Deep Learning for Pneumonia Classification in Chest Radiography Images using Wavelet Transform

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Abstract: - Chronic respiratory diseases constitute a prognostic severity factor for some respiratory illnesses. A case in point is pneumonia, a lung infection, whose effective management requires highly accurate diagnosis and precise treatment. Categorizing pneumonia as positive or negative does go through a process of classifying chest radiography images. This task plays a crucial role in medical diagnostics as it facilitates the detection of pneumonia and helps in making timely treatment decisions. Deep learning has shown remarkable effectiveness in various medical imaging applications, including the recognition and categorization of pneumonia in chest radiography images. The main aim of this research is to compare the efficacy of two convolutional neural network models for classifying pneumonia in chest radiography images. The first model was directly trained on the original images, achieving a training accuracy of 0.9266, whereas the second model was trained on images transformed using wavelets and achieved a training accuracy of 0.94. The second model demonstrated significantly superior results in terms of accuracy, sensitivity, and specificity.

Key-Words: - Pneumonia, Chest radiography images, Deep learning, Convolutional neural network, Wavelet transform, Image classification

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1 Introduction

Pneumonia presents a considerable threat to numerous individuals, especially in less developed regions. It is a respiratory ailment caused by the inhalation of viruses, bacteria, or fungi, resulting in an infection in the lungs. This infection leads to the build-up of fluid in the lungs, leading to respiratory challenges, [1]. Precise and timely respiratory treatment is crucial. Chest radiography is a widely employed diagnostic technique for pneumonia detection. Medical image analysis is a highly encouraging area of study that utilizes radiographic images to accomplish this objective. Indeed, radiography involves generating medical images using X-rays, [2]. This term includes different imaging techniques, such as X-ray imaging, which employs X-rays to produce diagnostic images of the human body. The diagnosis process can be demanding in terms of time and budget. Moreover, the interpretation of chest radiography images can be challenging and subjective, which can lead to diagnosis errors.

To improve the speed and efficiency of pneumonia diagnosis, many studies are using Convolutional Neural Network (CNN) models to automatically classify chest radiography images as normal or abnormal, [3]. CNNs are deep learning models particularly suited for image recognition works. In medical imaging tasks, the input layer of a neural network consists of carefully selected images, oftentimes with correlated pathologies which the network learns from by autonomously identifying relevant imaging features, [4].

In [5], the authors introduced a specialized CNN architecture with a shallow ConvLayer to classify lung disease image patches. Additionally, they discovered that the system's performance can be extended to other medical image datasets, indicating its potential for generalization. In another work, The study, [6], put forward a CNN-based solution for the automated identification and localization of pneumonia in chest radiography images. They conducted experiments using a dataset consisting of 26,684 images sourced from the Kaggle Pneumonia Detection Challenge. The attained results were found to be satisfactory. Similarly, the study, [7], provided a CNN-based mechanism for automatic pneumonia detection and classification from chest radiography. A number of 15,8323 chest radiographs from three institutions were used for their models. It was concluded that CNNs demonstrated exceptional accuracy and precision in determining the origin of a radiograph with extremely high precision. Nevertheless, the image dataset used in their study is not available to other researchers.

In this study, the effectiveness of two CNN models was compared for pneumonia classification. The first model was trained directly on raw images, maintaining the traditional approach to image analysis. On the other hand, the second model was trained using images transformed with wavelets, introducing a novel and potentially more informative method for feature extraction. Wavelets are a mathematical transformation that decomposes an image into different frequency components, which can improve the performance of CNN models by reducing noise and highlighting the most important details of the image as shown in Figure 1 and Figure 2, [8]. Wavelets are utilized to extract significant characteristics from medical images. Through the decomposition of the image into various frequency bands, wavelet analysis captures both intricate details and broader features, resulting in a more inclusive depiction of the image. These extracted features can be employed in CNN models to categorize medical images, enabling the identification of various diseases or abnormalities.

By harnessing the power of wavelets, this innovative method showcases the potential of merging advanced image processing techniques with deep learning algorithms, paving the way for enhanced medical image analysis and disease detection.

