International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 11 Issue: 12 | Dec 2024 www.irjet.net p-ISSN: 2395-0072

PNEUMONIA DETECTION BASED ON CONVOLUTION NEURAL NETWORK

Mr. Basant Rawot[1], Dr. Heli Shah[2],

[1]Parul Institute of Technology, Parul University, India.
[2]HOD of The Department, Parul Institute of Technology, Parul University, India.

---***---

Abstract:

In the past year, the novel coronavirus has affected over 1 million individuals and resulted in more than 50,000 deaths. COVID-19 infection has the potential to progress into pneumonia, a condition that can be identified through a chest x-ray and should be managed appropriately. This study presents a novel approach for automatically detecting COVID-19 infection using chest radiographs. The dataset compiled for this study comprises 480 X-rays obtained from patients diagnosed with coronavirus and from healthy patients. Due to the limited availability of COVID-19 patient images, we will utilize transfer learning principles for this undertaking. We employ various architectures of convolutional neural networks (CNNs) that have been trained on ImageNet. We then modify these networks to function as feature extractors specifically for X-ray images. CNNs are subsequently fused with integrated machine learning methodologies, including Support vector machines (SVM) and LSTM. The results indicate 93.75% accuracy with an F1 score of 93.86%. Hence, the suggested method exhibits efficacy in identifying pneumonia.

Keywords: Convolution neural networks, ImageNet, Multilayer perceptron, Support vector machine, X-ray images

1. Introduction

A lung air sac infection causes pneumonia. The lung structure is made up of pulmonary alveoli, bronchus, and lobes connected to the main veins. Every part has to work correctly to guarantee an effective exchange of carbon dioxide and oxygen. Along with fluids in their air sacs, pneumonia patients will have alveolar inflammation. There are only a few of the medical examination technologies developed such as CT scans, X-ray and ultrasound as a result of medical technology progress. Pneumonia diagnosis is regarded as best achieved with CT scans. VGG and ResNet networks are utilized to accurately classify lung ultrasound images of pneumonia according to different clinical phases using self-generated LUS datasets.

The introduction of deep learning in recent years has resulted in a paradigm shift in medical image analysis. Convolutional neural networks (CNNs) are highly effective at tasks like classifying images, segmenting parts of images, and identifying features within images. Because of these capabilities, CNNs are widely used in creating automated systems for medical imaging. CNNs have shown potential in detecting pneumonia, offering the possibility of quickly and independently identifying lung infections. This advancement could significantly transform patient care.

This study focuses on accurately detecting pneumonia in the lungs using chest X-rays, which can be used in the real world by medical practitioners to treat pneumonia. The problem with traditional methods involves lots of time and resource intensive in the diagnosis of pneumonia. Hence, the use of artificial technology such as convolution neural networks solves the problem by simplifying the process of diagnosis of pneumonia. The main objectives of this study are:

a) Integrating deep learning techniques for pneumonia detection.

b) Using feature extraction and Image classification for diagnosis.

2. Literature Review

The research paper "Pneumonia Detection Using CNN-based Feature Extraction" focuses on creating a Convolutional system to effectively diagnose pneumonia in X-rays. It highlighted the global impact of pneumonia as a leading cause of death and the difficulties in diagnosing it accurately. The authors then describe the proposed CNN-based approach for detection and categorization of images. The CNN model was trained on a dataset of 5856 chest X-ray images, consisting of 2,700 normal and

2,630 pneumonia images. The trained model achieved an accuracy of 96.07% on the testing dataset. The authors compared their proposed model with other existing models and reported a better performance in terms of accuracy, precision, recall, and F1-score. Finally, the paper concludes that the proposed CNN-based model can be useful for accurate and timely diagnosis of pneumonia, which can help in improving patient outcomes and reducing mortality rates [1]. Rajpurkar developed the CheXNet algorithm, which can automatically identify pneumonia in chest X-rays. This 121-layer DenseNet, trained on the ChestX-ray14 dataset, replaces the final fully connected layer with an output layer and achieves an F1 score of 0. 435. Carmany [3] created a diagnostic tool for treatable diseases that used chest X-rays to show discriminatory power. Islam [4] proposed a framework for automatically detecting pneumonia in radiographs.

