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PNEUMONIA DETECTION THROUGH CNN AND RESNET-50

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ARTICLE INFO	ABSTRACT
Article history: Received:2024-05-13 Received in revised form:2024-05-15 Accepted:2025-01-08 Available online *Keywords: Pneumonia, Convolutional Neural Network (CNN), ResNet-50, chest X-rays, deep learning.* *JEL codes:* *L86, O33, M15*	*Pneumonia is a prevalent illness that has a global impact, primarily affecting children and older individuals. Timely identification is essential for immediate intervention, particularly in regions with restricted healthcare availability. The purpose of this paper is to compare how well two methods work for finding pneumonia on chest X-rays creating a custom Convolutional Neural Network (CNN) and using a model that has been pre-trained, such as ResNet-50. The results indicated that although the customized CNN had difficulties achieving satisfactory performance, the ResNet-50 model demonstrated encouraging outcomes following the process of fine-tuning. This paper seeks to improve the detection of pneumonia, especially in disadvantaged places with limited medical resources, by utilizing modern technologies such as deep learning and pre-trained models. Considering the results gained to enhance patient outcomes and decrease mortality rates associated with pneumonia by enabling more precise and prompt detection, this has a beneficial effect on global public health*

ОБНАРУЖЕНИЕ ПНЕВМОНИИ С ПОМОЩЬЮ CNN И RESNET-50

РЕЗЮМЕ

Пневмония — широко распространенное заболевание, имеющее глобальные последствия и поражающее в первую очередь детей и пожилых людей. Своевременное выявление имеет важное значение для немедленного вмешательства, особенно в регионах с ограниченной доступностью медицинской помощи. Цель этой статьи — сравнить, насколько хорошо работают два метода обнаружения пневмонии на рентгенограммах грудной клетки, создавая специальную сверточную нейронную сеть (CNN) и используя предварительно обученную модель, такую как ResNet-50. Результаты показали, что, хотя у настроенной CNN возникли трудности с достижением удовлетворительной производительности, модель ResNet-50 продемонстрировала обнадеживающие результаты после процесса тонкой настройки. Эта статья направлена на улучшение выявления пневмонии, особенно в неблагополучных местах с ограниченными медицинскими ресурсами, за счет использования современных технологий, таких как глубокое обучение и предварительно обученные модели. Учитывая полученные результаты по улучшению результатов лечения пациентов и снижению уровня смертности, связанной с пневмонией, за счет обеспечения более точного и быстрого выявления, это оказывает благотворное влияние на глобальное общественное здравоохранение.

Ключевые слова: Пневмония, сверточная нейронная сеть (CNN), ResNet-50, рентгенография грудной клетки, глубокое обучение.

1 Introductions

The advent of artificial intelligence has resulted in the utilization of a novel artificial intelligence model capable of rapidly evaluating the gravity of pneumonia. The automated deep learning system, as outlined in the Journal of Medical Imaging, facilitates the assessment of disease development and the monitoring of therapy responses using computed tomography, with a high degree of accuracy. And as rapid as precise hand measures conducted by medical professionals.[1] Manually outlining 3D lung lesions on hundreds of CT lung slices, each up to 1 millimeter thick, is an exceedingly challenging task for doctors. However, artificial intelligence can greatly expedite this procedure and accurately determine the volumetric size of the defect by calculating the proportion of lungs involved. Segmentation is crucial in medical imaging for analyzing X-ray pictures, as it allows for the extraction of important information through the process of image segmentation. Doctors employ a range of non-surgical methods, such as X-rays, CT scans, ultrasound, and other imaging techniques, to visualize and analyze the inside organs and structures of the human body. Using deep learning techniques like CNN has shown to have a big impact on finding this illness by allowing for accurate convergence [2]. The main objective of our research is to evaluate the performance superiority of the custom CNN in comparison to established models like RESNET-50 and Efficient-Net. Additionally, the goal is to train and evaluate several CNNs and track their effectiveness in detecting pneumonia. We can utilize advanced image processing algorithms developed in recent decades, construct our own CNN model, and then evaluate the outcomes using the identical dataset. We utilize the dataset. We conducted extensive research on several websites and reached out to other institutes to acquire a dataset suitable for our research. After extensive research, we successfully located the dataset from the renowned website "Kaggle." The dataset comprises a total of 5683 pictures.

