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MANUEL GRAÑA ROMAY

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THE FEATURES OF USING NEURAL NETWORKS FOR CLASSIFICATION OF RESPIRATORY DISEASES ON X-RAY IMAGES

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KEYWORDS
Artificial intelligence, neural networks, x-ray images, classification problem, hyperparameters, model training, medical diagnostics.

ABSTRACT

In modern medicine, automated processing and analysis of medical images is a very relevant task, as it allows to increase the accuracy of diagnostics, reduce data processing time and reduce the burden on medical personnel. This paper investigates the use of neural networks to automate the process of classifying respiratory diseases based on X-ray images. The main focus is on the development and optimization of the architecture of convolutional neural networks (CNN), which allow detecting signs of diseases with high accuracy. It is expected that the proposed system will help medical professionals in quickly and accurately detecting diseases, which will contribute to reducing mortality. In addition, the paper investigates the impact of changing the values of hyperparameters on the quality of using the MobileNetV2 neural network, pre-trained on a large ImageNet dataset, to solve the problem of multi-class classification of medical images. The use of a pre-trained model allows for the effective use of the obtained universal features and significantly accelerates the learning process on specific medical data.

INTRODUCTION

Respiratory diseases, including pneumonia, atelectasis, and pneumothorax, remain among the most common causes of death worldwide (Alghamdi et al. 2024; Chumachenko et al. 2024, Kim et al. 2024; Malviya et al. 2025; Sidenko et al. 2025). Early diagnosis of these diseases is crucial for successful treatment and prevention of complications. However, the analysis of lung X-rays is a complex task that requires highly skilled medical professionals. Traditional diagnostics based on X-ray images are effective, but require significant experience of the doctor and can be subjective. That is why research into the use of neural networks for automatic classification of pathologies in chest images is of particular importance. Such approaches can increase the accuracy of disease detection, reduce the human factor and provide rapid support for medical decisions. The proposed system is primarily designed as a decision-support tool for general practitioners and radiologists. It can also serve as an educational resource for medical students to improve their diagnostic skills in analyzing X-ray images. (Bhimavarapu 2025; Kondratenko et al. 2018; Kondratenko et al. 2024; Lal 2023; Patil and Narawade 2024).

RELATED WORKS AND PROBLEM STATEMENT

Neural networks, in particular CNNs, have been widely used in the analysis of medical images, such as X-rays, CT scans, MRIs, and histological specimens (Kondratenko et al. 2021; Sheremet et al. 2021; Sidenko et al. 2020; Sokoliuk et al. 2020; Sova et al. 2020; Zhou et al. 2025).
In the article (Keidar et al. 2021) researchers presented a deep learning model for automatic detection of COVID-19 in chest X-rays. However, the authors emphasize limitations: training was conducted on data from a single region, which may affect the universality of the results. In addition, the model has little explanatory power, which limits its implementation in medical practice.
The article (Lakhani 2017) explores the application of deep convolutional neural networks (DCNN) for automatic classification of X-ray images, in particular for detecting the presence and correct position of an endotracheal tube (ET) in chest radiographs.
In the article (Moujahid et al. 2020) the authors investigate the effectiveness of convolutional neural networks with transfer learning for automatic classification of chest X-ray images. The main goal is to automatically recognize pneumonia and other pathologies from CXR images using deep learning models.

The article (Alshmrani et al. 2023) presents a deep learning architecture for multi-class classification of lung diseases, including pneumonia, lung cancer, tuberculosis, lung obscurations, and COVID-19.
From the analysis of publications it is clear that modern methods of automatic diagnosis, in particular based on CNNs, show high efficiency, however, the accuracy of models also depends on the choice of hyperparameters, such as batch size, learning rate and activation functions. Studying the impact of these parameters on network performance allows optimizing the model and increasing the accuracy of pathology classification. In addition, multi-label classification of diseases, which is an important task, is poorly studied.
The aim of the work is to investigate the features of the use of neural networks for the classification of respiratory diseases with studying the influence of various hyperparameters and indicators.