Furthermore, Rajaraman [5] developed a truncated VGG16-based artificial neural network that can diagnose pneumonia in pediatric X-rays. It has the deepest convolutional layers with gaps and dense layers. Even though these algorithms have improved deep networks, Rajpurkar and colleagues have sped up their networks by using a single output rather than the entire link layer; nevertheless, this operation did not produce the required accuracy. Rajaraman employed global average pooling to boost convolutional neural networks' performance, but he lost track of the target's location. As a result, research is currently being done on high-precision networks with excellent detection performance. Lee proposed DetNet in 2018 [6]. It was created with object detection in mind and uses fewer layers to produce better detection results. In order to detect and locate pneumonia, Shirajitdinov [7] suggested a framework that combines RetinaNet and Mask R-CNN. A dataset of 26,684 photos from the Kaggle Pneumonia Detection Challenge was used to validate this network. It is currently common practice to employ his bifurcated structural model [8]. The authors used transfer learning, a technique where pre-trained models are fine-tuned on a specific task, to train the EfficientNet-B0 model on the ChestX-ray14 dataset. They froze the lower layers of the model, which capture generic features from images, and trained the upper layers, which capture disease-specific features, on the pneumonia detection task. To further improve the model's performance, the authors also applied data augmentation techniques, such as horizontal flipping, rotation, and zooming, to increase the diversity of the training data and prevent overfitting.

The methodology used in Convolutional Sparse Support Estimator-Based COVID-19 Recognition from X-ray images involves the pre-processing of X-ray images, where the images are resized, normalized, and sharpened to enhance the features. The authors then use a CSSE model to extract important features from the pre-processed images. The CSSE model uses a sparse regularization term to select only relevant features, thus reducing the dimensionality of the feature set. The authors also introduce a transfer learning approach where the CSSE model is trained on pre-trained models such as ResNet-50, DenseNet-121, and VGG-16 [14]. Using a deep learning method, X-ray pictures were used to diagnose pneumonia. They compare performance between two well-known deep learning models—VGG-16 and ResNet-50—on the task of pneumonia detection. A data of 5,856 chest X-ray images (3,781 normal, 1,350 images of bacterial pneumonia and 725 images of viral pneumonia), authors use transfer learning to refine these models [15]. A method based on deep learning for automatically detecting pneumonia from chest X-ray pictures. Utilizing a dataset of 1,266 chest X-ray images (242 normal, 681 bacterial pneumonia, and 343 viral pneumonia images), they refined a pre-trained VGG-16 model. To increase their dataset size and improve model generalizability, the authors also employ data augmentation techniques [16].

Mrad et al. proposed a machine intelligence approach for screening patients based on their X-ray images. The authors address the issue of imbalanced classes, where the number of COVID-19 cases is significantly lower than the number of non-COVID-19 cases. They use a combination of data augmentation and oversampling techniques to balance the classes and then train a neural network for classification [17]. Vo-Dinh et al. also focused on the identification of COVID-19 cases from chest X-ray images. The authors propose a high-resolution network (HRNet) for this task and employ transfer learning for tuning of model. [18]. Wang and Chakraborty proposed a recurrent neural network (RNN)-based approach to evaluate the malignancy of lung nodules from CT images. The authors use a multi-stage approach where they first segment the lung nodules and then use a 3D RNN to classify them as malignant or benign [19].

"CIDC-Net: Chest-X Ray Image based Disease Classification Network using Deep Learning" by Meghana et al. presents a method to classify X-ray images into different disease categories [20]. "COVID-19 Classification using DCNNs and Exploration Correlation using Canonical Correlation Analysis" by Jullapak and Yampaka presents a deep learning-based approach for classifying COVID-19 images using deep convolutional neural networks (DCNNs) [21]. The paper "COVID-SEGNET: Diagnosis of COVID-19 Cases on Radiological Images using Mask R-CNN" by Kundu et al. presents an approach using radiological pictures. The proposed approach, called COVID-SEGNET, depends on Mask R-CNN architecture and is trained to identify the areas in images that indicate COVID [22]. In "X-ray Images Detection of COVID-19 Based on Deepwise Separable DenseNet" Wang et al. describe a deep learning-based method for COVID-19 image detection. The authors carried out tests as well to assess how well the suggested method stood up to various kinds of noise and perturbations [23]. Moreover, there's CNN algorithm for corona virus detection in chest X-rays [24]. Another approach involves using 2D convolutional neural network (CNN) for respiratory disease detection from recorded lung sounds [25]. They also created a network called MHA-CoroCapsule to categorize COVID-19 chest X-ray images, which utilizes multi-head attention routing.

