A Conv - MBDNN Model for the Classification and Detection of Pneumonia Using Transfer Learning on Chest X-Ray Images

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Abstract: ***Detecting and classifying pneumonia in X - ray images involves leveraging advanced technologies like Computer Vision (CV) and Machine Learning (ML) to identify and categorize respiratory ailments. The amalgamation of these methodologies holds the potential to aid healthcare professionals in swiftly recognizing and managing pneumonia cases, facilitating early diagnosis and effective treatment. The use of Deep Learning (DL) for the classification and detection of pneumonia in X - ray images has emerged as a successful approach for automated disease identification. As a subset of Artificial Intelligence (AI), DL concentrates on training neural networks with intricate layers to autonomously learn complex representations and patterns from data. In this study, we employ the Conv - MBDNN model to develop the Automatic Detection and Classification of Pneumonia disease. The proposed approach comprises multiple stages aimed at enhancing accuracy and diagnostic performance. Initially, a pre - processing stage is implemented, involving image resizing and the application of a Wiener Filter (WF) to enhance image quality. Subsequently, the feature extraction is conducted using the MobileNetV3 architecture. Finally, the extracted features are fed into an SVM classifier model to distinguish between different types and severity levels of pneumonia. A comprehensive analysis of experimental results demonstrates that the Conv - MBDNN technique outperforms other recent approaches in terms of performance and accuracy in pneumonia detection and classification using X - ray images.***

Keywords: Deep Learning, MobileNet, Lung Disease, Pneumonia, Machine Learning, Transfer Learning, Computer Vision.

1. Introduction

Pneumonia, a lung infection affecting both lungs and impacting the alveoli - tiny air sacs in the lungs - is characterized by symptoms such as chest pain, shortness of breath, fever, and dry cough [1]. The World Health Organization (WHO) recognizes computed tomography (CT) as the most effective method for pneumonia diagnosis [2]. In the realm of pneumonia detection and management, image analysis usually commences with traditional radiography, with the application of CT reserved for cases where radiography results are inconclusive. Chest X - rays (CXRs) are commonly recommended for patients with unclear pneumonia causes [3]. However, CXRs, utilizing ionizing radiation similar to other radiography methods, may not capture early - stage pneumonia and pose challenges for analysis [4]. Pneumonia is classified into four types—interstitial pneumonia, lobular pneumonia, lobar pneumonia, and bronchopneumonia—each presenting unique challenges for diagnosis [5]. The process of categorizing pneumonia types can be considered a complex task, particularly as X - ray detections may not be feasible in the early stages of the disease, leading to delayed diagnoses and making CXR analysis intricate [6].

Deep Learning (DL), a significant artificial intelligence (AI) technique, is instrumental in addressing complex computer vision (CV) challenges [7]. Convolutional Neural Networks (CNNs), a subset of DL, are extensively employed for image classification but necessitate large labeled datasets, posing challenges in the biomedical imaging domain where acquiring such data is both costly and time - consuming [8]. This proves especially advantageous in biomedical imaging, where the acquisition of extensive labeled data is often impractical [9]. Transfer learning (TL) offers a workaround, utilizing pre - trained models on large databases and applying network weights to address issues with smaller datasets [10].

This research introduces an innovative approach to the detection and classification of Pneumonia diseases through an effective deep learning (DL) model, namely the Conv - MBDNN model. The choice of the Conv - MBDNN model is justified by its ability to address challenges such as the vanishing - gradient problem, enhance feature propagation, promote feature reuse, and significantly reduce parameter count. The proposed model encompasses key stages, including pre - processing, MobileNetV3 - based feature extraction, and SVM based classification. Integration of deep features extracted from the MobileNetV3 model is carried out to assess the efficacy of these features.

The subsequent sections of this study are organized as follows: Section 2 provides a brief overview of related works, Section 3 introduces the Pneumonia disease detection and classification model, Section 4 presents the validation of the proposed model, and Section 5 concludes the study.

