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Classification of pathologies on digital chest radiographs using machine learning methods

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ABSTRACT

This article is devoted to the research and development of methods for classifying pathologies on digital chest radiographs using two different machine learning approaches: the eXtreme gradient boosting (XGBoost) algorithm and the deep convolutional neural network residual network (ResNet50). The goal of the study is to develop effective and accurate methods for automatically classifying various pathologies detected on chest X-rays. The study collected an extensive dataset of digital chest radiographs, including a variety of clinical cases and different classes of pathology. Developed and trained machine learning models based on the XGBoost algorithm and the ResNet50 convolutional neural network using pre-processed images. The performance and accuracy of both models were assessed on test data using quality metrics and a comparative analysis of the results was carried out. The expected results of the article are high accuracy and reliability of methods for classifying pathologies on chest radiographs, as well as an understanding of their effectiveness in the context of clinical practice. These results may have significant implications for improving the diagnosis and care of patients with chest diseases, as well as promoting the development of automated decision support systems in radiology.

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1. INTRODUCTION

Modern medical care is faced with the need to effectively and accurately detect pathologies on chest X-rays. Digital radiographs provide extensive information about the state of the respiratory and cardiovascular systems, but their analysis requires high qualifications and time on the part of medical specialists [1]. In this work, machine learning methods became a key tool to automate and improve the process of classifying pathologies in radiographs. One of the key challenges in this field is the automatic classification of pathologies in chest X-rays [2]–[4] with high accuracy and efficiency. Correct and rapid diagnosis of chest diseases such as lung cancer, tuberculosis, and other pathologies is critical for successful treatment and increasing patient survival. Machine learning techniques such as the eXtreme gradient boosting (XGBoost) algorithm and deep neural networks provide new opportunities for the automatic diagnosis and classification of these diseases.

In this paper, we present the results of a study on pathology classification in digital chest radiographs using two different machine learning methods: XGBoost [5]–[7] and the deep convolutional neural network residual network (ResNet50) [8]–[10]. We compare the performance and accuracy of both models and consider their advantages and limitations in the context of clinical practice. The main objective of this work is to find out which method is best suited to classify pathologies on chest radiographs, taking into account accuracy, sensitivity, and specificity. The results obtained will contribute to the development of automated diagnostic and disease monitoring systems, improving the quality of medical care and speeding up the decision-making process in clinical practice.

Koohbanani *et al.* [11] proposes a self-supervised convolutional neural network (CNN) structure that allows the use of unlabeled data to explore generalizable and domain-invariant representations in pathology images. The proposed structure, called Self-Path, uses multi-task learning, where the main task is tissue classification, and the pre-text tasks are various self-supervision tasks with labels inherent in the input images. They present novel pathology-specific self-monitoring tasks that use contextual, layered, and semantic features in pathology images for semi-supervised learning and domain adaptation. Azizi *et al.* [12] examines the effectiveness of self-guided learning as a pre-learning strategy for medical image classification. Conducted experiments on two different tasks: classifying dermatological conditions from digital camera images and classifying chest x-rays with multiple labels, and demonstrated that self-guided learning on ImageNet followed by additional self-supervised learning on domain-specific unlabeled medical images significantly improved the accuracy of medical image classifiers.

Chen *et al.* [13] proposes a novel label co-occurrence learning framework based on graph convolution networks (GCNs) for explicitly learning dependencies between pathologies for a multi-labeled chest X-ray (CXR) classification problem, which it calls chest X-ray graph convolution networks (CheXGCN). Ho and Gwak [14] precise localization and classification of lung anomalies on X-ray images are important for clinical diagnosis and treatment strategy. However, multi-label classification, in which medical images are interpreted to identify multiple existing or suspected pathologies, presents practical limitations. Zheng *et al.* [15] paper proposes a method for classifying cardiac pathology based on a novel approach to image-derived feature extraction to characterize the shape and movement of the heart. An original semi-supervised learning procedure that makes efficient use of a large number of unsegmented images and a small number of manually segmented images by experts is designed to generate a pixel-by-pixel visible stream between two 2D+t time points.

