Models and Image Training Issues in the Application of Artificial Intelligence in Radiology

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Abstract. This article explores the application of artificial intelligence (AI) in the field of radiology, focusing on the methods, algorithms, and models that enhance medical imaging and diagnostic processes. It examines the role of machine learning, particularly convolutional neural networks (CNN), in improving image recognition, segmentation, and classification. The study highlights the potential of AI in early disease detection, workflow optimization, and reducing diagnostic errors. Challenges such as validation of AI tools and addressing biases in training datasets are also discussed. Practical implementations, including the use of transfer learning and hybrid CNN-RNN models, are presented with an emphasis on their impact on medical imaging quality and efficiency. Key findings demonstrate the transformative potential of AI in radiology while outlining future directions for research and development.

Keywords: Machine learning, Deep learning, Convolutional Neural Network (CNN), Transfer learning.

INTRODUCTION

One of the fastest growing areas these days is artificial intelligence and we can see it being applied to many practical issues. In particular, knowledge-based systems, various types of mental games, machine translators, intelligent robots, recognition of images and images, teaching and self-education are developing.

One of them is the issue of application to the medical field. One of the first problems to be solved here is the organization of the patient database, as we know that AI works with large databases. In particular, there are diseases that are detected very late, they manifest themselves in 10-15 years. Examples of these are various oncological diseases and pathologies that take a long time to diagnose. Here, the application processes of artificial intelligence in the field of radiology include the issues of learning large volumes of images, recognizing and diagnosing their small parts.

The non-interpretative applications of AI in radiology hold significant value. These encompass advanced workflow optimization tools, support for adhering to clinical protocols, efficient scheduling of scanners and patients, and the enhancement of structured radiological reporting through natural language processing (NLP) [1]. In the domain of imaging, AI demonstrates its transformative potential by improving and assessing the quality of both raw and processed images, shortening MRI scan times, and minimizing radiation exposure during CT scans [2].

AI innovations also bring practical benefits for radiology practitioners [3]. According to Jalal et al., AI can help reduce diagnostic errors, alleviate workloads, and provide radiologists with more time to prioritize patient care and communication [6]. Moreover, as Mello-Thoms and Mello argue, AI has the potential to complement case interpretation, minimizing intra- and inter-reader variability while addressing burnout caused by high demands and workload pressures [7].

In medical imaging, deep learning has been effectively applied to four key computer vision tasks: classification, object detection, semantic segmentation, and instance segmentation.

Image Classification involves predicting the class or label of an entire image. This task can be either binary (two classes) or multiclass (more than two classes). A common example is the binary classification of chest radiographs as either normal or diseased, providing an overall assessment of the image.

PROCESSES AND MODELS

Deep learning training and image recognition systems require several important steps.

Installation, training and testing:

First, deep learning needs to know exactly what to look for. It is necessary to transfer the parameters decided to work on it. It is very important to determine the dimensions of the bounding boxes and what elements are inside. For this, machine learning needs to provide some data: images, videos or photos.

Second, it is necessary to ensure that the model goes into the training phase, that the data is entered into the program so that it works correctly. This step is designed to learn how to identify specific objects of Convolutional Neural Network (CNN) and organize them accurately in corresponding classes.

Convolutional Neural Networks (CNNs) are a specialized class of artificial neural networks distinguished by their use of convolutional layers, which set them apart from traditional neural networks. A standard CNN architecture typically comprises three key layers: a convolutional layer, a pooling layer, and a fully connected layer.

At the heart of a CNN lies the convolutional layer, which performs the core operation of convolution. In mathematical terms, convolution combines two functions to produce a third. In the context of CNNs, this involves applying a kernel (or filter, represented as a small matrix) to input data, resulting in a feature map. This operation is fundamental to extracting various features from input images, such as edges, textures, or other patterns, and has been widely applied in image processing tasks like edge detection and sharpening.

Following the convolutional layer is the pooling layer, which performs a down-sampling operation to reduce the spatial dimensions of the feature maps. This step simplifies computation and reduces the risk of overfitting. Two common pooling methods are:

Max Pooling, which extracts the maximum value from the target area.

Average Pooling, which computes the average value within the target area.

One of the standout advantages of CNNs is their efficiency in parameter training. Unlike fully connected neural networks, where every neuron in one layer connects to all neurons in the next layer, CNNs restrict connections to a small local region through shared kernels. This design drastically reduces the number of trainable parameters. For example, in a fully connected network with input and output layers of size 224×224. In contrast, using a 3×3 kernel in a CNN results in only 9 trainable parameters, showcasing its computational efficiency.

CNNs have consistently outperformed other algorithms in image analysis tasks, particularly in pattern and image recognition. They have become the backbone of many winning models in competitions such as the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). Notably, AlexNet, a CNN-based model, won the ILSVRC in 2012, marking a pivotal moment in deep learning history. Diseases can be diagnosed using the above models and algorithms.

