UDC 004.932.2

F. Smilianets, O. Finogenov

MULTI-CLASS CLASSIFICATION OF PULMONARY DISEASES USING COMPUTER TOMOGRAPHY IMAGES

Abstract: This paper examines approaches to classifying pulmonary diseases using neural networks. A modification of an existing neural network architecture for multi-class classification based on CT scans is proposed. The proposed architecture distinguishes between coronavirus pneumonia, non-hospital pneumonia, and healthy lungs. The training procedure of the proposed neural network, final parameters, and classification results are described. Conclusions are drawn regarding the potential applications of the proposed modification.

Keywords: multiclass classification, convolutional neural networks, computed tomography scan analysis

Introduction

The spread of the COVID-19 novel coronavirus pandemic in the years since 2020 has led to a significant increase in the workload for healthcare professionals and medical institutions. As of early May 2023, over 750 million cases of the disease had been registered, with nearly 7 million resulting in fatalities [1].

Despite the World Health Organization's declaration of the end of the global COVID-19 pandemic on May 5, 2023, respiratory illnesses still have the potential to cause epidemics and pandemics in the future, with corresponding consequences for healthcare systems. Therefore, further research into systems that can partially alleviate and optimize the workload of healthcare facilities remains relevant.

CT imaging is one of the primary diagnostic methods for lung diseases, as they provide three-dimensional and detailed imaging. The scanning process can be tailored for diagnosing specific illnesses, and it also allows for the convenient generation of arbitrary cross-sectional views within the scanned space.

Overview

The use of computer vision technologies, particularly deep learning and neural networks, is a common method for automating tasks across various domains.

Deep learning is a fundamental technique in computer vision that finds application in medical imaging analysis, including the interpretation of computed tomography (CT) scans. Among the investigated methods for analyzing CT images, convolutional neural networks (CNNs) play a pivotal role. Notably, architectures like DenseNet, ResNet, VGG, and

Xception are extensively studied [2]. Using these architectures, identification accuracy of up to 97% for COVID-19 on CT scans has been achieved. This study focuses on a modified neural network based on the ResNet architecture, as proposed in study [3]. It has been adapted for multi-class classification, departing from its original binary classification purpose.

Dataset

In this study, two datasets were merged: COVID-CTset (Dataset A) [4] and COVID-CT-MD (Dataset B) [5].

Dataset A was gathered at the Neghin Medical Center in Sarī, Iran, using a SOMATOM scanner and syngo CT VC30-easyIQ software. The images are provided in TIFF format, grayscale, with a 16-bit color depth.

It comprises images from 95 patients diagnosed with COVID-19 and 282 healthy individuals. However, Dataset A lacks images of individuals with non-hospital-acquired pneumonia. Therefore, Dataset B was incorporated to create training data for the neural network.

Dataset B was collected at the Babak Medical Center in Tehran, Iran, using a SOMATOM scanner. The images are provided in DICOM format, with a 16-bit color depth. It encompasses images from 169 individuals diagnosed with COVID-19, 76 healthy individuals, and 60 individuals diagnosed with community acquired pneumonia.

Consequently, images from Dataset B were converted to 16-bit TIFF format using a modified version of the dcm2hdr library [6] and added to the data from Dataset A.

The utilization of 16-bit grayscale TIFF images combines the advantages of both DICOM and standard image formats. Unlike standard 8-bit grayscale, 16-bit images retain the complete colour depth of DICOM, preserving the full data integrity of the original CT scan. This approach maintains the convenience of processing associated with common graphic formats while encompassing the benefits of DICOM and standard image formats.

As not every cross-section of CT scans encompass the internal lung structure, following the algorithm proposed in [3], image filtration was performed to isolate images where lungs predominantly occupy a significant portion of the content. The algorithm [3] conducts image filtration by examining the content of the central region of each image. If the central region is mostly dark, the image contains lung features; otherwise, it represents a body region preceding or following the lungs. Fig. 1 illustrates the distinction between images from different sections of the three-dimensional CT scan.

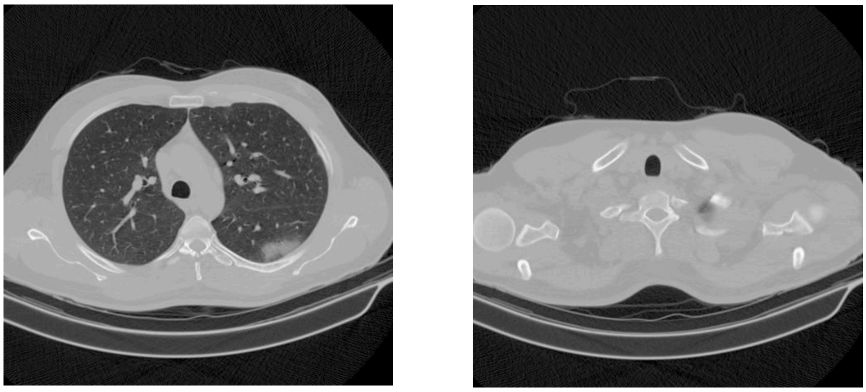

Fig. 1. Comparison of CT chest scan images at different cross-sectional levels of the scanned space