NEURAL NETWORKS FOR MEDICAL IMAGE CLASSIFICATION

The key to solving the problem of medical image classification is the selection of a high-quality, balanced and reliable dataset. A well-known and frequently used dataset in medical imaging research is the NIH ChestX-ray14, developed by the US National Institutes of Health (Chehade et al. 2024; Chen et al. 2022; Kansal et al. 2025).
This dataset contains over 112,000 chest X-rays from over 30,000 patients. For each image, it is indicated whether one or more of 14 pathologies are present, including pneumonia, pleural effusion, cardiomegaly, pulmonary infiltrates, fibrosis, pneumothorax, tumors, etc. Each image is also accompanied by metadata, including the patient's age, gender and body position when taking the image (e.g., PA or AP projection). Among the most productive and widely used in the field of medical imaging, the ResNet, DenseNet, and EfficientNet architectures should be highlighted. Each of them is characterized by unique properties that allow achieving better results due to deeper structure, efficient use of parameters, or optimization of computational resources.
The ResNet architecture was proposed to address the complexity of training extremely deep neural networks (Chen et al. 2025; Kang et al. 2024; Karaddi and Sharma 2025; Lakshmi and Sivagami 2025). One of the key challenges when increasing the network depth is the problem of gradient "explosion" or "fading", which negatively affects the training efficiency. This problem was overcome by using residual connections, which create a direct path for gradients during backpropagation (Figure 1).

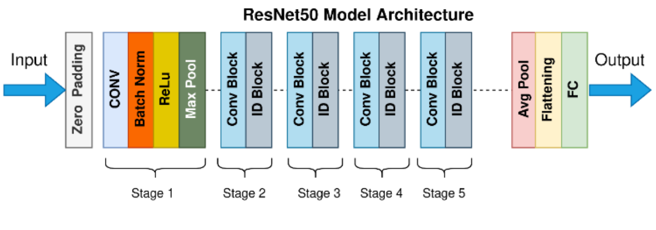

Figure 1: ResNet50 Architecture (Lakshmi and Sivagami 2025)

DenseNet architecture (Biradar and Virupakshappa 2025; Mary and Kavitha 2024; Shirani and Rastin 2025) is the dense coupling of layers: each layer uses as input not only the output of the previous layer, but also the outputs of all previous layers. This method promotes feature reuse, which significantly improves the efficiency of the network, both in terms of accuracy and parameter economy.
EfficientNet is a modern architecture for deep neural networks, designed to achieve the highest accuracy with minimal computational cost (Abdel-Wahab et al. 2025; Pessoa et al. 2025; Shastry et al. 2025; Sushma et al. 2025).
The key concept is the balanced scaling of the three main parameters of the neural network: depth, width, and dimensionality of the input image. Previously, models were usually scaled by only one of these parameters, which led to inefficient use of resources.

DEVELOPMENT OF A SYSTEM FOR RESPIRATORY DISEASES CLASSIFICATION

To solve the problems of medical image classification, Python was chosen, which provides all the necessary tools: from data processing to the development and training of neural networks (Wang et al. 2024).
In the selected dataset, a significant imbalance of classes is clearly visible, with some diseases represented in thousands of images, while others occur much less frequently.
To reduce the negative impact of imbalance during model training, binary crossentropy is used as the loss function. This is a standard approach in multi-class multi-label classification problems, especially when classes can coexist in the same sample. This approach allows the model to separately estimate the probability of each disease and does not force it to focus only on the more common classes. Binary crossentropy helps to reduce the impact of imbalance by giving each class the same importance when updating the model weights (Tekumudi and Ramanathan 2025). The dataset is split into training and testing samples in a ratio of 80:20 for further training and evaluation of the model. Prior to training, all images were resized to 224×224 and normalized. The dataset exhibits class imbalance, which was addressed using binary crossentropy loss suitable for multi-label classification. Hyperparameters (learning rate, batch size, optimizer, dropout) were selected based on common practices and further varied experimentally to evaluate their impact.
For the classification of respiratory diseases, several models were created based on the selected architectures ResNet50, DenseNet121 and EfficientNetB4 (Kondratenko et al. 2021; Kondratenko et al. 2024; Lakshmi and Sivagami 2025; Pessoa et al. 2025; Shirani and Rastin 2025).
The following parameter values were selected for model tuning: input image size is 224 × 224; loss function is binary_crossentropy; optimizer is Adam with the parameter learning_rate=1e-4; batch size is 16; number of learning epochs is 20; number of steps per epoch is 200; number of validation steps is 50. During model training, metrics such as Binary Accuracy and Area Under the ROC Curve (AUC) were used.
First, a base ResNet50 model is loaded with weights pre-trained on the ImageNet dataset. The parameter