In study [16], the study examined the applicability of artificial intelligence (AI) for dental radiography based on current research. They classified AI applications based on the similarity of the following purposes: diagnosis of dental caries, periapical pathologies, and periodontal bone loss; classification of cysts and tumors; cephalometric analysis; osteoporosis screening; tooth recognition and forensic odontology; recognition of dental implant systems; and improving image quality. The goal of the study [17] is to evaluate the real-time diagnostic performance of the deep convolutional neural network You Only Look Once (YOLO) v2, a deep learning algorithm that can simultaneously detect and classify an object, on panoramic images. radiographs. The images were classified and labeled into four categories: dentoalveolar cysts, odontogenic keratocysts, ameloblastomas, and no lesions. The results of this study indicate the usefulness of automatic detection of convolutional networks for detecting certain pathologies and therefore preventing morbidity in the field of oral and maxillofacial surgery. The work [18] applies various image preprocessing techniques. The input orthopantomogram (OPG) images are resized, pixels are scaled, and erroneous data is eliminated. The proposed algorithm is implemented using CNN with Dropout and the fully connected layer is trained using Genetic algorithms Back propagation error algorithm (GA-BP) hybrid learning. Using the Dropout regularization technique, overfitting was avoided, which allowed the network to correctly classify objects. The CNN was implemented with different convolutional layers, and the highest accuracy of 97.92% was obtained with two convolutional layers.

In a retrospective study [19], the you only look once (YOLO) algorithm was used to obtain hand images from original radiographs without data loss, and classification was performed by applying transfer learning with a trained visual geometry group (VGG-16) network. During training, the data augmentation method was used. Barisoni *et al.* [20] shows that the field of computer vision can now be effectively applied to histopathological objects by people who do not have in-depth knowledge of computer vision techniques. While these new approaches have already advanced disease detection, classification, and prognosis in the fields of radiology and oncology, renal pathology is just entering the digital age with the creation of consortia and digital pathology repositories to collect, analyze, and integrate pathology data with other domains.

2. METHOD

In this work, to solve the classification problem, all input images were initially segmented using the convolutional network for biomedical image segmentation (U-Net) model [21]–[23], which is a deep neural network specifically designed for image segmentation tasks in medical applications [24]–[26]. The main idea of U-Net is to create an efficient architecture for feature extraction and high-quality segmentation while preserving spatial information. The model has two main parts: an encoder and a decoder. When a model is trained on a large enough amount of labeled data, it can highlight areas of interest in images and create masks that can be used for further image analysis and processing. It should be noted that the use of U-Net in medical problems requires a lot of attention to additional aspects, such as data augmentation, class balancing, and model adaptation to specific conditions and data types. Using masks generated by the unified neural network (U-Net) model provides a powerful tool for automatic segmentation and cropping of images as shown in Figure 1. These masks, created using convolutional neural networks, can highlight objects of interest in images, such as lungs in X-rays, and then automatically crop the image around those objects.