3. Methodology

3.1. Proposed framework

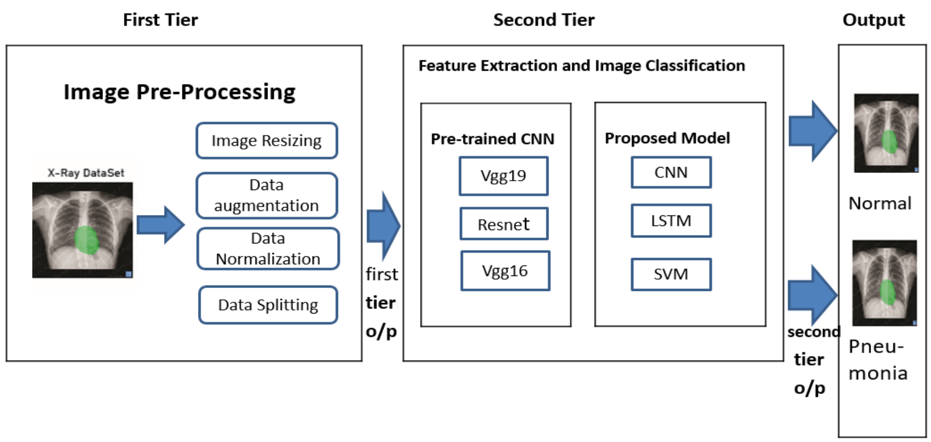

Figure 1: Framework for pneumonia detection

The CNN architecture used in the research consists of three tiers, each with its unique function. In the first tier, the image pre-processing is carried out, which includes image resizing, data augmentation, data normalization, and data splitting. The pre-processing step makes sure that all the images are uniform in size, and the training dataset includes a wide range of examples to handle real-world differences effectively. The image resizing is a crucial step before passing them to the CNN model.

In the second tier, two sub-parts carry out feature extraction and image classification. The first sub-part uses pre-trained CNN models such as VGG19, Resnet, and VGG16, which have excellent results in classification. These models have been trained on large datasets such as the ImageNet dataset, which includes more than 14 million images categorized into 1000 different classes. By using pre-trained models, CNN can leverage the learned features to classify the images accurately. In the second sub-part, a proposed model using CNN, LSTM, and SVM is used for feature extraction and image classification. The proposed model is trained on the pre-processed images, and the features are extracted using the CNN layers. The LSTM layer is employed to understand the order of images in a sequence. Finally, the SVM classifier is applied to categorize the images as either normal or pneumonia.

In the final tier, the output section shows whether the input image is normal or pneumonia. The model output is compared with the actual label of the image, and the accuracy is then calculated. The model's accuracy is an essential metric. If the accuracy is high, it means that the model is performing well and can be used for real-world applications such as pneumonia detection in medical imaging.

3.2 Convolution Neural Network

Convolutional Neural Networks (CNNs) are a special kind of neural network created to handle grid-like data, like images or audio spectrums. They consist of layers that gradually learn more intricate features from the input. The main components of CNNs are convolutional layers, which use filters to process the input, producing feature maps that emphasize different parts of the data.

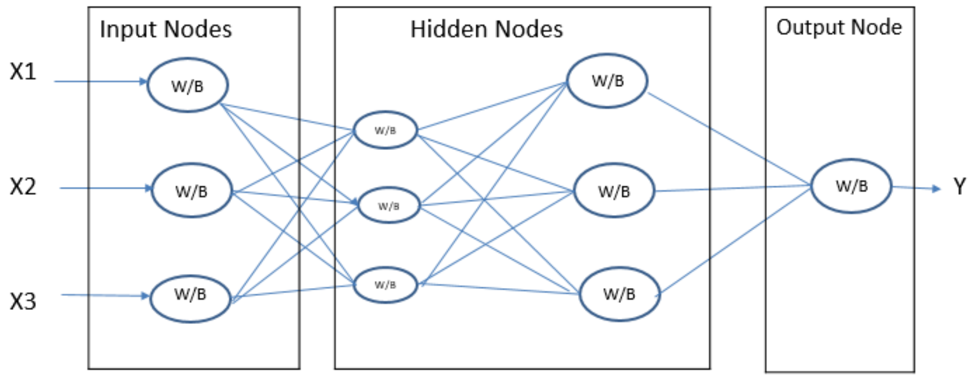

Figure 2: Convolution neural network with input, hidden and output nodes

A standard CNN design includes an initial layer for input, followed by multiple convolutional layers that incorporate ReLU, and pooling layers that downsample the feature maps. The output of the convolutional layers is typically flattened and fed into one or more fully connected layers, which learn to classify the input data into different categories. In addition to these core layers, modern CNN architectures often include additional layers such as batch normalization, dropout, and skip connections, which help to improve training stability and generalization performance.

Overall, the architecture of a CNN is carefully designed to learn hierarchical representations of the input data, starting with low-level features such as edges and corners, and building up to more abstract features that capture higher-level concepts such as object categories. This makes CNNs particularly effective for tasks such as image classification, object detection, and segmentation, where the goal is to accurately classify or localize objects within images.