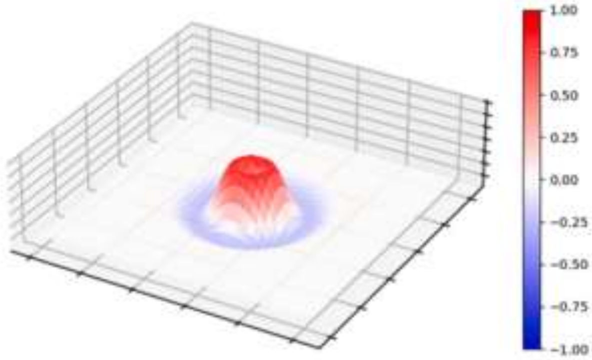

Fig. 1: An overview perspective of the wavelet, [8]


Fig. 2: Series of wavelets, [8]

The rest of this paper is structured as follows. Section 2 discusses relevant literature in the field. The proposed methods are described in Section 3. Section 4 presents the results obtained from the proposed models and provides an interpretation of these results. The final section presents the conclusion of the paper.

2 Related Works

2.1 Medical Image for Pneumonia

Accurate classification of medical images is vital for supporting clinical care and treatment. When it comes to pneumonia diagnosis, the analysis of radiography images is considered the most effective approach.

The study, [9], conducted the process of classifying image views obtained from chest X-rays. In resource-limited regions, they categorize images into two groups, namely frontal view and lateral view, as part of the process of screening for tuberculosis disease. Their method was tested on a large dataset (more than 8,200 images) and gave very high classification accuracy.

The study, [10], put forward a deep learning model (while maintaining classification accuracy and enhancing feature extraction) that utilizes a dataset consisting of 7,132 chest X-ray images. The findings indicate that their model provides convincing and coherent conclusions to medical experts regarding the identification and categorization of COVID-19, pneumonia, and tuberculosis.

The study, [11], offers a comprehensive survey of the literature concerning the intelligent identification of pneumonia from chest X-rays. Their research will assist professionals in choosing the most optimal and productive approaches from a current viewpoint, evaluating the accessible datasets, and comprehending the outcomes achieved within this field. They discuss the quality, usability, and size of existing chest X-ray (CXR) datasets, as well as approaches to address imbalanced datasets.

Table 1 summarizes some chest X-ray databases used in different studies, and Figure 3 shows an example of a chest X-ray image.

Table 1. Sample Chest X-ray dataset, [11]

Reference	**Dataset name**	**Number of images**
Kermany et al. [12]	Pediatric CXRs	5,856
Wang et al. [13]	X-ray14	108,948
Johnson et al. [14]	MIMIC–CXR–JPG	377,110
Demner-Fushman et al. [15]	OPEN-I INDIANA	7,470
Jaeger et al. [16]	MC DATASET	138
Jaeger et al. [16]	SHENZHEN DATASET	662
Ryoo and Kim [17]	KIT DATASET	10,848
Sugimoto et al. [18]	JSRT DATASET	247

Fig. 3: Example of chest X-ray image, [13]

2.2 CNN on Medical Image Classification

Medical image classification is a crucial aspect of clinical diagnosis and treatment. However, traditional methods have reached their performance limits. Deep learning, a rapidly advancing machine learning technique, has demonstrated great potential in various classification tasks. Among them, CNN has consistently shown superior performance in image classification. Numerous studies have explored the application of CNN-based algorithms on chest radiography datasets specifically for pneumonia classification.

In recent studies, [19], presented multiple approaches to guide CNNs in focusing on specific regions of medical images. Their research elaborates on the methods of deep learning for classification and segmentation, while also introducing both traditional and contemporary mainstream network models. These methods leverage domain knowledge to extract relevant information from the images.

The study, [20], introduced a technique that employs CNNs, to identify consolidations in chest radiography images. This method aims to assist radiologists in enhancing their diagnostic capabilities. The authors leverage a Deep CNN that has been pre-trained with ImageNet data to enhance the precision and reliability of the models.

The study, [21], presents a CNN-based stereo spatial decoupling network for medical image classification. The authors introduce a feature screening strategy to reduce redundant features and incorporate gating strategies to enhance the quality of the selected features. This research elaborates on the methods of deep learning for classification and segmentation, while also introducing both traditional and contemporary mainstream network models.