Neural Network architecture

The study employs a modified version of the network proposed in [3]. However, the original research only involved differentiating between two classes - "healthy" or "COVID-19," significantly limiting its practical application. Therefore, in this study, the existing neural network architecture was extended to perform multi-class classification and trained using a significantly larger dataset. The augmented neural network was designed to distinguish between COVID-19, community-acquired pneumonia, and healthy lungs.The standard ResNet50V2 architecture served as the basis. However, since the manifestations of both typical and COVID-19-induced pneumonia exhibit different characteristics at different scales, the Feature Pyramid Network method was applied. This method, proposed in [7], aims to enhance the network's capability to learn and recognize objects by addressing scale variations within the images.

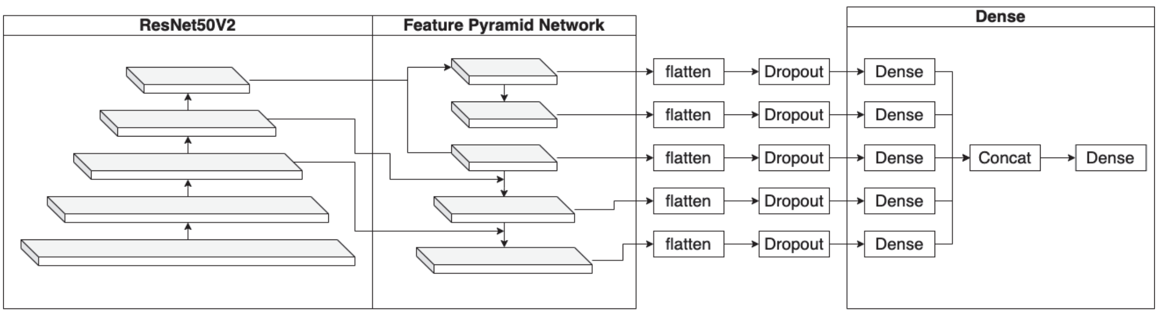

Fig. 2. Modified Neural Network Architecture

The achieved result is achieved by introducing a feature hierarchy. In this case, starting from the third layer of the ResNet network, the results of each convolutional layer's operation are forwarded to additional convolutional layers that process information from the main layers in reverse order. As a result, the final dense decision-making layers have broader

ISSN 1560-8956

access to information from the primary convolutional network. This enables the recognition of objects of various scales and levels of abstraction.

Training and validation.

The neural network was trained using the initial weights for a corresponding neural network trained on the ImageNet dataset. The data, consisting of selected images containing open lungs, was divided into three groups: 20,701 training images, 6,900 validation images, and 6,900 evaluation images. Training was conducted over 20 epochs. The network was saved and rated using the validation dataset each epoch.

Using the ratings acquired with the validation dataset, the model at the end of the 13th epoch of training with a validation accuracy of 94.96% was selected. Using the evaluation dataset, the true model behavior parameters were computed, confirming an accuracy of 95.086%. These parameters for all investigated classes are presented in Tabl. 1–3 and Fig. 3.

Table 1. **Confusion matrix for the class "COVID-19 pneumonia"**

COVID-19	**Predicted class**		
Actual class		Positive	Negative
	Positive	2707	83
	Negative	231	3879

Table 2. **Confusion matrix for the class «community acquired pneumonia»**

Community Acquired Pneumonia	**Predicted class**		
Actual class		Positive	Negative
	Positive	736	52
	Negative	15	6097

Table 3. **Confusion matrix for the class «Healthy lungs»**

Community Acquired Pneumonia	**Predicted class**		
Actual class		Positive	Negative
	Positive	3118	204
	Negative	93	3485