3.2.1 VGG architecture

The VGG16 architecture of a convolutional neural network (CNN) includes 16 layers overall, with the initial 13 layers as convolutional layers and the last three as fully connected layers. At the micro level, each layer in VGG16 has a specific purpose and learns its own set of parameters during training. The initial layer is a convolutional layer that processes the raw input image and uses filters to detect basic features like edges and corners. This process is repeated in subsequent layers, where each layer learns to identify increasingly more intricate and detailed features from the previous layer's output. After several layers of convolutional and max pooling operations, the feature maps generated are reshaped into a single vector and then fed into the dense layers for classification. These components learn to combine extracted features into high-level representations that are useful for discriminating between different classes.

The network's performance can be optimized at the micro level by adjusting the particular parameters for each layer, such as how to classify pneumonia lung ultrasonography images. For instance, the complexity of the learned features can be adjusted by changing the number of neurons in the dense layers, while the convolutional layers' filters can be modified to capture different levels of detail in the input image. An image of 224 x 224 goes to the input for the first convolutional layer (cov1). The image undergoes a series of convolutional layers, where 3x3 filters are applied—the smallest size effective for capturing various aspects in the image. Spatial padding in the convolutional layer maintains spatial resolution after processing, with a padding of 1 pixel for 3x3 convolution layers. The convolution stride remains fixed at 1 pixel. Following the convolution, there are five max-pooling layers for spatial pooling. Convolutional layer stack is succeeded by three fully connected (FC) layers. The first two have 4096 channels each, while the third has 1000 channels (one for each class) for 1000-way ILSVRC classification. The SoftMax layer acts as the final layer.

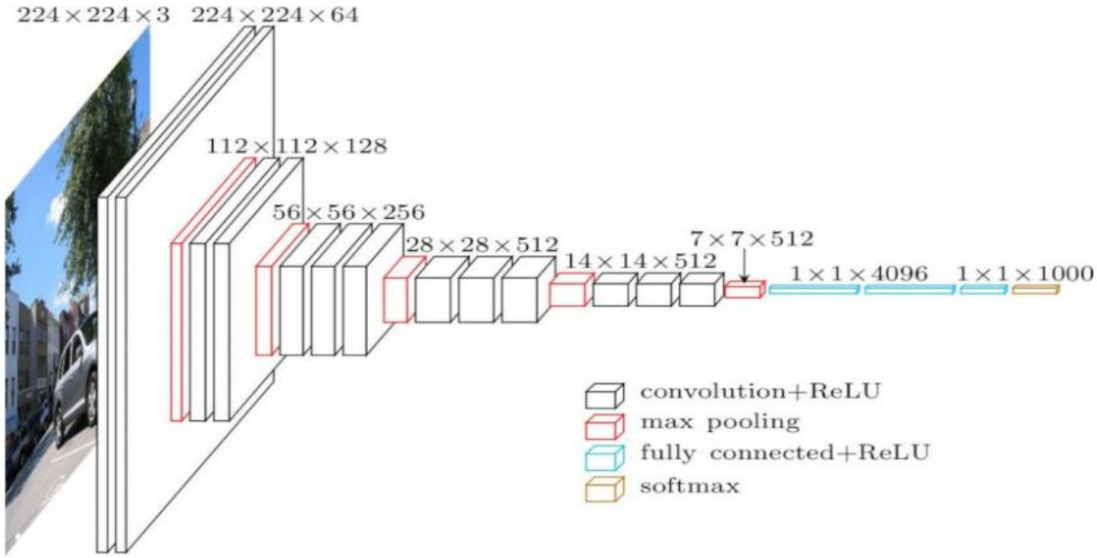

Figure 3: Vgg16 Architecture

3.2.2. Residual Network (ResNet)

Residual Network, is a deep learning architecture that was designed to help overcome the degradation problem in very deep neural networks. In pneumonia detection using CNN, ResNet plays crucial role in accurately categorizing chest X-ray images showing pneumonia. Its key job is to enable the neural network to learn from any leftover information in the input image. This is achieved by introducing skip connections or shortcuts that skip over one or more layers in the neural network. Such shortcuts provide an alternate path for the information to pass through the network, helping it effectively learn any remaining information. The residual connections are formed by adding the input feature maps to the output feature maps of one or more convolutional layers in the network. By doing so, the output feature maps will have additional information from the input feature maps, which helps the network to learn the residual information more efficiently. In other words, these shortcuts enable the network to grasp the distinction between the input and output feature maps, which is crucial for accurately classifying pneumonia in chest X-ray images.