The study, [22], presents a recently developed CNN model, trained from the ground up, designed specifically for pneumonia classification and detection using a diverse dataset of chest radiography images. To tackle the typical issues of reliability and interpretability in medical imaging, they demonstrated a method to accurately classify pneumonia data as positive or negative, employing a dataset of X-ray images. When compared to other methods, their model showed significantly higher validation accuracy.

2.3 Medical Image Classification using Wavelet Transform

Wavelet-based methods have found extensive applications in various domains, such as image and audio processing, biomedical signal analysis, data compression, and pattern recognition. These techniques provide a potent and adaptable approach for analyzing and processing signals, allowing for efficient and precise representation and manipulation of signals.

The study, [23], created a precise and automated system for diagnosing COVID-19, using only a small set of labeled CT images. The authors modify the COVID-Net architecture during training to make it more suitable for processing CT images. They introduce an additional task alongside the classification task, allowing for joint learning and the accumulation of similar semantic representations in categories with indistinct boundaries. To leverage all the image features effectively, they combined discrete wavelet transform with contrastive learning.

The study, [24], proposes a model to detect

COVID-19 from chest X-ray images. They use a wavelet and stack deep learning architecture. Their model attained highly accurate classification outcomes, making it a viable solution for COVID-19 diagnosis in practical settings. The authors assert that their proposed approach holds great potential in the healthcare sector, enabling faster and cost-effective detection of COVID-19 with improved accuracy.

Overall, wavelet-based methods have become indispensable tools across diverse disciplines, offering a powerful and efficient means of analyzing and processing signals and contributing to advancements in various areas of research and applications.

3 Materials and Methods

In this study, the Python programming language and open-source libraries TensorFlow were utilized for the purpose, [25], Keras, [25], PyWavelets, [26], Numpy, [27], and OpenCV, [28], to train and evaluate this CNN model for pneumonia classification from chest radiography images. Google Colab was employed to execute experiments using a high-level professional GPU, which significantly reduced computation times. The model was also tested locally on a computer with a reduced database.

3.1 Database

The database used in this work, [12], consists of 5,856 chest radiography images divided into two categories: one showing pneumonia and one showing normal results. The utilized dataset, referred to as pediatric CXRs, was obtained from the Guangzhou Women and Children's Medical Centre in China. These CXR images were captured as part of the regular clinical care provided to the patients. For this specific research, the authors chose a total of 5,856 CXR images from pediatric patients aged 1–5 years. Among these, there were 4,273 images depicting pneumonia (2,780 bacterial and 1,493 viral cases), while the remaining 1,583 images were classified as normal. Figure 4 and Figure 5 illustrate these categories. These images were split into a training set of 3,722 images and a validation set of 2,134 images, ensuring a balanced proportion of images from each category in the training set. The purpose of this distribution was to improve validation accuracy.

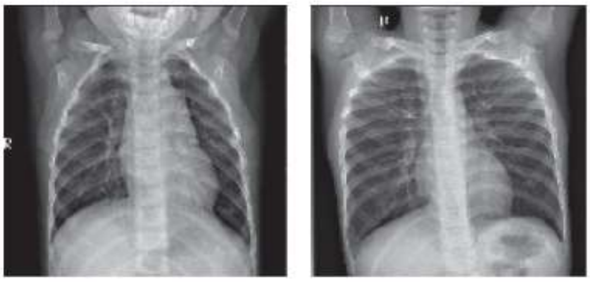

Fig. 4: Chest radiography images without pneumonia

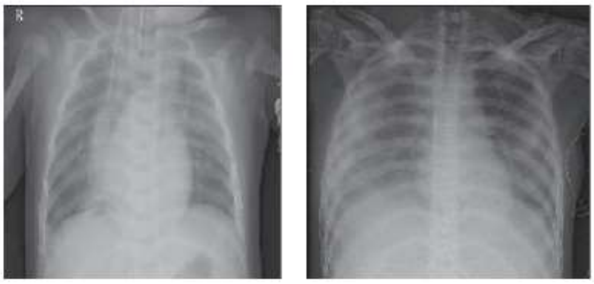

Fig. 5: Chest radiography images with pneumonia

3.2 Data Preprocessing and Augmentation

To preprocess the data, wavelet transformation was employed with the PyWavelets library and normalized the obtained coefficients using Numpy and OpenCV. These coefficients were used as inputs for the CNN model, which was built and trained using the Keras framework with TensorFlow as the backend.

