TECHNICAL SCIENCES

APPLICATION OF DEEP LEARNING METHODS FOR AUTOMATED DIAGNOSIS OF PULMONARY PATHOLOGIES BASED ON CHEST X-RAY ANALYSIS

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DOI: https://doi.org/10.30525/978-9934-26-683-6-1

Modern healthcare requires high-tech solutions for the rapid analysis of large-scale visual data, a need further highlighted by the COVID-19 pandemic's demand for efficient lung lesion screening [1, p. 5]. Although chest radiography is a cost-effective and widespread diagnostic tool, its manual interpretation is often limited by the subjectivity of human perception and high radiologist workloads, leading to potential diagnostic errors [2, p. 102]. The use of artificial neural networks, particularly convolutional architectures (CNN), opens new possibilities for creating clinical decision support systems. The object of this study is the process of automated recognition of COVID-19 and other pathologies (notably tuberculosis) on digital X-ray images.

The VGG16 architecture was chosen to solve the task. This network is characterized by the use of sequential blocks of convolutional layers with small filters (3x3), which allows for the effective extraction of both low-level features (edges, textures) and complex semantic image structures [3, p. 2]. One of the main challenges in developing medical systems is the limited amount of annotated data. To overcome this barrier, a Transfer Learning strategy was applied. The essence of the method lies in using the weights of a model pre-trained on the ImageNet dataset, followed by fine-tuning on a specific set of X-ray images [1, p. 7].

Mathematically, the training process involves minimizing the Binary Cross-Entropy (BCE) loss function, which for binary classification is defined as:

$$Loss = -\frac{1}{N}\sum_{i=1}^{N} [y_i * log(p_i) + (1 - y_i) * log(1 - p_i)]$$

where N is the number of samples, y_i is the true class, and p_i is the predicted probability of belonging to the pathology class.

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The software system is implemented in Python 3 using the PyTorch library [4, p. 121]. The data preparation process included image normalization, resizing to 224x224 pixels, and augmentation (random rotations and flips) to increase the model's robustness to variations in images. The experimental part consisted of two stages. In the first stage, the model was trained to recognize COVID-19. In the second stage, a study was conducted on the architecture's ability to generalize using the example of tuberculosis diagnosis [5, p. 24]. This confirmed the hypothesis that the deep features extracted by VGG16 are universal for different types of inflammatory processes in the lungs.

The quality of the system's performance was evaluated on an independent test set. The obtained results demonstrate the high efficiency of the chosen approach. The main metrics were Accuracy, Recall, and F1-score. For the COVID-19 recognition task, the average model accuracy exceeded 92% [5, p. 30]. The Recall rate, which is critical for medicine (as it indicates the ability not to miss sick patients), reached a value of 0.94. The F1-score calculation was performed using the formula:

$$F1 = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Analysis of the Confusion Matrix showed that the model rarely makes mistakes in cases of clear pathologies, although it sometimes shows uncertainty in the presence of artifacts on images or low quality of the X-ray machine's exposure [1, p. 8].

This research successfully developed and tested a VGG16-based method for automated pulmonary pathology detection, demonstrating that Transfer Learning enables high accuracy even with limited medical datasets [5, p. 40]. The practical value of this approach lies in its potential integration into medical information systems as a "second opinion" tool, significantly accelerating real-time image processing in resource-constrained settings. Future work will focus on transitioning to multi-class classification for the differential diagnosis of COVID-19, tuberculosis, and pneumonia, while incorporating Explainable AI (XAI) mechanisms to visualize decision-making regions and enhance clinical trust in automated diagnostics.

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