2 Related work

2.1. Convolutional Neural Network

Deep learning is an artificial intelligence technique that enables computers to interpret data using algorithms that mimic the functioning of the human brain. Deep learning models utilize advanced algorithms to identify intricate patterns in many forms of data, such as photos, text, audio, and more, to generate precise insights and predictions [3]. Deep learning

techniques can be employed to automate tasks that traditionally necessitate human intellect, such as providing descriptions for photographs or converting an audio recording into written language. Deep learning algorithms are artificial neural networks that are designed to mimic the structure and functioning of the human brain. As an illustration, the human brain comprises several interconnected neurons that collaborate to acquire knowledge and handle data. Similarly, deep learning neural networks, also known as artificial neural networks, comprise multiple layers of artificial neurons collaborating within a computer [4]. Artificial neurons, known as nodes, are software units that employ mathematical computations to analyze inputs. Artificial neural networks are sophisticated deep learning algorithms that employ nodes to address intricate challenges.

2.2. Lung segmentation with deep learning

Deep learning has proven effective in medical picture segmentation, specifically lung segmentation. Lung segmentation is essential in multiple medical applications, including illness diagnosis, therapy planning, and monitoring.[1] Convolutional neural networks (CNNs), specifically deep learning models, have demonstrated impressive outcomes in precisely segmenting lung areas from chest X-ray and MRI images. These models utilize the capacity of CNNs to autonomously acquire and extract pertinent characteristics from the input images, allowing them to accurately capture the intricate anatomical structures and variances in lung imaging. [5] People widely use the U-Net architecture for lung segmentation. It incorporates skip connections and deep supervision to combine low-level and high-level information, allowing for multi-scale prediction and enhanced segmentation accuracy.[6] Another strategy entails employing residual blocks, which mitigate the issue of "vanishing gradient" and facilitate enhanced information dissemination in deep networks.[7] The deep learning models have undergone training and evaluation using benchmark datasets, which has shown their capacity to accurately separate lung areas with robustness and dependability. In summary, the application of deep learning in lung segmentation has significant potential to enhance the analysis of medical images and improve the quality of patient care [8].

2.3. Application of deep learning techniques for the classification of pneumonia

Deep learning has become a potent method for classifying pneumonia, especially when analyzing chest X-ray pictures. Pneumonia is a prevalent respiratory illness caused by different types of pathogens, such as bacteria, viruses, and fungi. Convolutional neural networks (CNNs), a type of deep learning model, have demonstrated significant promise in properly detecting and categorizing pneumonia cases using these images [5].

An effective method for classifying pneumonia using deep learning is to build convolutional neural network (CNN) models on extensive collections of chest X-ray images. These models are trained to identify important characteristics in images and categorize them into distinct groups, including normal, bacterial pneumonia, viral pneumonia, or COVID-19 pneumonia. Using deep learning, these models can identify intricate patterns and

irregularities in X-ray pictures that may not be readily detectable by human experts. [9] Transfer learning is a frequently employed technique in deep learning-based pneumonia categorization. Transfer learning involves using pre-trained convolutional neural network (CNN) models, such as AlexNet or CheXNet, as a starting point. These models have undergone training using extensive picture datasets, allowing them to acquire broad knowledge that may be utilized for various purposes, including the classification of pneumonia. Researchers can achieve excellent accuracy and efficiency in pneumonia classification tasks by refining these pre-trained models using pneumonia-specific datasets [1]. Utilizing deep learning for pneumonia categorization offers numerous benefits. Firstly, technology can aid in automating the diagnosis process, thus lessening the workload on medical practitioners, and perhaps enhancing the promptness and precision of diagnosis [2]. Furthermore, deep learning models can rapidly analyze extensive quantities of data, enabling the effective examination of chest X-ray pictures and the detection of possible pneumonia cases. Furthermore, deep learning models possess the capacity to acquire knowledge from a wide range of datasets, allowing them to exhibit strong generalization abilities and efficiently handle novel and unfamiliar scenarios. Ultimately, deep learning methods, including convolutional neural networks (CNNs) and transfer learning, have demonstrated encouraging outcomes in the categorization of pneumonia based on chest X-ray pictures.[10] These models possess the capacity to precisely detect and categorize instances of pneumonia, including distinguishing between bacterial, viral, and COVID-19 pneumonia. Utilizing deep learning in the classification of pneumonia can boost diagnostic precision, optimize productivity, and aid healthcare practitioners in delivering prompt and efficient treatment [11].