CNN-based techniques employ diverse strategies to enhance the performance of image classification on limited datasets. Among these methods, data augmentation is one approach commonly used, [29]. To artificially increase the size and quality of the dataset, various data augmentation methods were used. This process helps address overfitting issues and improves the model's generalization ability during training. The parameters employed in image augmentation are indicated in Table 2.

Table 2. Parameters for image augmentation

Method	Setting
Rescale	1/255
Rotation range	40
width shift	0.2
Height shift	0.2
Shear range	0.2
Zoom range	0.2
Horizontal	flip True

3.3 Transformed using Wavelets

In signal processing, wavelets are utilized for various tasks, including signal denoising, compression, feature extraction, and time-frequency analysis. The

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key advantage of wavelets is their ability to provide a multi-resolution analysis, which allows for a detailed examination of signal properties at different scales. This technique is often used to analyze images because it permits the accentuation of particulars and structures present at different scales.

In this pneumonia classification project, the wavelet transform was applied to transform the database of radiographic images. Specifically, the low-low component of the wavelet transform was preserved, which captures signal features present at a specific scale. By saving this low-low component, the technique enables the extraction and preservation of specific characteristics of the images. As illustrated in Figure 6, this approach allows the highlighting of particular image attributes, contributing to a more effective classification process. The transformed images with their emphasized characteristics serve as valuable inputs for the CNN model, ultimately enhancing its performance in accurately classifying pneumonia cases.

3.4 Convolutional Neural Network Model

Numerous variations of CNN architectures have been created to suit various tasks such as classification, detection, and segmentation. Among them, the classification task is the most widely utilized architecture, where the network is tasked with determining whether a given set of input images belongs to a specific category, [3]. This classification architecture has proven to be highly effective and efficient, with applications spanning a wide range of fields, from object recognition to medical diagnosis.

The model used for this classification is a CNN illustrated in Figure 7. This model consists of two main parts: feature extractors and the classifier. The feature extractors consist of convolutional layers, max-pooling layers, and combined classification layers. Their primary function is to extract significant features from the input data.

