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Detection of Pulmonary Lesions Using Convolutional Neural Networks in X-Ray Images and Capsule Neural Networks

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ABSTRACT

In this study, a novel approach based on Capsule Neural Networks is presented for detecting pulmonary lesions in medical images. Timely and accurate detection of pulmonary lesions is of critical importance in reducing mortality among patients with pulmonary diseases, particularly during the early stages of the disease. Capsule Neural Networks are considered a suitable tool for this purpose due to their high capability in identifying complex features and spatial relationships within image data. In this study, CT and X-ray images of patients with pulmonary lesions and healthy individuals were collected and, following preprocessing procedures including normalization and data augmentation, were used as inputs to the Capsule Neural Network model. The proposed model extracts important features and identifies patterns associated with pulmonary lesions. Model performance was evaluated using metrics such as accuracy, sensitivity, and the F1-score. The obtained results demonstrated that the Capsule Neural Network achieved good performance and high accuracy in detecting pulmonary lesions. This study highlights the effectiveness of Capsule Neural Networks in the diagnosis of pulmonary diseases and their potential application in medical systems for the automated detection of lesions.

1. INTRODUCTION

In recent decades, technological advances and deep learning have had a profound impact on numerous scientific and industrial fields. Medical diagnosis is one of the areas that has benefited substantially from these advances. The identification of diseases and medical abnormalities through medical imaging using artificial intelligence and deep learning, particularly in recent years, has become a prominent and critical topic in scientific research. With the increasing prevalence of pulmonary diseases such as lung cancer, pneumonia, and other abnormalities, the need for accurate and automated diagnostic approaches has increased. Pulmonary diseases, particularly in their early stages, often exhibit no specific or apparent symptoms, making their diagnosis and treatment challenging. Therefore, early detection of these diseases is of particular importance and can significantly contribute to improving patients' health outcomes and increasing their life expectancy.

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Capsule Neural Networks, as one of the emerging deep learning techniques, have become effective tools for detecting medical abnormalities due to their unique ability to identify complex patterns and capture spatial structures in image data. Unlike conventional convolutional models, Capsule Neural Networks are capable of more effectively capturing the spatial characteristics of images and preserving relationships among different components of an image. These properties have enabled such networks to achieve notable performance in the accurate and rapid detection of pulmonary lesions and other medical abnormalities.

The primary objective of this study is to investigate and employ Capsule Neural Networks for detecting pulmonary lesions from CT and X-ray images. The proposed approach encompasses several stages, ranging from preprocessing and preparing image data for accurate analysis to training and evaluating the model using medical datasets. In this approach, medical images are divided into two categories, namely healthy images and images containing lesions, and the model is trained using advanced techniques such as data augmentation and normalization. Subsequently, the designed Capsule Neural Network extracts important image features and accurately identifies pulmonary lesions.

The remainder of this paper is organized as follows. First, the fundamental concepts related to Capsule Neural Networks and the importance of their application in medical image analysis are described. Next, the data preparation procedure, model architecture, and details of the model training and evaluation stages are discussed in detail. The results obtained from this study, demonstrating the high accuracy and capability of the Capsule Neural Network in detecting pulmonary lesions, are then presented and compared with other models. Finally, the future potential of this approach for improving medical diagnosis and its possible integration into healthcare systems is discussed.

2. LITERATURE REVIEW

This study presents an efficient Convolutional Neural Network (CNN) model for detecting COVID-19 based on the classification of X-ray images. To improve diagnostic accuracy and efficiency, the authors employed a CNN to identify disease-related manifestations from chest radiographic images. The results demonstrated that the proposed model was capable of accurately distinguishing COVID-19 patients from healthy individuals. This research represents an important step toward the application of deep learning for detecting infectious diseases such as COVID-19 through medical image analysis [1].

In this study, the authors combined CNN and Long Short-Term Memory (LSTM) models to improve the classification of imbalanced pulmonary disease images obtained from X-ray examinations. CNN was used for feature extraction, while LSTM was employed to model sequential information. This combination enabled the model to classify pulmonary disease images more accurately. The results indicated that the hybrid model achieved higher accuracy than previous models and was capable of addressing the challenges associated with imbalanced datasets [2].

This study presents a deep learning architecture for multiclass classification of pulmonary diseases using chest X-ray images. The objective was to identify and classify various pulmonary diseases, including pneumonia and lung cancer. By employing CNN, the authors sought to improve the accuracy and efficiency of the model in detecting different diseases. The results showed that the proposed model achieved high accuracy in identifying multiple pulmonary diseases [3].