In pneumonia detection, ResNet is effective in accurately classifying the different clinical stages of pneumonia. This is because ResNet can capture and learn from the subtle differences in lung ultrasound images that may be missed by other neural network architectures. Additionally, the use of residual connections in ResNet helps to prevent the degradation problem commonly faced by very deep neural networks, allowing for better accuracy and performance. ResNet is a type of artificial neural network (ANN) inspired by the structure of pyramidal cells in the brain's cortex. ResNet models typically include double- or triple-layer skips with nonlinearities like ReLU and batch normalization in between. These skips allow the network to learn more effectively. HighwayNets are ResNet models where the skip weights can be adjusted using an extra weight matrix. DenseNets are models with multiple parallel skips. In contrast, a non-residual network is considered a regular network when compared to a residual neural network. A residual neural network's canonical form is depicted in the figure. Activation from layer $\ell - 2$ is bypassed in favor of layer $\ell - 1$.

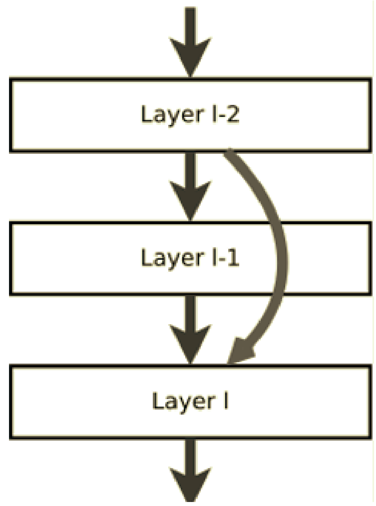

Figure 4: Resnet Architecture

3.3.3 LSTM and SVM

LSTM is a type of Recurrent Neural Network (RNN) that is particularly effective for sequence prediction problems. It is designed to model temporal sequences and their long-range dependencies more accurately than conventional RNNs. LSTMs have memory cells that can store information in memory for extended periods. This feature helps LSTMs avoid the vanishing gradient problem that standard RNNs suffer from, allowing them to learn long-term dependencies. LSTMs are composed of layers of LSTM units, where each unit contains the memory cell and the three gates. They process data sequences one step at a time, maintaining the state through the sequence.

SVM is a type of supervised learning method used for tasks like classification and regression. It finds the best hyperplane to divide data into different classes in a high-dimensional space. A hyperplane is like a decision boundary that separates classes, with the optimal one maximizing the margin between them. Data points closest to the hyperplane affect its position and direction, and only these points are used to create it. SVM can handle non-linear classification using a kernel trick, which maps input features into higher-dimensional spaces.

3.3.3. Training and Testing Process

The libraries used in Pneumonia Detection Based on Convolution Neural Network research are all important for various tasks related to the processing and analysis of X-ray images. Keras is a library used for data preprocessing which is necessary for preparing the data before it can be fed into the neural network. In such case, it is used to import the X-ray images and provide utilities for working with image data. The sklearn is for how well the machine learning model detects pneumonia in X-ray images. It offers several metrics like accuracy, precision, and recall to measure the model's performance. TensorFlow is a widely used machine-learning library that is specifically designed for numerical computation. It is used in this research to build and train the convolution neural network model, which is the backbone of the pneumonia detection system. Seaborn and matplotlib are both visualization libraries that are used to create informative statistical graphics. In this case, they are used to generate visual representations of the model's performance, making it easier to interpret and understand the results. Finally, NumPy is a library used for numerical computing and provides objects for multi-dimensional arrays. It is used in this research to perform arithmetic operations and handle complex numbers while processing the X-ray images.

In the research on Pneumonia Detection using Convolutional Neural Networks, they assessed the combined CNN-LSTM-SVM model's performance with various metrics. The evaluation had two phases: training and testing. During training, they tracked metrics like accuracy, loss, precision, recall, and F1 scores across 50 epochs to gauge the model's performance. They selected the model with the best performance on testing set. After training, they tested the model on an independent test set to check how well it generalizes. They used metrics such as accuracy, precision, recall, and F1 score for evaluation. Additionally, they analyzed the model's performance using confusion matrices, which detail true positives, true negatives, false positives, and false negatives for each class to assess classification accuracy.

The results of the evaluation and analysis showed that the combined CNN-LSTM-SVM model was able to accurately detect pneumonia in chest X-rays with a high level of precision and recall. The analysis also showed that the model was able to accurately differentiate between normal and abnormal X-rays. In this research, the dataset of X-ray images for pneumonia detection was obtained from Kaggle and then uploaded to Google Drive. The necessary path was provided to mount the drive for easy access to the dataset. The dataset was divided into two categories, namely test and training. Each category further had three sub-categories - normal, COVID, and pneumonia datasets. The number of images in each sub-category was calculated using the panda's library, which helped in understanding the distribution of data. To get a better understanding of the dataset, it was visualized using graphs and charts. The testing and training datasets were plotted into bar charts to visualize the distribution of images. The model architecture was also visualized using max-pooling. The history of the model was visualized and plotted in a graph to understand the performance of the model during the training phase. This helped in understanding the accuracy of the model and its ability to classify the X-ray images accurately. Overall, these visualizations and calculations were crucial for assessing the model's performance and implementing improvements to attain superior results.