2. Related Works

Author [11] propose an innovative model for predicting lung diseases, including Covid19 and pneumonia, from chest X - rays (CXR) of patients. The dataset used comprises two widely available CXR datasets. Due to the potential decrease in image quality during X - ray acquisition, the authors employ image quality improvement techniques, specifically Median Filtering (MF) followed by Histogram Equalization (HE). In [12], the authorpresent a multi - channel deep learning (DL) approach for identifying lung diseases using chest X - rays. The models leverage pre - trained EfficientNetB0, EfficientNetB1, and EfficientNetB2 models, and their features are combined. The combined features enter a stacked Ensemble Learning (EL) classifier for disease detection, incorporating Random Forest (RF) and Support Vector Machine (SVM) in the initial phase and Logistic Regression (LR) in the second phase. Author [13] develop a computer - aided diagnostics scheme for CXR, focusing on common pulmonary diseases in children. They employ a YOLOv3 framework for automatic lung region localization and compare different classification approaches, including one versus all and one versus one schemes, training a CNN - based classifier.

In [14], the authors propose a new DL method for automatically detecting pneumonia using deep transfer learning to enhance identification accuracy. The method pre - processes input CXR, classifying pneumonia as abnormal (viral, bacterial) or normal. Pre - trained models on ImageNet datasets, such as InceptionResNetV2, InceptionV3, ResNet50, and UNet architectures for segmentation, are employed. Two optimizers, SGD and Adam, are used to extract effective features and improve accuracy, with performance analyzed for batch sizes of 16 and 32. In [15], the study suggest lightweight, adaptable, and accurate techniques to aid pneumonia identification. They enhance CNN architectures using various techniques of changing kernel sizes. The results are integrated using a weighted ensemble technique with adjustable threshold values to modify diagnostic capabilities as needed.

3. The Proposed Conv - MBDNN Model

The Conv - MBDNN technique follows a comprehensive workflow, as depicted in Fig 1. The initial step involves pre - processing to enhance image quality. The MobileNetV3 model is then employed for feature extraction, and finally, the is used for image classification into distinct class labels. The details of each stage are elaborated in the subsequent sections.

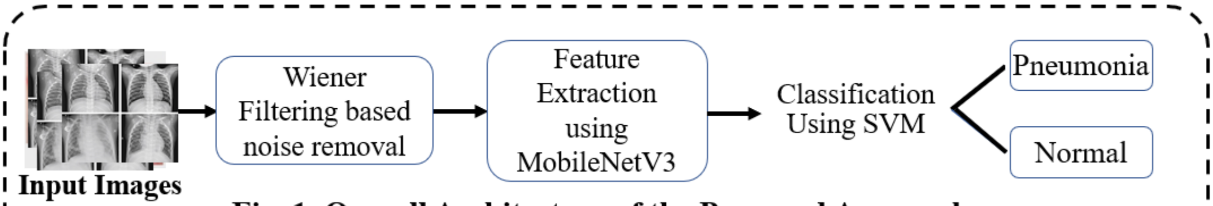

Fig. 1. Overall Architecture of the Proposed Approach

3.1. Wiener Filtering

The Wiener filter is a signal processing technique widely utilized in pneumonia detection tasks on chest X - ray images, serving to enhance image quality and improve diagnostic accuracy. It plays a pivotal role by effectively reducing noise, sharpening edges, and improving the visibility of subtle features associated with pneumonia. The filter's adaptability to different imaging conditions ensures consistent performance across varied chest X - ray datasets. In mathematical terms, the Wiener filter is expressed by the following formula:

$$\mathbf{G\ (f) = H^{*}\ (f).\ F\ (f) / |\ H\ (f)\ |^{2} + 1\ / s_{N}^{\ (f)}}$$

Here, G (f) is the frequency representation of the restored image, H (f) is the frequency representation of the point spread function (PSF), F (f) is the frequency representation of the observed image, and SN (f) is the power spectral density of the additive noise. The Wiener filter dynamically adjusts its parameters based on these components, contributing to noise reduction, feature enhancement, and improved diagnostic outcomes in pneumonia detection on chest X - ray images [16]. Its application, either as a standalone method or as part of a comprehensive image processing pipeline, underscores its significance in refining medical imaging for accurate disease diagnosis.