3 Research Methodology

Deep convolutional neural networks have demonstrated superior accuracy in handling massive datasets, making them widely adopted by academics as the default choice. This was achieved through the utilization of transfer learning, a technique that involves using pre-trained models learned on extensive datasets such as Efficient Net. It is a linear guide that outlines the steps to follow to make a comparison, starting from the first point. The dataset contains photos that are formatted as RGBA, which stands for Red, Green, Blue, and Alpha. The dataset initially consisted of three directories (train, validation, and test). [1] We developed our script to process the entire dataset instead of directly using code from Kaggle. We saved the processed dataset in a variable. After completing this step successfully, we divided the data into separate training and testing sets. During the model training process, we further divided the training data into a training set and a validation set. The CNNs were trained using Keras and TensorFlow, which are open-source Python frameworks, to distinguish characteristics for classifying pneumonia from chest X-ray pictures [5].

3.1. Dataset description

An alternative database that is more dependable than GitHub is the highly renowned chest X-ray database on "Kaggle." This collection comprises 5856 photos depicting normal, bacterial, and viral pneumonia cases. However, this investigation solely utilized chest X-ray pictures depicting normal and viral pneumonia, as illustrated in Fig 1. The dataset was divided into training, testing, and validation sets, with each set having annotated photos of both normal and pneumonia cases. A total of 3875 pictures were utilized for testing pneumonia cases. There are 234 cases of normal pneumonia and 390 cases of pneumonia for training. For validation, there are 1341 cases of normal pneumonia and 3875 cases of pneumonia. Additionally, there are 8 cases of normal pneumonia and 8 cases of pneumonia.