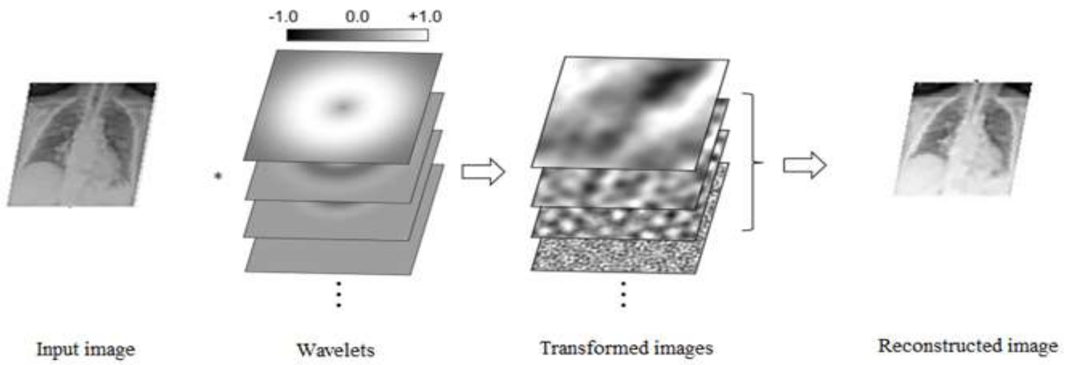

Fig. 6: Proposed method

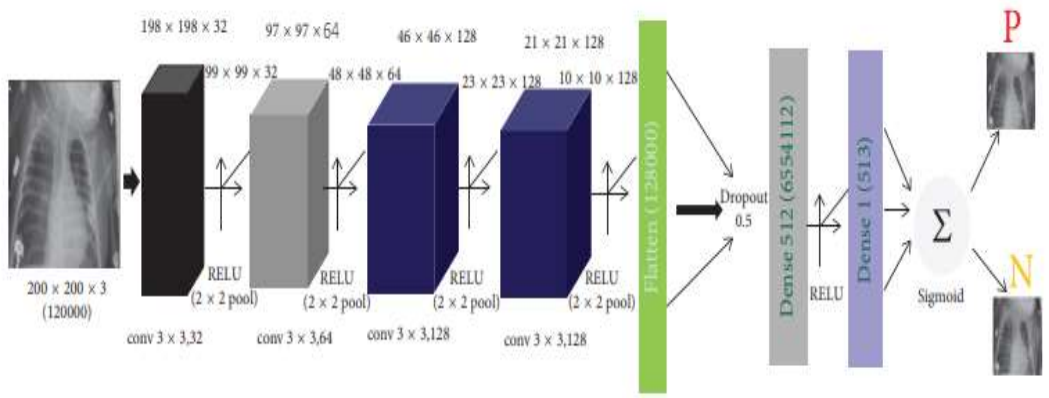

Fig. 7: Proposed architecture

The classifier positioned at the end of the CNN consists of a dense layer composed of artificial neurons. It takes advantage of the features extracted by the feature extractors to conduct the ultimate data classification. This involves converting the output of the feature extractor into a 1D feature vector, which is then utilized by the dense classifier layer as shown in Table 3. To enhance the classification task, the classification layer includes a flattening layer, a dropout layer, and a sigmoid activation function, collectively contributing to the effective execution of the classification process.

To conclude, the employed CNN3 model proves to be an effective classification approach utilizing convolutional and max-pooling layers to extract crucial data features, along with a dense layer of artificial neurons responsible for the ultimate classification process.

Table. 3 The result of the suggested network architecture

Layer (type)	**Output shape**	**Turtles**
conv2d9 (conv2D)	(None, 198, 198, 32)	896
max_Pooling2d9 (MaxP_ooling2)	(None, 99, 99, 32)	0
conv2d10 (conv2D)	(None, 97, 97, 64)	18496
max_Pooling2d10 (MaxP_ooling2)	(None, 48, 48, 64)	0
conv2d11 (conv2D)	(None, 46, 46, 128)	73856
max_Pooling2d11 (MaxP_ooling2)	(None, 23, 23, 128)	0
conv2d12(conv2D)	(None, 21, 21, 128)	147584
max_Pooling2d12 (MaxP_ooling2)	(None, 10, 10, 128)	0
dropout3 (Dropout)	(None, 12800)	0
dense5 (Dense)	(None, 512)	6554112
dense6 (Dense)	(None, 2)	1026

Initially, the model was applied to the raw database without applying the wavelet transform. In the second part, the model was applied to the same database but performed the wavelet transform to extract efficient features and visualize the added value of the wavelet transform on the performance of the model.

4 Results and Discussion

Standard metrics were utilized to report the performance of the entire model. Sensitivity, specificity, and accuracy were specifically assessed and measured:

$$\text{Sensitivity}=\frac{TP}{TP+FN} \quad (1)$$

$$\text{Specificity}=\frac{TN}{TN+FP} \quad (2)$$

$$\text{Accuracy}=\frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

where: TP – True positive,
TN – True negative,
FP – False positive,
FN – False negative.

To assess and confirm the efficacy of the proposed approach, both programs were run one applied to the original database, and the other applied to the database after wavelet transformation and obtained the following results:

4.1 Model without Wavelets

Figure 8 and Figure 9 portray the results of this CNN model without wavelets for pneumonia classification, which were promising. A database of 5,856 chest radiograph images was used, which were divided into a training set and a test set. The proposed model achieved a training accuracy of 0.9266 and a training loss of 0.207, with a test accuracy of 0.9 and a test loss of 0.287. These results suggest that it is capable of reliably detecting the presence of pneumonia in chest radiographs.

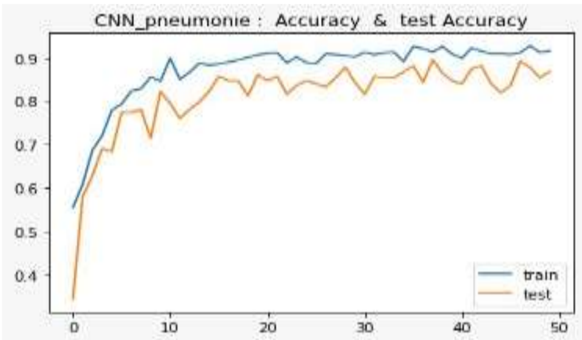

Fig. 8: Performance of the classification model without wavelets/Accuracy and test Accuracy