The original dataset, sourced from the Guangzhou Women and Children's Medical Center, comprised a total of 5,836 chest X-ray images. These images represented both healthy cases and pneumonia-infected cases, with 1,583 images of healthy chest X-rays and 4,273 images of pneumonia-infected chest X-rays.

To facilitate model development and evaluation, the dataset was split into training and test sets. The training set contained 5,136 images, while the test set included 700 images, ensuring a robust foundation for both model training and performance assessment. This distribution reflects the emphasis on maintaining sufficient data diversity in the training set while preserving a representative subset for validation in the test set.

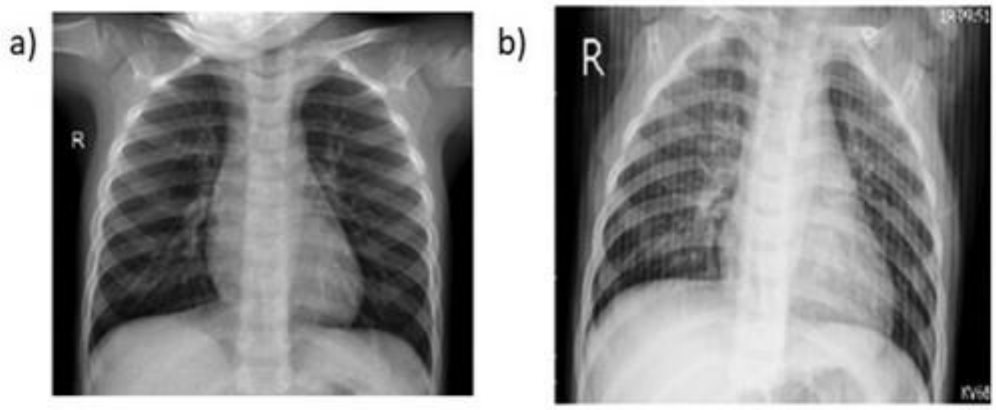


Figure 1. Chest X-ray of a healthy person (a) and a person with pneumonia (b).

The following clinics were selected for research: Fergana District Medical Association, Fergana Region Multidisciplinary Emergency Medical Department, Fargona Medical Diagnostic Center. We created images suitable for research using the following devices. SMART DRIVE digital X-ray system at Fargona District Medical Association (hospital), High-frequency mobile X-ray system in the multi-sector emergency medical department of Fergana region C-ARM SM 25 HF UZ (hospital), Fergana Region Medical Diagnostic Center High-frequency mobile X-ray system C-ARM SM 25 HF US (hospital).

The architecture of our modified model is as follows (refer to Fig. 2):

1. Four convolutional layers, each followed by corresponding MaxPooling layers to down-sample feature maps and retain the most significant information.
2. A Flatten layer, designed to transform the output of the final convolutional layer into a one-dimensional vector suitable for fully connected layers.
3. Three fully connected layers, which process the flattened features and map them to increasingly abstract representations.
4. The output layer, derived from the last fully connected layer, generates the final predictions .

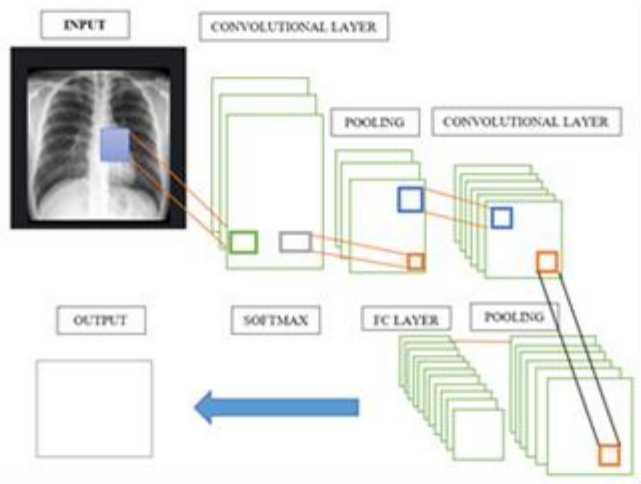
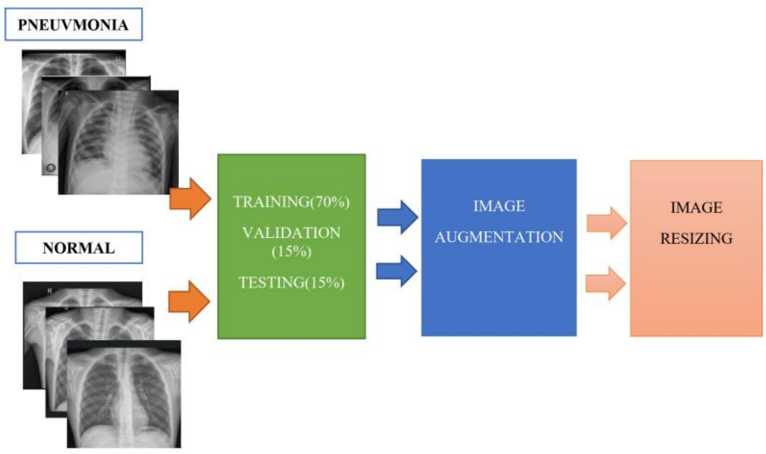


Figure 2. Architecture of the CNN.