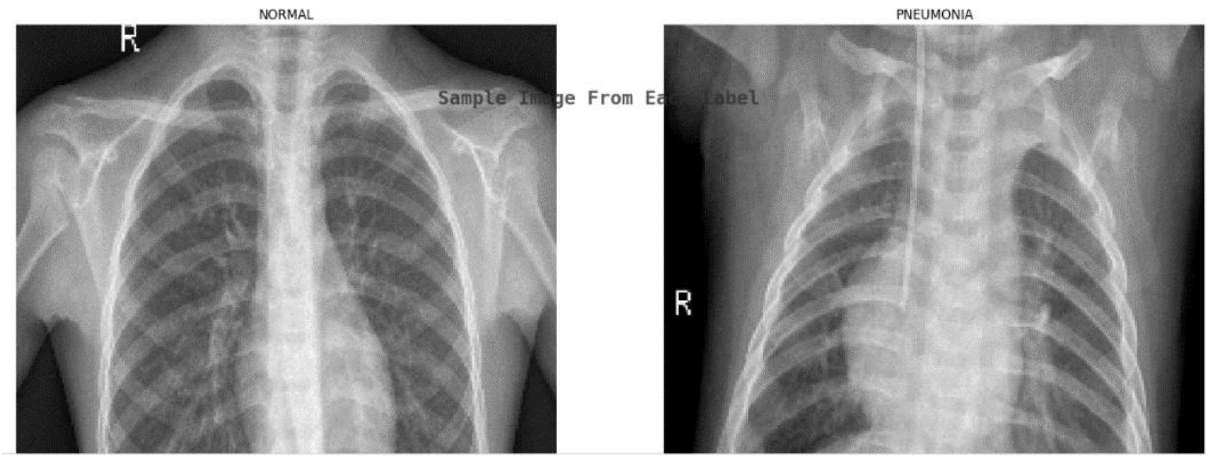

Fig. 1. Normal, and pneumonia

3.2. System requirements tools

Hardware for the studies included an 8th generation Core i7 laptop PC with 16GB of RAM, an NVIDIA GeForce 1060Ti GPU with 6GB of memory, and a 256GB SSD running the standard Windows operating system. When working on a deep learning project, the choice of operating system is generally not crucial, as we mostly rely on the Python environment. Miniconda and Anaconda are robust tools for managing the Python environment. Conda offers a versatile and user-friendly platform for the Python environment and essential libraries. Both Anaconda and Miniconda can be utilized, depending on the user's choices and requirements. Python is the primary programming language for our project. I specifically utilized version 3.10 for the development process. Methodology: We experimented with various approaches to determine the optimal answer. We encountered a significant amount of failure while striving for success, whether it was with our own customized CNN or the efficient network model. We will discuss several training experiments that have been conducted and present graphs illustrating the models' training progress.

3.3. ResNet-50

ResNet-50 is a popular convolutional neural network (CNN) structure comprising of 50 layers, which include 48 convolutional layers, one MaxPool layer, and one average pool

layer. The publication "Deep Residual Learning for Image Recognition" introduced it.[1], [12], [13] ResNet, also known as Residual Network, is an artificial neural network that employs residual blocks to construct deep networks. ResNet-50 utilizes skip connections, which are alternatively referred to as shortcut connections or identity mappings. These connections facilitate the network in circumventing specific layers, hence facilitating the smoother flow of the gradient during training. This aids in mitigating the issue of the vanishing gradient and enables the training of highly complex networks. ResNet-50 consists of residual blocks, which are fundamental units that comprise several convolutional layers. The residual blocks facilitate the network in acquiring residual mappings, which capture the disparity between the input and output of each block. This methodology enables the training of more complex networks with enhanced precision. ResNet-50 is commonly employed as a pretrained model, indicating that it has undergone training on a substantial dataset like ImageNet. It can be further adjusted or utilized as a feature extractor for diverse computer vision assignments. Pretrained models such as ResNet-50 offer a foundation for transfer learning, enabling researchers and practitioners to utilize the acquired features and customize them for specific tasks using smaller datasets. [12]ResNet-50 is a very influential and extensively utilized convolutional neural network (CNN) architecture that has made substantial contributions to the field of computer vision. The popularity of this method stems from its capacity to train deep networks and utilize skip connections, which are advantageous for various image-related applications.in Fig 2. Describe ResNet-50 A architecture.

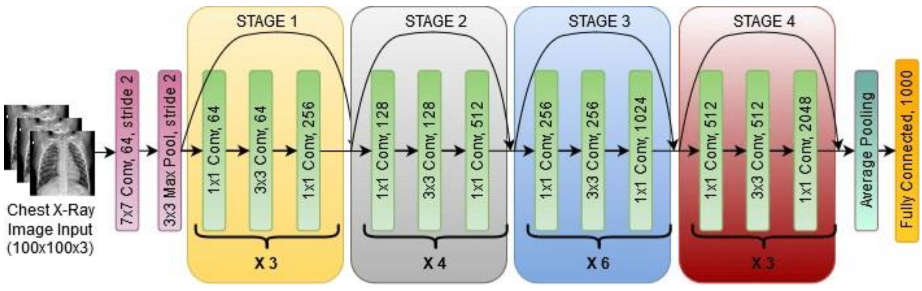

Fig.2. Describe ResNet-50 A architecture.

4 Experiential Results

Two distinct methodologies yielded the findings. We performed tests utilizing CNN and ResNet-50, pre-trained models, to differentiate between pneumonia images and normal chest X-ray images captured in high resolution from the anterior to posterior (AP/PA) direction. We chose ResNet-50 to address the constraints imposed by our limited resources. We used a conventional methodology to downsize the image into smaller dimensions, and then input them into the CNN for classification. The validation accuracy of our model surpassed that of other conventional approaches due to the efficacy of utilizing pre-trained models.

At the outset, while training the customized Convolutional Neural Network (CNN) model on the novel dataset, we encountered a difficulty: the validation score appeared unpromising. Despite conducting extensive experimentation with various dropout layers and

approaches, we were unable to achieve any significant improvements. As depicted in the training and validation loss graph above, the validation loss experienced a sudden increase, reaching a value of 0.70, while the validation accuracy remained at 50%. In Fig.3. training and validation loss in CNN and Fig.4.traning in validation accuracy in CNN.