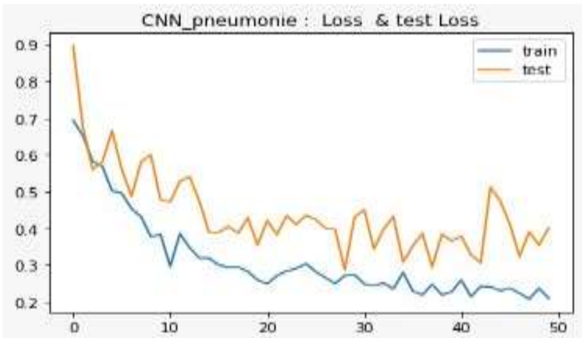

Fig. 9: Performance of the classification model without wavelets/Loss and test Loss

4.2 Model with Wavelets

Figure 10 and Figure 11 demonstrate the promising results of the CNN model with wavelets for pneumonia classification. The study utilized the same database of chest radiograph images after applying wavelet transform, dividing it into a training set and a test set. The proposed model achieved a training accuracy of 0.94 and a training loss of 0.1755 while achieving a test accuracy of 0.75 and a test loss of 0.65.

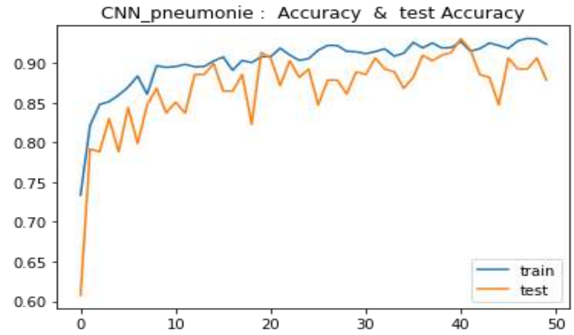

Fig. 10: Performance of the classification model with wavelets/Accuracy and test Accuracy

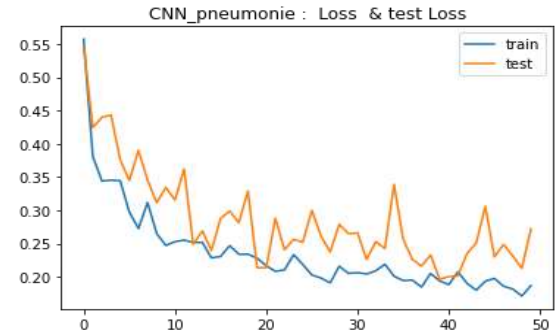

Fig. 11: Performance of the classification model with wavelets/Loss and test Loss

4.3 Discussion

The application of wavelets in pneumonia classification using a CNN model has proven to be highly effective. Training the model on wavelet-transformed images instead of raw images enables the model to emphasize specific image features that may be challenging to detect through traditional raw image analysis methods. Wavelets can accentuate contours and structures within the image, providing valuable insights for pneumonia detection.

This approach enhances the model's performance in distinguishing subtle patterns indicative of pneumonia, which might not be easily discernible in the original images. As a result, the CNN model becomes more adept at accurately identifying pneumonia cases, ultimately contributing to improved diagnostic accuracy and aiding healthcare professionals in making informed decisions.

It should be emphasized that employing wavelets may result in heightened complexity of the model and an increase in the computational load it requires. Indeed, wavelet transformation generally involves the use of special filters and decomposing the image into different frequency components, which can increase the size of the model and the computation time. This can result in a decrease in the model's execution speed and an increase in memory consumption.

The proposed model achieved a training accuracy of 94%. Some studies have used wavelet transform and found results to compare with the study. For example. The study, [23], achieved 93.55% accuracy in their study, the researchers merged discrete wavelet transformation with their learning approach to preserve all the features from the input images, thus maximizing the utilization of the available data sources. In another work, the study, [30], achieved 93.47% accuracy in the realm of automated diagnosis of COVID stages from lung CT images, researchers have proposed a method that employs statistical features within the 2-dimensional flexible analytic wavelet transform.