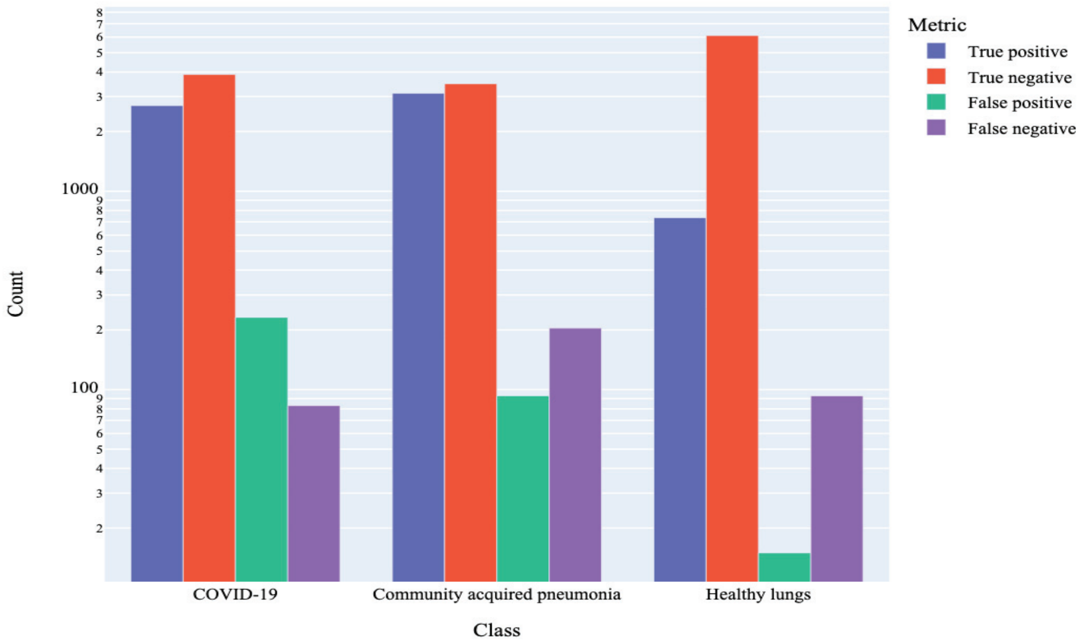

Fig. 3. Number of images falsely or correctly identified as positive or negative (logarithmic scale)

To assess the results of the neural network's performance, a series of metrics were determined, calculated as follows (1-4):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}, \quad (1)$$

$$Sensitivity = \frac{TP}{TP+FN}, \quad (2)$$

$$Specificity = \frac{TN}{TN+FP}, \quad (3)$$

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

where TP – true positive, FP – false positive, TN – true negative, FN – false positive.

The metric values for the proposed neural network based on the confusion matrices' results (Tables 1-3) are presented in Tab. 4.

Table 4. **Metrics of the trained neural network's performance for each class**

Class/Metric	Accuracy	Sensitivity	Specificity	Precision
COVID-19	95.44%	97.025%	94.37%	92.13%
Community Acquired Pneumonia	99.02%	93.40%	99.75%	98.00%
Healthy lungs	95.69%	93.85%	94.40%	97.10%

The obtained values demonstrate high-quality characteristics for the practical implementation of the proposed modification in multi-class classification.

ISSN 1560-8956

Conclusions

The existing neural network for binary classification of COVID-19 based on CT scans has been modified to perform multi-class classification among three classes - COVID-19, non-hospital pneumonia, and healthy lungs. The trained neural network demonstrates high classification accuracy, approaching benchmark results in the industry. It can serve as a valuable tool for rapid and efficient COVID-19 diagnosis and as a foundation for neural networks capable of recognizing other diseases.

REFERENCES

1. WHO Coronavirus (COVID-19) Dashboard [Web resource]. – Resource access mode: https://covid19.who.int/.

2. Огляд методів ідентифікації захворювань на основі знімків комп’ютерної томографії / Смілянець Ф.А., Фіногенов О.Д. // XII Міжнародна науково-практична конференція «Комплексне забезпечення якості технологічних процесів та систем» – Т. 2 – С. 220-221

3. A fully automated deep learning-based network for detecting COVID-19 from a new and large lung CT scan dataset. / Rahimzadeh, M., Attar, A., & Sakhaei, S. // Biomedical Signal Processing and Control. – 2021. – P. 102588. – URL: https://doi.org/10.1016/j.bspc.2021.102588.

4. COVID-CTset: A Large COVID-19 CT Scans dataset [Web resource]. – Resource access mode: https://github.com/mr7495/COVID-CTset.

5. COVID-CT-MD, COVID-19 computed tomography scan dataset applicable in machine learning and deep learning. / Afshar P., Heidarian S., Enshaei N., Naderkhani F., Rafiee M., Oikonomou A., Fard F., Samimi K., Plataniotis K., & Mohammadi A. // Scientific Data – 2021. – T. 8(1). – P. 121. – URL: https://doi.org/10.1038/s41597-021-00900-3.

6. DCM2HDR: DICOM to HDR image conversion. [Web resource]. – Resource access mode: https://doi.org/10.5281/zenodo.1246724.

7. Feature pyramid networks for object detection / T.-Y. Lin, P. Dollár, R. Girshick, K. He, B. Hariharan, S. Belongie. // Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (2017). – 2017. – P. 2117-2125.