include_top=False specifies that the top (last) fully connected layer of the model will not be added, which allows the model to be adapted to a given task. The size of the input images is set to (224, 224, 3), which corresponds to the usual ResNet50 settings. After training is complete, information about the accuracy on the training and validation datasets is displayed, as well as graphs of changes in accuracy and loss over epochs, which allows you to assess the quality of training and identify possible overtraining. The graph in Figure 2 shows that the AUC for the training and validation sets gradually increases over the epochs, stabilizing near 0.78. This indicates successful training without overtraining: the validation curve does not show a significant drop, but remains at or above the training curve.

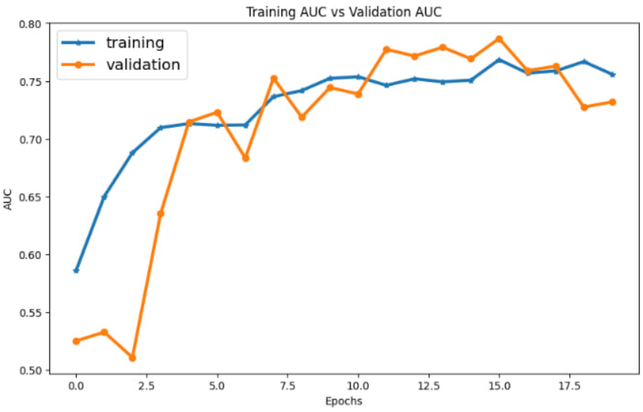

Figure 2: Graph of AUC versus Training Epoch of the ResNet50 Model

The ROC curves for each class show a fairly high quality of the model. The AUC (area under the curve) varies from 0.67 to 0.88, indicating a good ability of the model to distinguish the presence and absence of each pathology. The highest AUC values are observed for diseases such as Cardiomegaly, Edema, Effusion, Pneumothorax and Emphysema, indicating the confidence of the model in classifying these conditions.
The model demonstrates good generalization ability on new data. Most pathologies are classified with high accuracy, and the learning process was stable and efficient. The network is potentially suitable for application in a clinical environment as an image pre-sorting tool.
The creation and configuration for the DenseNet121 model follows the example of ResNet50. The ROC curves show the classification quality for each class (pathology) separately. Most classes have AUC values above 0.75, with some particularly high results – for example, Cardiomegaly, Edema, Effusion and Pneumothorax achieve AUC ≈ 0.85–0.86. This indicates a high ability of the model to correctly classify positive and negative cases for these labels. The less accurate classes – Infiltration and Pneumonia (AUC ≈ 0.70) – probably suffer from less data or unclear visual features. Overall, the model shows good results for multi-class multi-valued classification of medical images, with a good balance between training and validation scores.
The EfficientNetB4 model is also created following the example of the ResNet50 and DenseNet121 models. The ROC curves for individual classes demonstrate the complete inability of the model to classify any of the pathologies - the AUC values for all classes range between 0.49 and 0.51, which is practically no different from a random guess. It is especially alarming that even for such typical pathologies as cardiomegaly or pneumothorax, the model shows AUC=0.5, which makes it completely unsuitable for clinical use.
To illustrate the application and verify the accuracy of model predictions on test data, an image of an X-ray with the expected diagnosis of "Cardiomegaly" will be provided.
Figure 3 demonstrates the operation of the developed system, in particular for predicting the diagnosis of "Cardiomegaly" by the ResNet50 model on a test image.