5 Conclusion

This work aims to compare two CNN models for pneumonia classification on chest radiography images. The first model underwent training using raw images, whereas the second model was trained on images that underwent wavelet transformation. The accuracy obtained in the first model is 0.9266, but when chest radiograph images were used after applying wavelet transform, the proposed model achieved a training accuracy of 0.94. It was observed that the second model exhibited notably superior outcomes in terms of accuracy. Pneumonia classification using CNNs can be an effective means of diagnosing and treating such severe respiratory infections as early as possible. Utilizing chest radiographic images, a CNN model can be trained to detect signs of pneumonia and predict the type of pathogen responsible for the infection. Nevertheless, it is crucial to highlight that while utilizing CNNs for pneumonia classification, it is essential to supplement them with other diagnostic methods such as clinical examination and laboratory analyses. This integrated approach ensures precise diagnosis and appropriate treatment decisions. Furthermore, employing CNNs for pneumonia classification requires a high-quality database and accurate image annotations to guarantee the reliability and accuracy of the obtained results.

While the use of wavelets offers significant advantages in highlighting essential image features and improving the model's performance, researchers and developers should consider the trade-off between accuracy and computational complexity. Efficient hardware resources and optimization techniques should be explored to manage the increased computational demands and ensure that the benefits of wavelet-based classification outweigh the associated challenges.

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References:
[1] S. Singh and B. K. Tripathi, "Pneumonia classification using quaternion deep learning," *Multimedia Tools and Applications*, vol. 81, no. 2, pp. 1743–1764, 2022.
[2] S. Sharma and K. Guleria, "A Deep Learning based model for the Detection of Pneumonia from Chest X-Ray Images using VGG-16 and Neural Networks," *Procedia Computer Science*, vol. 218, pp. 357–366, 2023.
[3] S. S. Yadav and S. M. Jadhav, "Deep convolutional neural network based medical image classification for disease diagnosis," *Journal of Big Data*, vol. 6, no. 1, 2019.
[4] S. Mutasa, S. Sun, and R. Ha, "Understanding artificial intelligence based radiology studies: CNN architecture," *Clinical Imaging*, vol. 80, no. June, pp. 72–76, 2021.
[5] Q. Li, W. Cai, X. Wang, Y. Zhou, D. D. Feng, and M. Chen, "Medical image classification with convolutional neural network," *2014 13th International Conference on Control Automation Robotics and Vision, ICARCV 2014*, vol. 2014, no. December, pp. 844–848, 2014.
[6] 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," *Computers and Electrical Engineering*, vol. 78, pp. 388–399, 2019.
[7] J. R. Zech, M. A. Badgeley, M. Liu, A. B. Costa, J. J. Titano, and E. K. Oermann, "Variable generalization performance of a deep learning model to detect pneumonia in chest radiographs: A cross-sectional study," *PLoS Medicine*, vol. 15, no. 11, pp. 1–17, 2018.
[8] F. Uesugi, "Novel image processing method inspired by wavelet transform," *Micron*, vol. 168, no. December 2022, p. 103442, 2023.
[9] Z. Xue, D. You, S. Candemir, S. Jaeger, S. Antani, L. R. Long, G. R. Thoma, "Chest x-ray image view classification," *Proceedings - IEEE Symposium on Computer-Based Medical Systems*, vol. 2015-July, pp. 66–71, 2015.
[10] M. Bhandari, T. B. Shahi, B. Siku, and A. Neupane, "Explanatory classification of CXR images into COVID-19, Pneumonia and Tuberculosis using deep learning and XAI," *Computers in Biology and Medicine*, vol. 150, no. June, 2022.
[11] W. Khan, N. Zaki, and L. Ali, "Intelligent Pneumonia Identification from Chest X-Rays: A Systematic Literature Review," *IEEE Access*, vol. 9, pp. 51747–51771, 2021.
[12] D. Kermany, K. Zhang, and M. Goldbaum, "Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images for Classification," vol. 2, 2018.
[13] X. Wang, Y. Peng, L. Lu, Z. Lu, M. Bagheri, and R. M. Summers, "dataset noisy labels ChestX-ray8 multidisease ChestX-ray14," pp. 2097–2106,
[14] A. E. W. Johnson *et al.*, "MIMIC-CXR-JPG, a large publicly available database of labeled chest radiographs," vol. 14, pp. 1–7, 2019.
[15] D. Demner-Fushman, M. D. Kohli , M. B. Rosenman, S. E. Shooshan, L. Rodriguez, S. Antani, "Preparing a collection of radiology examinations for distribution and retrieval," *Journal of the American Medical Informatics Association*, vol. 23, no. 2, pp. 304–310, 2016.
[16] S. Jaeger, S. Candemir, S. Antani, Y.-X. J. Wáng, P.-X. Lu, and G. Thoma, "Two public chest X-ray datasets for computer-aided screening of pulmonary diseases.," *Quantitative imaging in medicine and surgery*, vol. 4, no. 6, pp. 475–7, 2014.
[17] S. Ryoo and H. J. Kim, "Activities of the Korean Institute of Tuberculosis," *Osong Public Health and Research Perspectives*, vol. 5, no. S, pp. S43–S49, 2014.
[18] K. Sugimoto, F. Moriyasu, J. Shiraishi, et *al.*, "Assessment of arterial hypervascularity of hepatocellular carcinoma: Comparison of contrast-enhanced US and gadoxetate disodium-enhanced MR imaging," *European Radiology*, vol. 22, no. 6, pp. 1205–1213, 2012.
[19] L. Cai, J. Gao, D. Z.-A. of translational medicine, and undefined 2020, "A review of the application of deep learning in medical