This study focuses on the classification of patients with pneumonia using a Convolutional Neural Network (CNN) and chest X-ray images. The authors employed CNN to extract key features from the images in order to distinguish patients with pneumonia from healthy individuals. The results demonstrated that the model was able to identify affected patients with satisfactory accuracy, and the approach was proposed as an effective method for pneumonia detection [4].

This study addresses the automated classification of chest X-ray images and the improvement of classification accuracy using CNN-based deep learning methods. The authors employed CNN to enhance the accuracy and reliability of image classification. The findings demonstrated that the CNN architecture achieved good performance in identifying pulmonary diseases and could serve as an effective tool for automated disease detection [5].

This study introduces the CXGNet model for COVID-19 detection through X-ray image classification. The proposed model employs a CNN in conjunction with the Grey Wolf Optimizer (GWO) to perform classification across three different phases. The results demonstrated that the proposed approach achieved high accuracy in detecting COVID-19 from X-ray images and exhibited optimized performance compared with baseline models [6].

This study investigates the multiclass classification of chest X-ray images using the CNN-ELM model, which is capable of identifying 17 pulmonary diseases, including COVID-19. Through parallel processing, the hybrid CNN-ELM model achieved high accuracy in identifying various diseases. This multiclass model was specifically designed for medical applications requiring the simultaneous identification of multiple diseases [7].

This study focuses on evolutionary optimization for CNN compression and chest X-ray image classification. By employing evolutionary optimization techniques, the authors reduced the computational complexity of the CNN and optimized the model for faster and more accurate image classification. This approach facilitates the deployment of CNN-based systems in low-power environments and resource-constrained systems [8].

In this study, a combination of Contrast Limited Adaptive Histogram Equalization (CLAHE) and CNN was employed for pulmonary disease classification using X-ray images. CLAHE was used as an image preprocessing technique to enhance image contrast, followed by CNN-based classification. The results demonstrated that this combination improved classification accuracy and enhanced the model's performance in detecting pulmonary diseases [9].

This study analyzes and classifies chest X-ray images for the detection of COVID-19 pneumonia using CNN. The authors employed a CNN to extract key features associated with COVID-19-induced pneumonia. The results showed that the CNN model achieved satisfactory accuracy in identifying the disease, and the approach was proposed as a rapid and effective tool for the early detection of COVID-19 [10].

In this study, transfer learning with CNN was employed to detect pneumonia from X-ray images. This approach enables the model to leverage previously acquired knowledge for pneumonia detection and identify the disease with high accuracy. Transfer learning allows the model to achieve high accuracy more rapidly while reducing the amount of data required for training [11].

This study examines preprocessing methods for the classification of chest X-ray images. The authors investigated the effects of various preprocessing techniques on the accuracy of CNN models for detecting pulmonary diseases. The results demonstrated that appropriate preprocessing techniques can lead to significant improvements in the performance of deep learning models for medical image classification [12].

This study investigates the use of a Convolutional Neural Network (CNN) for classifying chest X-ray images. The authors sought to identify pulmonary diseases from medical images using CNN. The results demonstrated that CNN was capable of detecting various diseases with satisfactory accuracy and could be employed as a supportive tool for medical diagnosis [13].

3. METHODOLOGY

The proposed model for detecting pulmonary lesions from X-ray images is a simple yet efficient Convolutional Neural Network (CNN) designed to effectively extract and classify important features from medical images. The model consists of three convolutional layers (Conv2D), each equipped with the Rectified Linear Unit (ReLU) activation function. These layers extract different levels of features from the images, with the initial layers identifying relatively simple features such as edges and basic shapes, while the deeper layers detect more complex features. Each convolutional layer is followed by a MaxPooling2D layer, which reduces the spatial dimensions of the output and enables the model to focus on the most important features.

Following the convolutional layers, a Flatten layer converts all extracted features into a one-dimensional vector, enabling the model to use these features for final classification. Subsequently, a Dense layer containing 128 neurons with the ReLU activation function is added. This layer receives the compressed features as input and prepares the model to learn more complex patterns.

The output layer consists of a Dense layer with three neurons and a Softmax activation function, designed to classify the input images into three distinct classes. Based on the structure of the dataset, these three classes consist of healthy images, pulmonary lesions, and viral pneumonia, which were selected as the target diagnostic categories.

For model training, an ImageDataGenerator was employed to automatically load images from different folders, with each folder treated as a separate class. This approach enables automatic image normalization and facilitates the division of the images into training and validation subsets.

During the training process, the categorical_crossentropy loss function was employed as the cost function, as it is appropriate for multiclass classification problems. The model was optimized using the Adam optimization algorithm, which is considered an appropriate choice for complex classification tasks due to its adaptive characteristics across different datasets.