4. Result and discussion

The findings from the Pneumonia Detection Based on CNN research, aimed at identifying pneumonia in X-ray images, were promising. For the metrics like accuracy, precision, recall, and F1-score were implemented. The proposed model demonstrated an overall accuracy of 93.75%, which indicates that the model is reliable and effective in detecting pneumonia. Furthermore, the model achieved a high precision of 93.99% and a recall of 93.75%. This means that the model can accurately detect pneumonia while minimizing false positives. The F1-score, which reflects the model's accuracy, was calculated at 93.86%, indicating its overall performance in terms of precision and recall.

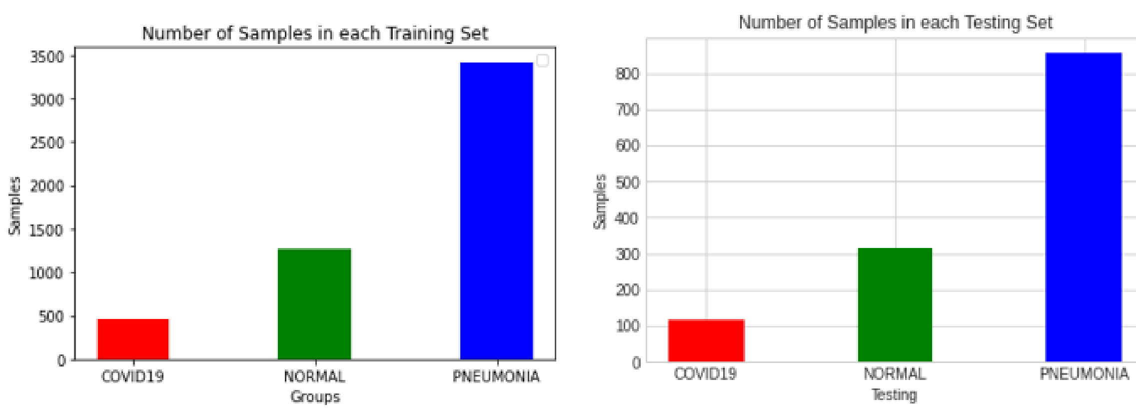

Figure 5: Classifying the dataset into 3 groups

Table 1: Metrics computed

Metrics	**Obtained value (%)**
Accuracy	93.75%,
Precision	93.99%,
Recall	93.75%,
F-score	93.86%.

The table shows the metrics value obtained from our model. Moreover, the comparison of different models was done, and it was observed that the proposed model outperformed the models such as VGG16, VGG19, and ResNet50. It achieved a higher accuracy rate and reduced the number of false positive cases.

The confusion matrix was also used to analyze the performance of the model. The confusion matrix showed that out of 480 test images, the model correctly classified 450 images, and misclassified 30 images. These results indicate the model is effective for detecting pneumonia in chest X-ray.