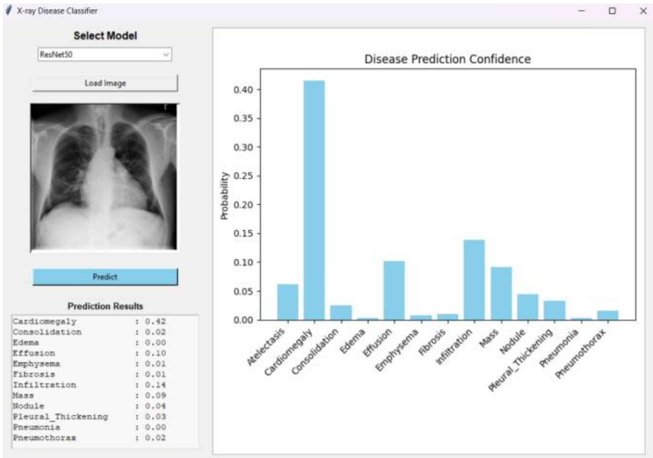

Figure 3: Prediction of the Diagnosis "Cardiomegaly" by the ResNet50 Model

The highest probability for "Cardiomegaly" was shown by the DenseNet121 model – 0.63, indicating a high level of confidence in the presence of this condition. This is the best result among all models and may indicate a correct diagnosis. The ResNet50 model also showed a good probability for "Cardiomegaly" – 0.42 (Figure 3), which is lower than that of DenseNet121, but still the second highest indicator in its results table. That is, the model detected signs of pathology, but with less confidence. The EfficientNetB4 model showed the lowest probability for "Cardiomegaly" – only 0.03, which is significantly different from the results of the other models. The highest indicator in this model is "Infiltration" (0.24), while most of the other values are also very low. Since the dataset also includes multi-label classification, it would be appropriate to also test the accuracy of the models' predictions in cases where multiple diseases are diagnosed at once. Therefore, in the following example, the models will be given an X-ray image as input with the expected diagnosis of "Emphysema" and "Pneumothorax". In this example, the ResNet50 model showed a less confident result than last time, but still identified 2 main diagnoses that coincide with the expected ones. Here, the model provided indicators of 0.26 for the label "Emphysema" and 0.21 for "Pneumothorax". These are not very high indicators, but they still dominate among the others. The DenseNet121 model again showed the best result compared to other models. In this example, the model quite accurately identified the expected labels "Emphysema" and "Pneumothorax" with probabilities of 0.50 and 0.52, respectively. The model also excluded other labels, which is a good indicator for a model in a multi-label classification problem. Just like in the previous example, the EfficientNetB4 model shows the worst result and does not highlight the expected labels at all. Instead, the highest indicator is again “Infiltration” (0.28), which is false for this case. To compare the training quality of deep learning models in the multi-label classification of respiratory diseases task, several main metrics were used: AUC, Accuracy, and Loss. Each of them allows us to evaluate the model from different aspects and identify its strengths and weaknesses when working with medical images (Table 1).

Table 1: Test Results

Model / Metrics	AUC	Accuracy	Loss
ResNet50	0.7867	0.9434	0.1758
DenseNet121	0.8059	0.9491	0.1557
EfficientNetB4	0.6007	0.9470	0.1974

Analyzing Table 1, we can conclude that the best overall performance was shown by the DenseNet121 model, which achieved the highest AUC value (0.8059) and the lowest loss value (Loss = 0.1557). The ResNet50 model is slightly inferior, with a lower AUC (0.7867) and a higher Loss (0.1758), but also demonstrates high accuracy. On the other hand, EfficientNetB4 showed a significantly worse result in AUC (0.6007), which indicates a weak ability of the model to distinguish classes, despite a high Binary Accuracy (0.9470). This may indicate that the model mostly correctly predicts the absence of diseases, but does not cope with their detection. The superior performance of DenseNet121 can be explained by its dense connectivity, which improves feature reuse and gradient flow. In contrast, EfficientNetB4 showed poor performance, likely due to suboptimal adaptation to the dataset and sensitivity to hyperparameter settings.