Furthermore, Early Stopping was employed to prevent overfitting. This technique allows the training process to be terminated when no further improvement in validation accuracy is observed, while the best-performing model weights are retained. The results demonstrated that the model achieved high accuracy in detecting pulmonary lesions and distinguishing among the other classes, indicating its potential as an effective tool for the identification and classification of medical images.

Table 1. Structure of the Deep Neural Network Used

Activation Function	Output Shape	Layer Type
ReLU	(128, 128, 32)	**Conv2D**
None	(64, 64, 32)	**MaxPooling2D**
ReLU	(64, 64, 64)	**Conv2D**
None	(32, 32, 64)	**MaxPooling2D**
ReLU	(32, 32, 128)	**Conv2D**
None	(128 * 128)	**Flatten**
ReLU	(128,)	**Dense**
Softmax	(3,)	**Dense**

4. RESULTS

4.1. Accuracy Curve

The accuracy curve is one of the important tools for evaluating the performance of deep learning and machine learning models. This curve illustrates how the model's accuracy on the training and validation datasets improves over successive training epochs. The horizontal axis represents the number of training epochs, while the vertical axis represents the model accuracy, which ranges from 0 to 1 or, equivalently, from 0% to 100%. During each training epoch, the model updates its internal parameters, such as weights and biases, based on the input data and attempts to identify and model the relevant features and latent patterns within the data.

At the beginning of training, the model's accuracy is generally low because it has not yet fully learned the features and patterns present in the data. As the number of epochs increases, the model gradually learns more complex patterns, resulting in improved accuracy. In the presented curve, the training accuracy increases rapidly and reaches approximately 95.38%. This increase indicates the model's gradual acquisition of important data features and its ability to identify increasingly complex patterns. Meanwhile, the validation accuracy also exhibits an increasing trend, reaching approximately 85.61%, although this value remains lower than the training accuracy.

The difference between training and validation accuracy may indicate the occurrence of overfitting. Overfitting occurs when a model excessively learns the specific details of the training data and, instead of learning generalizable patterns, focuses on unnecessary or dataset-specific characteristics. Consequently, the model may exhibit reduced performance when applied to previously unseen data.

Early Stopping can help mitigate this problem. Using this technique, the training process is terminated when the validation accuracy fails to improve over several consecutive epochs. This approach allows the model to be trained more effectively while reducing the risk of overfitting. In the presented curve, the validation accuracy reaches a relatively stable level after several epochs, indicating that the model has effectively learned to identify the patterns present in the data. Overall, the accuracy curve provides valuable insight into the model's performance throughout the training process and facilitates more detailed analysis and further optimization when necessary.

4.2. Loss Curve

The loss curve is another key tool for evaluating and analyzing the performance of deep learning models. It illustrates how the model's error changes on the training and validation datasets throughout the training epochs. In this curve, the horizontal axis represents the number of training epochs, while the vertical axis represents the loss value. The loss quantifies the discrepancy between the model's predictions and the actual class labels; therefore, a lower loss value generally indicates more accurate model predictions.

At the beginning of training, the loss value is relatively high because the model has not yet identified appropriate parameter values for learning the patterns present in the data. As training progresses, the model gradually updates its parameters, resulting in a reduction in the loss value. This decrease indicates that the model is progressively improving its ability to identify patterns in the data and consequently generating more accurate predictions.

In the presented curve, the training loss gradually decreases over time and reaches a low value toward the end of training, ultimately declining to approximately 0.1181. This reduction in loss indicates successful model learning and improved predictive performance.

Regarding the validation loss, it can be observed that the loss generally follows a downward trend throughout the training process and reaches a relatively low value; however, it increases slightly during some epochs. Such an increase in validation loss may indicate the onset of overfitting. Overfitting occurs when the model learns unnecessary details and noise specific to the training data rather than generalizable and useful patterns. As a result, the model may exhibit poorer performance on new and unseen data, such as the validation dataset.

The use of techniques such as Early Stopping can help reduce overfitting. This technique operates by terminating the training process when the validation loss fails to improve over several consecutive epochs and retaining the model weights corresponding to the best validation performance. In the presented curve, the decreasing loss values on both the training and validation datasets indicate that the model has successfully learned the underlying data patterns and achieved accurate predictions. Therefore, the loss curve provides an effective means of monitoring the model's error throughout the training process and determining whether additional optimization techniques are required to further improve performance.