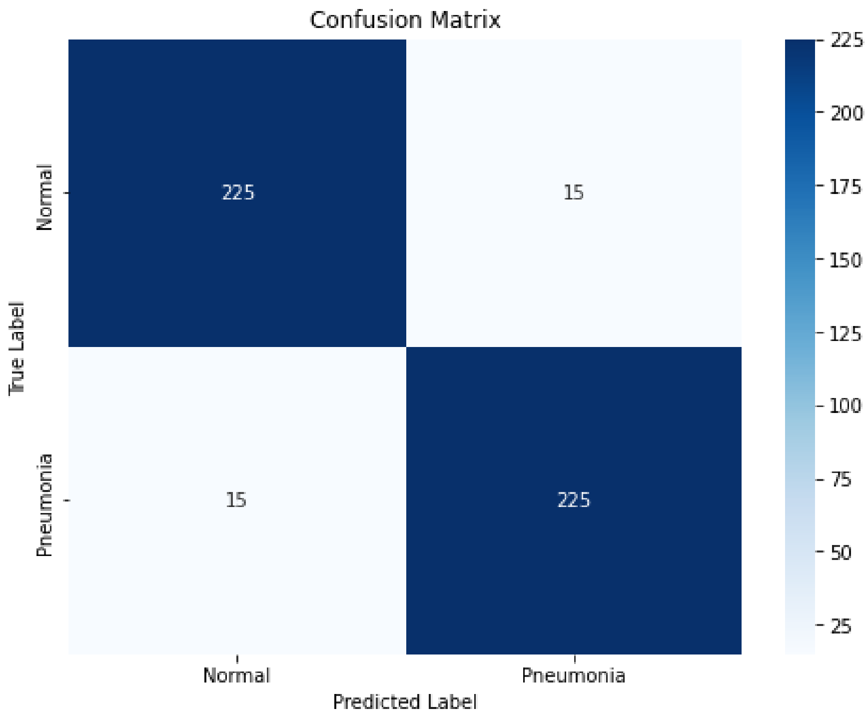

Figure 6: Confusion matrix

5. Conclusion

In conclusion, the combination of CNN models like Resnet, VGG16 and VGG19 with LSTM and SVM has outstanding results in spotting pneumonia in X-ray. The model we developed provided 93.75% accuracy, 93.99% precision, 93.75% recall with an F1 score of 93.86%. The evaluation metrics show that the model has a high level of accuracy in detecting pneumonia, which can be utilized in the real world by medical practitioners to treat pneumonia. The study also demonstrates the importance of image preprocessing, feature extraction, and classification in achieving accurate results. Overall, the research suggests that the proposed model can be a valuable tool in assisting medical practitioners in pneumonia diagnosis and treatment. While CNNs have been effective, future exploration of other network architectures like recurrent neural networks and attention-based models could further enhance accuracy.

References

1. 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.
2. P. Rajpurkar, J. Irvin, K. Zhu, B. Yang, H. Mehta, T. Duan, D. Ding, A. Bagul, C. Langlotz, K. Shpanskaya, M. P. Lungren, and A. Y. Ng, ``CheXNet: Radiologist-level pneumonia detection on chest X-rays with deep learning,'' 2017, arXiv:1711.05225. [Online].Available: https://arxiv. org/abs/1711.05225

3. D. S. Kermany, M. Goldbaum, W. Cai, C. C. Valentim, H. Liang, S. L. Baxter, A. McKeown, G. Yang, X. Wu, F. Yan, and J. Dong, ``Identifying medical diagnoses and treatable diseases by image-based deep learning,'' Cell, vol. 172, no. 5, pp. 1122_1131.e9, Feb. 2018.
4. S. R. Islam, S. P. Maity, A. K. Ray, and M. Mandal, ``Automatic detection of pneumonia on compressed sensing images using deep learning,'' in Proc. IEEE Can. Conf. Elect. Comput. Eng. (CCECE), May 2019, pp. 1_4.
5. S. Rajaraman, S. Candemir, G. Thoma, S. Antani, ``Visualizing and explaining deep learning predictions for pneumonia detection in pediatric chest radiographs,'' Proc. SPIE, vol. 10950, Mar. 2019, Art. no. 109500S.
6. Z. Li, C. Peng, G. Yu, X. Zhang, Y. Deng, and J. Sun, ``DetNet: Design backbone for object detection,'' in Proc. Eur. Conf. Comput. Vis. (ECCV), 2018, pp. 334_350.
7. I. Sirazitdinov, M. Kholiavchenko, T. Mustafaev, Y. Yixuan, R. Kuleev, and B. Ibragimov, ``Deep neural network ensemble for pneumonia localization from a large-scale chest X-ray database,'' Comput. Electr. Eng., vol. 78, pp. 388_399, Sep. 2019.
8. S. Yao, Y. Chen, X. Tian and R. Jiang, "GeminiNet: Combine Fully Convolution Network With Structure of Receptive Fields for Object Detection," in IEEE Access, vol. 8, pp. 60305-60313, 2020, doi: 10.1109/ACCESS.2020.2982939.
9. L. Račić, T. Popović, S. čakić and S. Šandi, "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.
10. Lamia A, Fawaz A. Detection of Pneumonia Infection by Using Deep Learning on a Mobile Platform. Comput Intell Neurosci. 2022 Jul 30;2022:7925668. doi: 10.1155/2022/7925668. PMID: 35942467; PMCID: PMC9356824.
11. Mabrouk A, Díaz Redondo RP, Dahou A, Abd Elaziz M, Kayed M. Pneumonia Detection on Chest X-ray Images Using Ensemble of Deep Convolutional Neural Networks. *Applied Sciences*. 2022; 12(13):6448. https://doi.org/10.3390/app12136448
12. M. Yaseliani, A. Z. Hamadani, A. I. Maghsoodi and A. Mosavi, "Pneumonia Detection Proposing a Hybrid Deep Convolutional Neural Network Based on Two Parallel Visual Geometry Group Architectures and Machine Learning Classifiers," in IEEE Access, vol. 10, pp. 62110-62128, 2022, doi: 10.1109/ACCESS.2022.3182498.
13. M. Shaikh, Q. A. Arain, I. F. Siddiqui and H. A. Shaikh, "Automated Classification of Pneumonia from Chest X-Ray Images using Deep Transfer Learning EfficientNet-B0 Model," 2022 14th International Conference on Mathematics, Actuarial Science, Computer Science and Statistics (MACS), Karachi, Pakistan, 2022, pp. 1-6, doi: 10.1109/MACS56771.2022.10022700.
14. M. Yamaç, M. Ahishali, A. Degerli, S. Kiranyaz, M. E. H. Chowdhury and M. Gabbouj, "Convolutional Sparse Support Estimator-Based COVID-19 Recognition From X-Ray Images," in IEEE Transactions on Neural Networks and Learning Systems, vol. 32, no. 5, pp. 1810-1820, May 2021, doi: 10.1109/TNNLS.2021.3070467.
15. D. Saikrishna et al., "Pneumonia Detection Using Deep Learning Algorithms," 2021 2nd International Conference on Intelligent Engineering and Management (ICIEM), London, United Kingdom, 2021, pp. 282-287, doi: 10.1109/ICIEM51511.2021.9445310.
16. T. Gabruseva, D. Poplavskiy and A. Kalinin, "Deep Learning for Automatic Pneumonia Detection," 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Seattle, WA, USA, 2020, pp. 1436-1443, doi: 10.1109/CVPRW50498.2020.00183.
17. I. Mrad, R. Hamila, A. Erbad, T. Hamid, R. Mazhar and N. Al-Emadi, "Machine Learning Screening of COVID-19 Patients Based on X-ray Images for Imbalanced Classes," 2021 9th European Workshop on Visual Information Processing (EUVIP), Paris, France, 2021, pp. 1-6, doi: 10.1109/EUVIP50544.2021.9484001.
18. N. Vo-Dinh, A. Ha-Bao and H. T. Huynh, "An Approach for COVID-19 Identification from Chest X-ray Images Using High-Resolution Networks," 2022 RIVF International Conference on Computing and Communication Technologies (RIVF), Ho Chi Minh City, Vietnam, 2022, pp. 140-144, doi: 10.1109/RIVF55975.2022.10013838.
19. W. Wang and G. Chakraborty, "Evaluation of Malignancy of Lung Nodules from CT Image Using Recurrent Neural Network," 2019 IEEE International Conference on Systems, Man and Cybernetics (SMC), Bari, Italy, 2019, pp. 2992-2997, doi: 10.1109/SMC.2019.8913885.
20. M. Meghana, M. Bhargavaram and V. Sannareddy, "CIDC-Net: Chest-X Ray Image based Disease Classification Network using Deep Learning," 2022 6th International Conference on Electronics, Communication and Aerospace Technology, Coimbatore, India, 2022, pp. 1148-1152, doi: 10.1109/ICECA55336.2022.10009383.
21. R. Jullapak and T. Yampaka, "COVID-19 Classification using DCNNs and Exploration Correlation using Canonical Correlation Analysis," 2021 18th International Joint Conference on Computer Science and Software Engineering (JCSSE), Lampang, Thailand, 2021, pp. 1-6, doi: 10.1109/JCSSE53117.2021.9493846.