3.2. Feature Extraction using MobileNetV3

In the domain of pneumonia detection and classification on chest X - ray images, the MobileNetV3 model is commonly utilized as a pretrained model for feature extraction. MobileNetV3 is a lightweight convolutional neural network architecture specifically designed for efficient deployment on mobile and resource - constrained devices. It is pretrained on a comprehensive dataset, such as ImageNet, for general feature learning [17]. Throughout this training phase, the model acquires knowledge to recognize a diverse array of features, patterns, and textures from various images.

For the pneumonia detection and classification task on chest X - ray images, the pretrained MobileNetV3 model undergoes transfer learning. Transfer learning involves leveraging the knowledge gained from its initial training on a different task (e. g., ImageNet classification) and applying it to the specific task at hand (pneumonia detection and classification). The convolutional layers of the pretrained MobileNetV3 model function as feature extractors, proficient at capturing hierarchical and abstract features from input images, including intricate patterns indicative of pneumonia in chest X - rays. To reduce the dimensionality of the extracted features, global average pooling is often employed. This entails taking the average of each feature map, resulting in a condensed representation that retains essential information about the input.

The extracted features are then fed into fully connected layers constituting the classification head of the model, analogous to Fig 3. These layers further transform the features and generate output predictions for different classes of pneumonia. The final layer typically employs a softmax activation function to convert the network's raw output into probability scores for each pneumonia class. The class with the highest probability serves as the predicted class for a given input chest X - ray image. This approach harnesses the pretrained MobileNetV3 model's ability to discern relevant features from diverse images, facilitating effective pneumonia detection and classification in medical imaging.

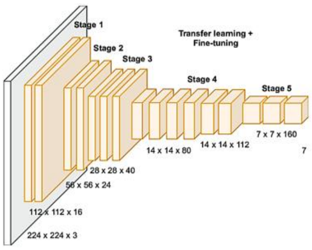

Fig. 3. Feature Extraction using MobileNetV3 model

3.3. Classification using SVM

The MobileNetV3 model generates a feature vector for each chest X - ray image, serving as a comprehensive representation of learned features relevant to pneumonia detection. This vector encapsulates both global and local characteristics critical for the accurate classification of diseases. Support Vector Machine (SVM), a supervised machine learning algorithm, is applied for classification tasks. In pneumonia detection, SVM seeks an optimal hyperplane that effectively separates different classes within the feature space. The utilization of a kernel function, such as the radial basis function (RBF) kernel, allows SVM to map feature vectors into a higher - dimensional space, facilitating the identification of non - linear decision boundaries [18]. The margin, representing the distance between data points and the hyperplane, is maximized to bolster classification robustness. By leveraging MobileNetV3 for feature extraction, the model benefits from transfer learning, capitalizing on knowledge gained from a diverse dataset. SVM's efficiency in handling high - dimensional feature spaces makes it well - suited for classification tasks with intricate and non - linear relationships. The amalgamation of MobileNetV3 feature extraction and SVM classification enhances the accuracy and efficiency of pneumonia detection on chest X - ray images, offering a robust solution for medical diagnostics.

4. Performance Validation

4.1. Implementation Setup

In this section, we conducted experimental validation of the Conv - MBDNN technique for pneumonia detection and classification on chest X - ray images, considering various factors. The simulations were executed using Python 3.6.5 on a PC equipped with an i5 - 8600K processor, 250GB SSD, GeForce 1050Ti 4GB GPU, 16GB RAM, and a 1TB HDD. The performance evaluation of the Conv - MBDNN model was measured using key metrics such as Sensitivity, Specificity, Precision, Accuracy, F - score, and MCC. The validation process utilized a benchmark Kaggle dataset comprising chest X - ray images [19]. Sample test images representing each class are illustrated in Fig 5, and the corresponding number of samples is detailed in Table 1.