For additional research into the hyperparameters of the neural network model, a new pre-trained network MobileNetV2 (Arya and Mishra 2024) was chosen, which, due to its lightweight and optimized architecture, is well suited for classification tasks with limited computational resources. The model, pre-trained on the large ImageNet dataset, already has the ability to extract universal image features, which significantly speeds up the retraining process and improves the quality of classification on medical data.

To train the first (base) model, the following parameter values were selected: input image size is 224 × 224; loss function si binary_crossentropy; optimizer is Adam with learning_rate=1e-4; dropout is 0.5; batch size is 16; number of training epochs is 10; number of steps per epoch is 200; number of validation steps is 50.

As part of this study, four additional models were trained, each of which will differ by one parameter from the main one. The impact of changing the values of such parameters as learning_rate, dropout, batch size and optimizer was studied. Thus, each new model replaces one of the parameters: Model 1 with standard settings are specified above; Model 2 with learning_rate, which reduced from 1e-4 to 5e-5; Model 3 with dropout, which reduced from 0.5 to 0.3; Model 4 with batch_size, which increased from 16 to 32; Model 5 with optimizer, which changed from Adam to SGD. On average, the models achieve AUC values in the range of 0.65 to 0.80 for most classes, which is an acceptable result for multiclass medical diagnostic tasks, considering the simultaneous presence of fourteen pathologies, the possibility of their intersection, and the high complexity of the NIH Chest X-ray data set (Table 2).

Analysis of individual models shows that the base Model 1 with typical settings achieved an average AUC of 0.7543, which corresponds to acceptable indicators for multi-class medical diagnostic tasks.

Table 2: Comparison of Trained Neural Network Models

Model / Metrics	AUC	Accuracy	Loss
Model 1	0.7543	0.9481	0.1768
Model 2	0.8159	0.9432	0.1705
Model 3	0.7113	0.9432	0.1964
Model 4	0.7461	0.9443	0.2049
Model 5	0.5562	0.9442	0.2451

Modifications of individual hyperparameters allow us to assess their impact on the classification quality. For example, reducing learning_rate in Model 2 to 5e-5 led to the highest AUC value (~0.8159), although greater instability was observed in the initial training epochs. This indicates that reducing the training step can contribute to more accurate weight matching, but at the same time increases the metric fluctuations in the early stages. Decreasing the dropout to 0.3 in Model 3 reduced the average AUC to 0.7113, which indicates the risk of overtraining with insufficient regularization. At the same time, increasing the batch size in Model 4 contributed to more stable learning dynamics and better generalization on validation data, although the maximum performance remained slightly lower than the base model. Changing the optimizer to SGD in Model 5 negatively affected the classification quality: AUC decreased to 0.5562, indicating the model’s inability to effectively recognize pathologies under the given settings. Using the Adam optimizer turns out to be more effective for X-ray image classification tasks compared to SGD.

CONCLUSION

Neural network models based on the ResNet50, DenseNet121, and EfficientNetB4 architectures were developed and trained. In general, it can be concluded that models based on DenseNet121 and ResNet50 have the potential to be used in medical practice for automated diagnosis of respiratory diseases from X-ray images. Also, within the framework of the study, five models based on the MobileNetV2 architecture were trained with a step-by-step change in individual hyperparameters, which made it possible to assess their impact on the quality of classification of medical images from the NIH Chest X-ray set. The results showed that the learning_rate parameter has the greatest impact on the quality of the model in this task, while changing dropout and batch_size leads to less pronounced but noticeable changes in performance. A critical next step is the clinical validation of the developed system using real-time data within hospital environments.

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