Additionally, there was no notable enhancement in validation accuracy. We opted for an alternative strategy and implemented modifications to our code base. Instead of applying a freezer to the model's layers, we enabled them to be trainable during the training process. The modification had encouraging outcomes. By adjusting the dropout rate, specifically to achieve a training accuracy of 0.95% while maintaining a validation accuracy of 0.75%, we saw additional improvements in the model's performance.in Fig 5. Resnet50, and Fig.6. training and validation ResNet-50 accuracy.

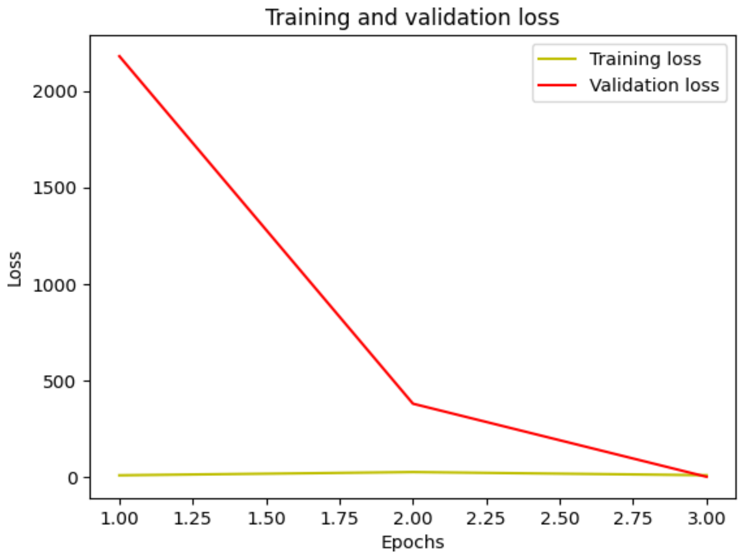

Fig.3. training and validation loss in CNN

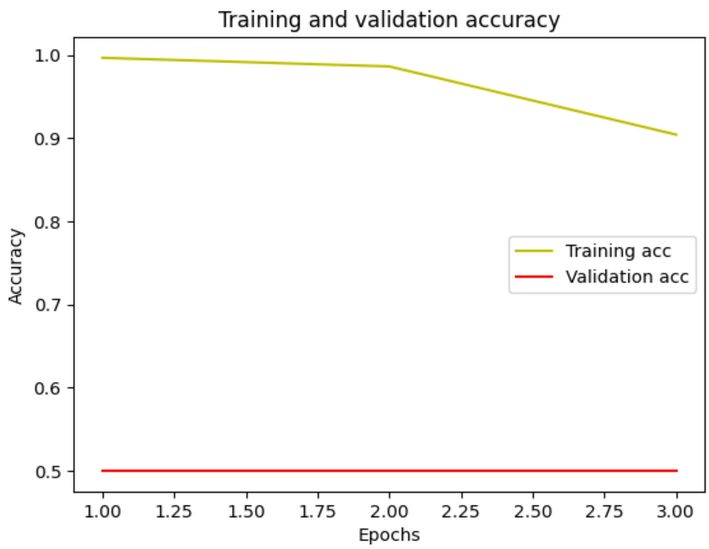

Fig.4. Traning in validation accuracy in CNN

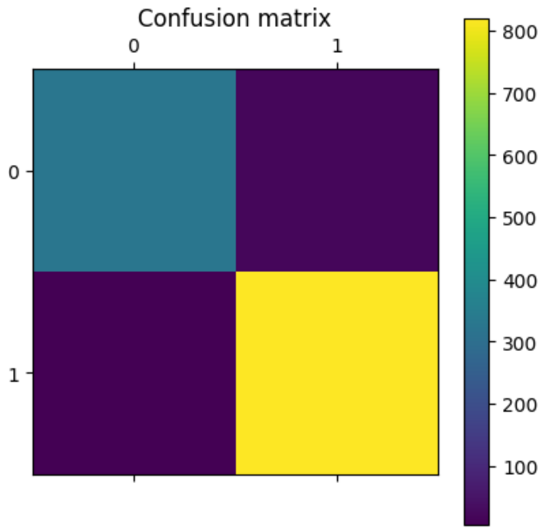

Fig 5. ResNet-50

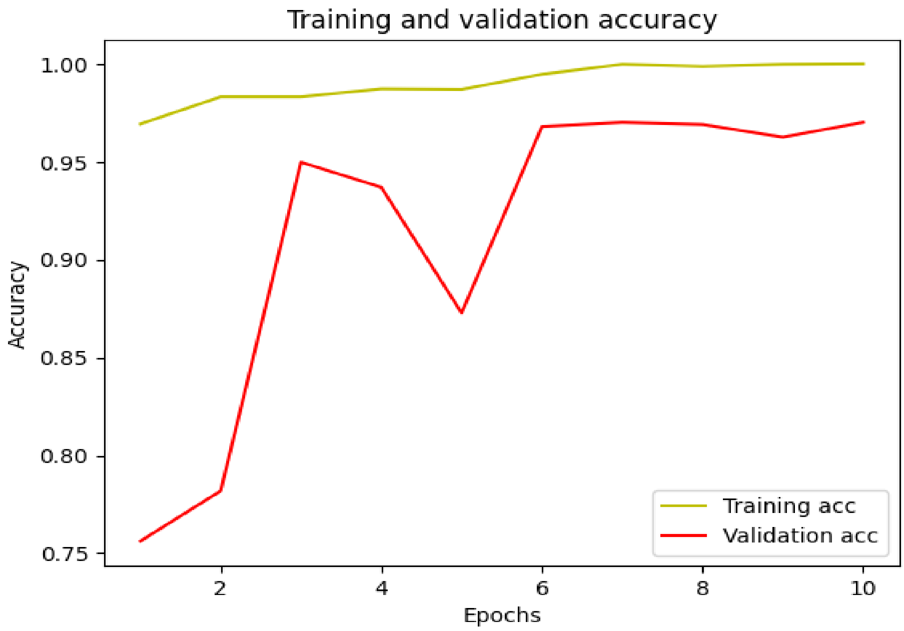

Fig.6. Training and validation ResNet-50 accuracy Experiment 1: Convolutional Neural Network (CNN):

The preliminary experiment demonstrated that the model encountered difficulties in comprehending the intricacy of the data, resulting in its ineffectiveness in acquiring any noticeable patterns. As a result, the model demonstrated inadequate performance on data that it had not before encountered or on data used for validation. Despite these disheartening outcomes, it prompts the inquiry of whether investing effort in building a CNN from the beginning is valuable. This experiment also yielded vital insights into the underlying process of Convolutional Neural Network (CNN) development. The statement emphasizes the significance of utilizing advanced models already designed for similar issue areas instead of starting from scratch.

Experiment 2: Utilizing the ResNet-50 model