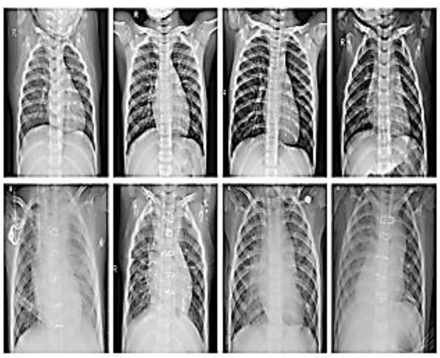

Fig. 4. Sample Images

Table 1. Dataset Description

Class	No.of.Samples
Normal	1566
Pneumonia	4220
Total	**5786**

4.2. Results and Discussion

In Fig.5, the confusion matrix, is presented, showcasing the Conv - MBDNN model's accurate classifications across different classes during its execution. The performance assessment of the Conv - MBDNN model, as illustrated in Table 2 and Fig.6, highlights its efficacy in classifying chest X - ray images for Pneumonia detection. Here 70% is used for training and 30% is used for testing. Notably, the model exhibits outstanding performance in identifying Pneumonia disease, achieving maximum sensitivity, specificity, precision, and accuracy, and an F - score of 93.16%, an impressive overall accuracy of 95.67%, and a substantial F - score of 87.59%.

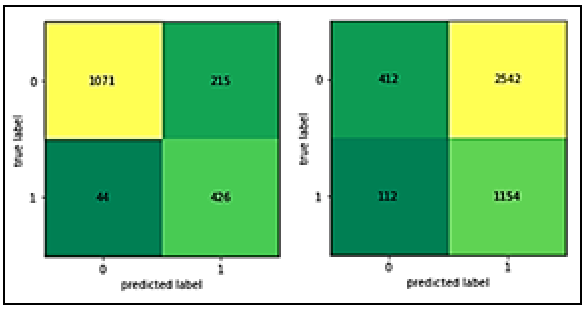

Figure 5 (a): Confusion Matrix based on TR set **(b)** Confusion Matrix based on TS set

Table 2: Performance Evaluation of test images on the proposed Conv - MBDNN Model

Labels	Accuracy	Sensitivity	Specificity	F Score	MCC
TR set (70%)					
Pneumonia	93.79	77.87	97.30	81.91	78.33
Normal	95.43	66.29	99.59	78.38	77.53
Average	**93.86**	**80.90**	**91.72**	**85.00**	**79.23**
TS set (30%)					
Pneumonia	95.00	85.12	97.49	87.29	84.22
Normal	94.67	67.09	100.00	8030	79.94
Average	**95.67**	**83.74**	**93.16**	**87.59**	**83.07**

