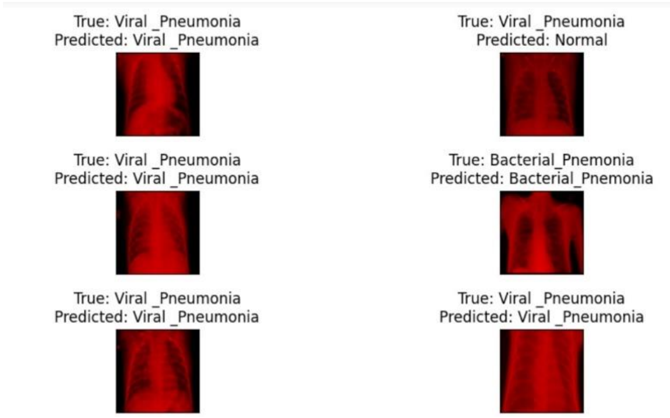


Fig. 4. Prediction

6. CONCLUSIONS

It provides a CNN-based method for categorizing lung disease images into five groups: cancer, viral pneumonia, Covid-19, tuberculosis, and normal. The experimental results show that the suggested model can reliably identify different types of lung illnesses from chest X-ray images. Our technique has the potential to help healthcare providers diagnose lung disorders more quickly and accurately, thereby improving patient outcomes.

The creation of deep learning model for detecting pneumonia marks a big step forward in automated illness diagnosis using medical pictures. The customized CNN model for pneumonia detection have demonstrated promising accuracy in recognizing abnormal lung patterns more clearly.

The machine learning algorithms can help healthcare practitioners diagnose diseases fast and effectively by using convolutional neural networks. These models provide useful tools for screening huge numbers of medical pictures, especially in resource-constrained settings where access to qualified medical personnel is limited.

6. REFERENCES

[1] S. Singh,"Pneumonia Detection using Deep Learning," 2021 4th Biennial International Conference on Nascent Technologies in Engineering (ICNTE), NaviMumbai, India, 2021, pp. 1-6, doi: 10.1109/ICNTE51185.2021.9487731.

[2] D. Varshni, K. Thakral, L. Agarwal, R. Nijhawan and A. Mittal,"Pneumonia Detection Using CNN based Feature Extraction," 2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT), Coimbatore, India, 2019, pp. 1-7, doi: 10.1109/ICECCT.2019.8869364.

[3] E. J. Palomo, M. A. Zafra-Santisteban and R. M. LuqueBaena, "Pneumonia Detection in Chest X-ray Images using Convolutional Neural Networks," 2022 IEEE International Conference on Metrology for Extended Reality, Artificial Intelligence and Neural Engineering (MetroXRAINE), Rome, Italy, 2022.

[4] L. Raciˇ c, T. Popovi ´ c, S. ´ caki ˇ c and S. ´ Sandi, "Pneumonia Detection Using Deep Learning Based on Convolutional Neural Network," 2021 25th International Conference on Information Technology (IT), Zabljak, Montenegro, 2021, pp. 1-4, doi: 10.1109/IT51528.2021.9390137.

[5] W. Khan, N. Zaki and L. Ali, "Intelligent Pneumonia Identification from Chest X-Rays: A Systematic Literature Review," in IEEE Access, vol. 9, pp. 51747-51771, 2021, doi: 10.1109/ACCESS.2021.3069937.

[6] Ortiz-Toro, C.; Garc´ıa-Pedrero, A.; Lillo-Saavedra, M.; Gonzalo-Mart´ın, C. "Automatic pneumonia detection in chest X-ray images using textural features." Comput. Biol. Med. 2022, 145, 105466. [CrossRef].

[7] B. Montalico and J. C. Herrera, "Classification and Detection of Pneumonia in X-Ray Images Using Deep Learning Techniques," 2022 IEEE Sixth Ecuador Technical Chapters Meeting (ETCM), Quito, Ecuador, 2022, pp. 01-05, doi: 10.1109/ETCM56276.2022.9935757.

[8] Malhotra, P.; Gupta, S.; Koundal, D.; Zaguia, A.; Kaur, M.; Lee, H.N. "Deep Learning-Based Computer-Aided Pneumothorax Detection Using Chest X-ray Images." Sensors 2022, 22, 2278. [CrossRef].

[9] M. Z. Hossain, K. I. Mostafa, M. M. Rahman and M. S. Mia, "Pneumonia Detection from Chest X-Ray Images Using Convolutional Neural Network," 2024 International Conference on Advances in Computing, Communication, Electrical, and Smart Systems (iCACCESS), Dhaka, Bangladesh, 2024, pp. 1-6, doi: 10.1109/iCACCESS61735.2024.10499549.

[10] Kirankumarhumse et al.,"A Deep Learning Model Using VGG-16 and Neural Networks to Identify Pneumonia from Chest X-Ray Images," 2024 International Conference on Integrated Circuits and Communication Systems (ICI-CACS), Raichur, India, 2024, pp. 1-6, doi: 10.1109/ICI-CACS60521.2024.10498410.

[11] A. B. Godbin, M. Revathi, S. N. Bushra and S. A. Sibi"An Efficient AI model for identification and classification of pneumonia from chest x-ray images," 2022 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES), Chennai, India, 2022, pp. 1-7, doi: 10.1109/ICSES55317.2022.9914292.

[12] S. Phine,"Pneumonia Classification Using Deep Learning VGG19 Model," 2023 IEEE Conference on Computer Applications (ICCA), Yangon, Myanmar, 2023, pp. 67-71, doi: 10.1109/ICCA51723.2023.10181954.

[13] Furtado, A.; Andrade, L.; Frias, D.; Maia, T.; Badaro,´ R.; Nascimento, E.G.S. "Deep Learning Applied to Chest Radiograph Classification—A COVID-19 Pneumonia Experience." Appl. Sci. 2022, 12, 3712. [CrossRef]

[14] Wang, L.; Wang, H.; Huang, Y.; Yan, B.; Chang, Z.; Liu, Z.; Zhao, M.; Cui, L.; Song, J.; Li, F. "Trends in the application of deep learning networks in medical image analysis: Evolution between 2012 and 2020." Eur. J. Radiol. 2022, 146, 110069.

[15] D. Jain, P. Singh, V. Rohatgi, R. Raj, A. Sharma and S. Bansal,"Pneumonia Detection using Customized CNN," 2022 4th International Conference on Advances in Computing, Communication Control and Networking (ICAC3N), Greater Noida, India, 2022, pp. 261-264, doi: 10.1109/ICAC3N56670.2022.10074473