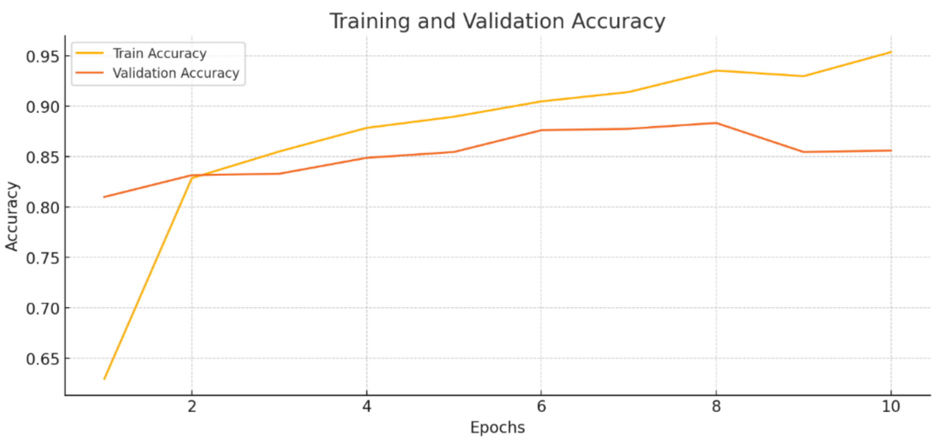

Fig. 1. Accuracy Curve

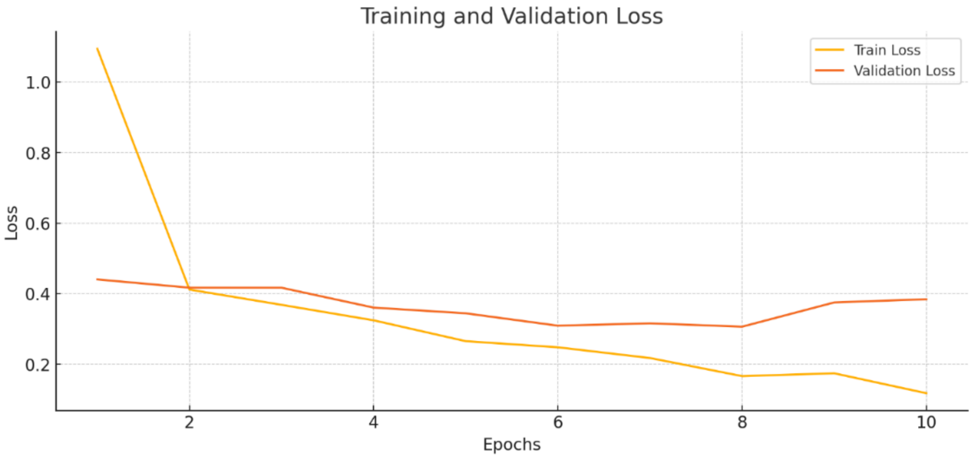

Fig. 2. Loss Curve

5. CONCLUSION

In conclusion, the Convolutional Neural Network (CNN) model developed in this study demonstrated satisfactory performance in detecting pulmonary lesions from X-ray images. By employing a multilayer architecture, the model was able to extract complex features from the images and, through the use of convolutional and pooling layers, acquire the capability to identify patterns associated with pulmonary lesions and distinguish them from healthy tissues.

The results obtained from model training and validation showed that the model achieved a training accuracy of more than 95%, indicating a strong ability to learn the patterns present in the training data. However, the validation accuracy was approximately 85%, which was lower than the training accuracy and suggests that the model experienced a certain degree of overfitting. This issue may be attributed to the limited amount of available data or the relatively high complexity of the model. To mitigate overfitting and improve the model's performance on unseen data, techniques such as Early Stopping were employed. This approach helped the model reach an optimal learning point and prevented excessive training that could lead to learning noise and unnecessary details.

The accuracy and loss curves throughout the training epochs demonstrated that the model progressively improved over time, with the training loss decreasing and accuracy increasing. In contrast, the validation loss exhibited a downward trend after the initial epochs and subsequently reached a relatively stable level. This trend indicates that the model was able to effectively identify the important and useful patterns within the data. At the same time, the model demonstrated sufficient flexibility to process unseen data, although further improvements remain possible.

To achieve higher accuracy and better performance on unseen data, techniques such as Data Augmentation can be employed, allowing the model to be trained on a greater variety of images. In addition, more sophisticated architectures or Capsule Neural Networks can be utilized, as their specialized structure enables them to better capture complex features and spatial relationships in medical images.

Overall, this study demonstrated that Convolutional Neural Networks can serve as a powerful and efficient tool for the automated detection of pulmonary lesions. With improvements in training strategies and the use of more diverse datasets, the proposed approach has the potential to achieve higher accuracy and serve as a complementary tool for physicians and healthcare professionals in the faster and more accurate identification of pulmonary lesions.

Declaration

We acknowledge that we used ChatGPT to enhance the academic writing of our manuscript while ensuring the originality and integrity of our work.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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