22. A. Kundu, C. Mishra and S. Bilgaiyan, "COVID-SEGNET: Diagnosis of Covid-19 Cases on Radiological Images using Mask R-CNN," 2021 Seventh International conference on Bio Signals, Images, and Instrumentation (ICBSII), Chennai, India, 2021, pp. 1-5, doi: 10.1109/ICBSII51839.2021.9445190.
23. Q. Wang, B. Yang, W. Liu and G. Chen, "X-ray Images Detection of COVID-19 Based on Deepwise Separable DenseNet," 2021 IEEE 6th International Conference on Signal and Image Processing (ICSIP), Nanjing, China, 2021, pp. 294-298, doi: 10.1109/ICSIP52628.2021.9688876.
24. K. Duraipandian and S. Somasundaram, "Detection of Corona Virus from Chest X-Rays Using CNN Algorithm," 2022 Fourth International Conference on Emerging Research in Electronics, Computer Science and Technology (ICERECT), Mandya, India, 2022, pp. 1-6, doi: 10.1109/ICERECT56837.2022.10059923.
25. R. Hazra and S. Majhi, "Detecting Respiratory Diseases from Recorded Lung Sounds by 2D CNN," 2020 5th International Conference on Computing, Communication and Security (ICCCS), Patna, India, 2020, pp. 1-6, doi: 10.1109/ICCCS49678.2020.9277101.
26. F. Li, X. Lu and J. Yuan, "MHA-CoroCapsule: Multi-Head Attention Routing-Based Capsule Network for COVID-19 Chest X-Ray Image Classification," in IEEE Transactions on Medical Imaging, vol. 41, no. 5, pp. 1208-1218, May 2022, doi: 10.1109/TMI.2021.3134270.