image classification and segmentation," *ncbi.nlm.nih.gov*, Accessed: May 17, 2023.

[20] H. Behzadi-khormouji, H. Rostami, S. Salehi, T. Derakhshande-Rishehri, M. Masoumi, S. Salemi, A. Keshavarzc, A. Gholamrezanezhadd, M. Assadi, A. Batouli, "Deep learning, reusable and problem-based architectures for detection of consolidation on chest X-ray images," *Computer Methods and Programs in Biomedicine*, vol. 185, p. 105162, 2020.

[21] H. You, L. Yu, S. Tian, and W. Cai, "A stereo spatial decoupling network for medical image classification," *Complex and Intelligent Systems*, 2023.

[22] O. Stephen, M. Sain, U. J. Maduh, and D. U. Jeong, "An Efficient Deep Learning Approach to Pneumonia Classification in Healthcare," *Journal of Healthcare Engineering*, vol. 2019, 2019.

[23] Y. Wu, Q. Dai, and H. Lu, "COVID-19 diagnosis utilizing wavelet-based contrastive learning with chest CT images," *Chemometrics and Intelligent Laboratory Systems*, vol. 236, no. January, p. 104799, 2023.

[24] R. Soundrapandiyan, H. Naidu, M. Karuppiah, M. Maheswari, and R. C. Poonia, "AI-based wavelet and stacked deep learning architecture for detecting coronavirus (COVID-19) from chest X-ray images," *Computers and Electrical Engineering*, vol. 108, no. April, p. 108711, 2023.

[25] L. Parisi, R. Ma, N. RaviChandran, and M. Lanzillotta, "hyper-sinh: An accurate and reliable function from shallow to deep learning in TensorFlow and Keras," *Machine Learning with Applications*, vol. 6, no. July, p. 100112, 2021.

[26] E. Lavrova, S. Primakov, Z. Salahuddin, M. Beuque, D. Verstappen, H. C. Woodruff, P. Lambin, "Precision-medicine-toolbox: An open-source python package for the quantitative medical image analysis," *Software Impacts*, vol. 16, no. April, p. 100508, 2023.

[27] C. Abert, F. Bruckner, C. Vogler, R. Windl, R. Thanhoffer, and D. Suess, "A full-fledged micromagnetic code in fewer than 70 lines of NumPy," *Journal of Magnetism and Magnetic Materials*, vol. 387, pp. 13–18, 2015.

[28] H. Sugano and R. Miyamoto, "Highly optimized implementation of OpenCV for the Cell Broadband Engine," *Computer Vision and Image Understanding*, vol. 114, no. 11, pp. 1273–1281, 2010.

[29] M. Frid-Adar, I. Diamant, E. Klang, M. Amitai, J. Goldberger, and H. Greenspan, "GAN-based synthetic medical image augmentation for increased CNN performance in liver lesion classification," *Neurocomputing*, vol. 321, pp. 321–331, 2018.

[30] R. K. Patel and M. Kashyap, "Automated diagnosis of COVID stages from lung CT images using statistical features in 2-dimensional flexible analytic wavelet transform," *Biocybernetics and Biomedical Engineering*, vol. 42, no. 3, pp. 829–841, 2022.

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Conflict of Interest

The authors have no conflicts of interest to declare.