This study introduces an optimal algorithm for pneumonia detection utilizing chest X-ray images. To overcome the challenge of a limited dataset, data augmentation techniques were employed, effectively increasing the dataset size and diversity to enhance model performance.

The block diagram illustrating the proposed methodology is presented in Figure 5, detailing the workflow and key components of the algorithm. This methodology demonstrates a robust combination of transfer learning, data augmentation, and architectural optimization for effective pneumonia detection.



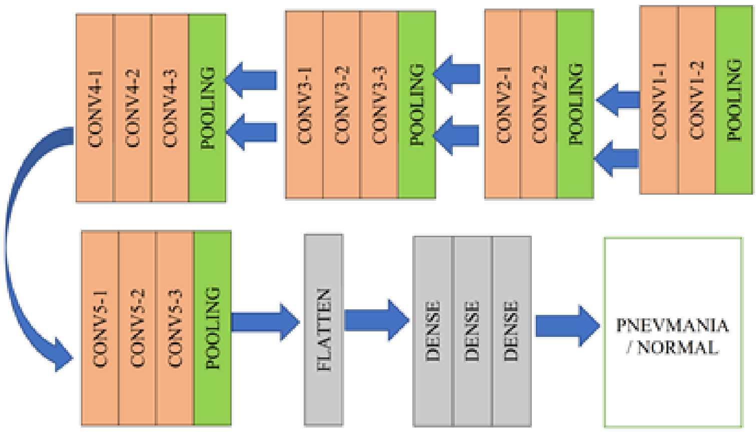


Figure 3. The block diagram of the proposed methodology

RESULTS

The final layer is the output layer, utilizing the sigmoid activation function, which maps the output to a probability range between 0 and 1. This enables the model to effectively classify the results into two distinct classes, aligning with the binary nature of the pneumonia detection task.

Our model is trained three times: 5, 7, 10 epochs. We obtained the following results for these epochs.When used in epoch 5, loss: 0.2681, accuracy: 0.9544, validation loss: 1.6885, validation accuracy: 0.8462. Overall, it can be seen that the accuracy is 72%.

When used in 7 epochs, loss: 0.2125, accuracy: 0.9618, validation loss: 0.6798, validation accuracy: 0.9119. Overall, it can be seen that the accuracy is 86%.

When used in 10 epochs, it was loss: 0.2057, accuracy: 0.9684, validation loss: 0.8387, validation accuracy: 0.9103, and the accuracy in this epoch was 92%.

EPOCHS	Loss	Accuracy	Validation loss	Validation accuracy
5	0.2681	0.9544	1.6885	0.8462
7	0.2125	0.9618	0.6798	0.9119
10	0.2057	0.9684	0.8387	0.9103

In this study, experiments were conducted to train a deep learning model for pneumonia detection using chest X-ray images. The training process was evaluated using two different hardware configurations to analyze the impact of computational power on training performance. The key metrics monitored during training included loss, accuracy, validation loss, and validation accuracy. Additionally, the training times for different epoch counts (5, 7, and 10) were recorded for both hardware setups.

The model demonstrated consistent improvement in accuracy with an increasing number of epochs. At 5 epochs, the model achieved a training accuracy of 95.44% and a validation accuracy of 84.62%. By increasing the epochs to 7, both metrics improved significantly, with a training accuracy of 96.18% and a validation accuracy of 91.19%. However, at 10 epochs, while the training accuracy further increased to 96.84%, the validation accuracy slightly decreased to 91.03%, potentially indicating the onset of overfitting. Similarly, the validation loss, which dropped significantly between 5 and 7 epochs, increased slightly at 10 epochs.

CONCLUSION

These methodologies are in-depth TensorFlow, PyTorch and Keras, which comprehensively support learning it is implemented in special environments using Python libraries such as and simulated. Artificial intelligence systems help to reduce the radiation dose, improve the image quality of medical scanners and diagnose patients at an early stage [8]. According to the obtained results, changing the size of the image has a direct impact on the quality of the image and leads to an increase in validation loss, besides, it was determined that the focus of the image depends on the type of X-ray technical equipment. In addition, it was found that the differences between the trained samples and the real X-ray images also affect the accuracy of the model. The experiments highlight the relationship between computational power and training efficiency. While both hardware configurations achieved similar model performance in terms of accuracy and loss metrics, the time required to train the model varied greatly. The i7-8750H with 64 GB RAM completed training up to 16 times faster than the i3-1215U with 4 GB RAM, demonstrating the critical role of hardware in deep learning workflows. These findings underline the importance of selecting appropriate hardware configurations for deep learning tasks, particularly when working with larger datasets or computationally intensive models.

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