We chose to omit the freezing step. In addition to this modification, we made some modifications to our code base. The model demonstrated substantial enhancements, namely following the adjustment of the dropout rate, resulting in the identification of an optimal-performing ResNet50 model. This experiment highlighted the importance of updating the weights of all layers, emphasizing that none should be kept unchanged. The dropout rate of 0.3, which is considered optimal, indicates that just a small number of layers need to be removed. This demonstrates the model's capacity to adapt to our specific use case and dataset with minimum modifications

5 Conclusion

Ultimately, the utilization of CNN and ResNet-50 in pneumonia identification has demonstrated encouraging outcomes in precisely discerning and categorizing instances of pneumonia from chest X-ray images. The improved ResNet-50 model had the best level of accuracy, reaching 95%, when compared to alternative techniques. Deep learning models, such as ResNet-50, can autonomously acquire and identify important characteristics from images. This allows them to accurately detect and analyze the intricate patterns and irregularities linked to pneumonia. These models have the capacity to enhance the precision and efficiency of diagnosing pneumonia, hence assisting in the early identification and prompt treatment of the condition. Utilizing deep learning techniques in pneumonia identification improves overall diagnostic accuracy and offers a quicker and more efficient method for diagnosing pneumonia cases, bringing fresh optimism for patients. Additional investigation and advancement in this field have the potential to enhance healthcare results and enhance patient care.

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