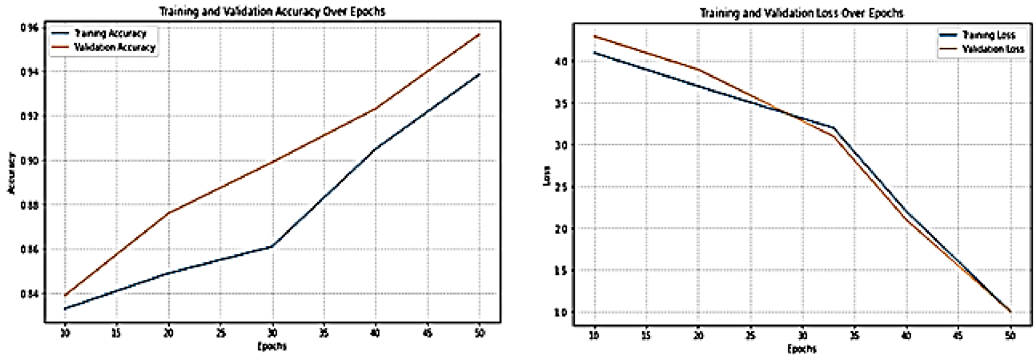

Fig. 6. Accuracy & Loss graph based on TR and TS set

In Table 3, an accuracy analysis is presented for the Conv - MBDNN method in the realm of pneumonia detection and classification, in comparison to previously utilized methods [12]. Significantly, the Conv - MBDNN approach outperforms all other methods, achieving an impressive accuracy of 95.67%. These empirical findings validate the robust detection and classification capabilities of the Conv - MBDNN model, specifically tailored for Pneumonia detection in chest X - ray images. The heightened performance is attributed to the inherent strengths derived from the pre - trained MobileNetV3 model. Consequently, the proposed model emerges as a compelling solution for real - time Pneumonia diagnosis, providing crucial support to medical professionals and contributing to advancements in healthcare outcomes.

Table 3: Comparative Outcome of Kaggle Dataset with Existing Systems

Model	$Accu_y$	$Prec_n$	$Reca_l$	F - score
Conv - MBDNN	**95.67**	**83.74**	**93.16**	**97.59**
Visualization - CNN	92.20	97.00	98.85	98.56
ADFL - mRMR	94.84	96.88	96.83	96.80
X - ray Images - NN	93.40	94.30	94.50	94.50
DPC X - Rat - Dl	84.50	91.30	89.10	87.00
CNN Model	93.00	97.00	99.00	98.00
Chest Xray - DTL	94.43	98.26	99.00	99.00

5. Conclusion

This research is centered around the creation of automated models for the detection and classification of pneumonia in chest X - ray (CXR) images. The objective of the study is Pneumonia Detection and Classification on CXRs. The development of the Conv - MBDNN technique is an automated pneumonia detection and classification model for CXR images. To assess the performance of these model, CXR pneumonia dataset from the Kaggle repository, comprising 1566 normal and 4220 pneumonia samples, is utilized. The experimental results affirm the efficacy of the proposed model in accurately identifying pneumonia cases in CXR images. This interpretability serves as a valuable tool for radiologists and clinicians, instilling confidence in model predictions and aiding in making more informed clinical decisions. Future endeavors could explore various deep - learning techniques or employ ensemble methods to enhance the overall performance and robustness of pneumonia identification models. Additionally, integrating multi - modal data such as medical reports and laboratory outcomes has the potential to improve the diagnostic capabilities of deep learning algorithms, allowing for a more comprehensive understanding of a patient's condition.

References

[1] Kassania, S. H., Kassanib, P. H., Wesolowskic, M. J., Schneidera, K. A. and Detersa, R., 2021. Automatic detection of coronavirus disease (COVID - 19) in X - ray and CT images: a machine learning based approach. *Biocybernetics and Biomedical Engineering*, *41* (3), pp.867 - 879.

[2] Rahman, T., Chowdhury, M. E., Khandakar, A., Islam, K. R., Islam, K. F., Mahbub, Z. B., Kadir, M. A. and Kashem, S., 2020. Transfer learning with deep convolutional neural network (CNN) for pneumonia detection using chest X - ray. *Applied Sciences*, *10* (9), p.3233.

[3] Johri, S., Goyal, M., Jain, S., Baranwal, M., Kumar, V. and Upadhyay, R., 2021. A novel machine learning-based analytical framework for automatic detection of COVID-19 using chest X-ray images. *International Journal of Imaging Systems and Technology*, *31* (3), pp.1105 - 1119.

[4] Yee, S. L. K. and Raymond, W. J. K., 2020, September. Pneumonia diagnosis using chest X - ray images and machine learning. In *proceedings of the 2020 10th international conference on biomedical engineering and technology* (pp.101 - 105).

[5] Çelik, A. and Demirel, S., 2023. Enhanced Pneumonia Diagnosis Using Chest X - Ray Image Features and Multilayer Perceptron and k - NN Machine Learning Algorithms. *Traitement du Signal*, *40* (3), p.1015.

[6] Katsamenis, I., Protopapadakis, E., Voulodimos, A., Doulamis, A. and Doulamis, N., 2020, November. Transfer learning for COVID - 19 pneumonia detection and classification in chest X - ray images. In *Proceedings of the 24th Pan - Hellenic Conference on Informatics* (pp.170 - 174).

[7] Alsharif, R., Al - Issa, Y., Alqudah, A. M., Qasmieh, I. A., Mustafa, W. A. and Alquran, H., 2021. PneumoniaNet: Automated detection and classification of pediatric pneumonia using chest X - ray images and CNN approach. *Electronics*, *10* (23), p.2949.

[8] Chamoli, S. and Tamboli, A. I., 2023. Machine Learning for Early Detection of Pneumonia from Chest X - ray Images. *International Journal of Intelligent Systems and Applications in Engineering*, *11* (7s), pp.111 - 118.

[9] Kumar, R., Arora, R., Bansal, V., Sahayasheela, V. J., Buckchash, H., Imran, J., Narayanan, N., Pandian, G. N. and Raman, B., 2020. Accurate prediction of COVID - 19 using chest X - ray images through deep feature learning model with SMOTE and machine learning classifiers. *MedRxiv*, pp.2020 - 04.

[10] Alquran, H., Alsleti, M., Alsharif, R., Qasmieh, I. A., Alqudah, A. M. and Harun, N. H. B., 2021, June. Employing texture features of chest x - ray images and machine learning in covid - 19 detection and classification. In *Mendel* (Vol.27, No.1, pp.9 - 17).

[11] Goyal, S. and Singh, R., 2021. Detection and classification of lung diseases for pneumonia and Covid - 19 using machine and deep learning techniques. *Journal of Ambient Intelligence and Humanized Computing*, pp.1 - 21.

[12] Ravi, V., Acharya, V. and Alazab, M., 2023. A multichannel EfficientNet deep learning - based stacking ensemble approach for lung disease detection using chest X - ray images. *Cluster Computing*, *26* (2), pp.1181 - 1203.

[13] Chen, K. C., Yu, H. R., Chen, W. S., Lin, W. C., Lee, Y. C., Chen, H. H., Jiang, J. H., Su, T. Y., Tsai, C. K., Tsai, T. A. and Tsai, C. M., 2020. Diagnosis of common pulmonary diseases in children by X - ray images and deep learning. *Scientific reports*, *10* (1), p.17374.

[14] Manickam, A., Jiang, J., Zhou, Y., Sagar, A., Soundrapandiyan, R. and Samuel, R. D. J., 2021. Automated pneumonia detection on chest X - ray images: A deep learning approach with different optimizers and transfer learning architectures. *Measurement*, *184*, p.109953.

[15] Bhatt, H. and Shah, M., 2023. A Convolutional Neural Network ensemble model for Pneumonia Detection using chest X - ray images. *Healthcare Analytics*, *3*, p.100176.

[16] Avşar, Ercan. "Effects of image preprocessing on the performance of convolutional neural networks for pneumonia detection. " *2021 International Conference on INnovations in Intelligent SysTems and Applications (INISTA).* IEEE, 2021.

[17] Cococi, Alin, et al. "Pneumonia detection on chest X - ray images using convolutional neural networks designed for resource constrained environments. " *2020 International Conference on e - Health and Bioengineering (EHB).* IEEE, 2020.

[18] Singh, Nitin, Rajneesh Sharma, and Amit Kukker. "Wavelet transform based pneumonia classification of chest X - ray images. " *2019 International Conference on Computing, Power and Communication Technologies (GUCON).* IEEE, 2019.

[19] https: //www.kaggle. com/datasets/paultimothymooney/chest - xray - pneumonia