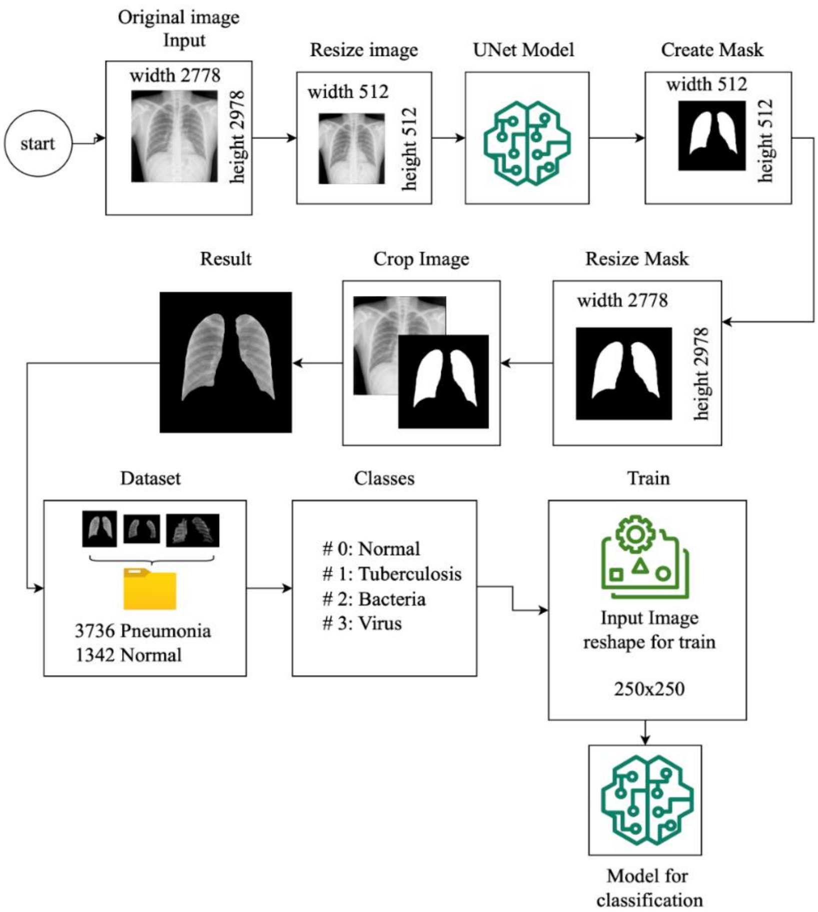

Figure 1. Architecture for creating masks using a trained model U-Net

To implement pathology classification on digital chest radiographs, machine learning methods such as the XGBoost algorithm and the ResNet50 deep convolutional neural network were used. The experiment collected datasets with chest X-rays and associated medical annotations. Augmentation techniques were applied to increase the size of the dataset and improve model training. Data normalization was also carried out for data preprocessing. When training the models, the data was divided into training, validation, and test sets. The XGBoost machine learning method extracts key features from X-ray images using computer vision techniques or simple statistics. The XGBoost model is trained on training data and tuned on hyperparameters for better performance. The machine learning method logistic regression is a statistical method used to model the probability of a binary or multi-class event. In this work, it is used for classification tasks. When classifying pathologies on chest radiographs, logistic regression was used to model the likelihood of the presence or absence of a particular pathology.

For the ResNet50 method, we applied a pre-trained convolutional neural network with 50 layers. The model was further trained on our data to extract high-level features. The performance of both models was evaluated using various metrics such as precision, recall, F1-measure, and receiver operating characteristic (ROC) curve on a test dataset. We conducted a comparative analysis of classification results, comparing the performance of the XGBoost and ResNet50 methods. Using two different machine learning methods allowed us to evaluate their performance and select the most appropriate method for the task of classifying pathologies on chest X-rays. The application of these methods should allow the creation of an effective system for classifying pathologies on digital chest radiographs.

3. RESULTS AND DISCUSSION

We consider a comparison of two popular machine learning methods, XGBoost and ResNet50, in the task of automatic diagnosis of pneumonia based on fluorographic images. Both algorithms were trained on a set of 3,736 pneumonia images and 1,342 normal fluorographic images. The original images had a high resolution (3000×3000 pixels) and were pre-segmented using a neural network to highlight lung areas. The images were then scaled to 250×250 pixels for training the models. Preprocessing is a critical step in any machine learning project, and in this case, it involved two key steps such as segmentation and resizing. To improve accuracy, a segmentation method performed using a neural network was applied. This stage made it possible to get rid of areas of the image that were irrelevant for diagnosis, leaving only fragments of the lungs. After segmentation, the images were scaled to 250×250 pixels to speed up the training process and reduce computational requirements.

The XGBoost method used was shown to have good performance and accuracy in classifying pathologies on radiographs. This model showed excellent performance on training data, achieving 100% accuracy. However, on the validation set the indicators were lower: accuracy was 85.83%, and F1-Score was 85.46% as shown in Figure 2. The performance of the XGBoost method showed good results, which indicates its applicability in the task of classifying pathologies on radiographs. However, it should be noted that this method relies on manual feature extraction, which may require more effort in data preprocessing.

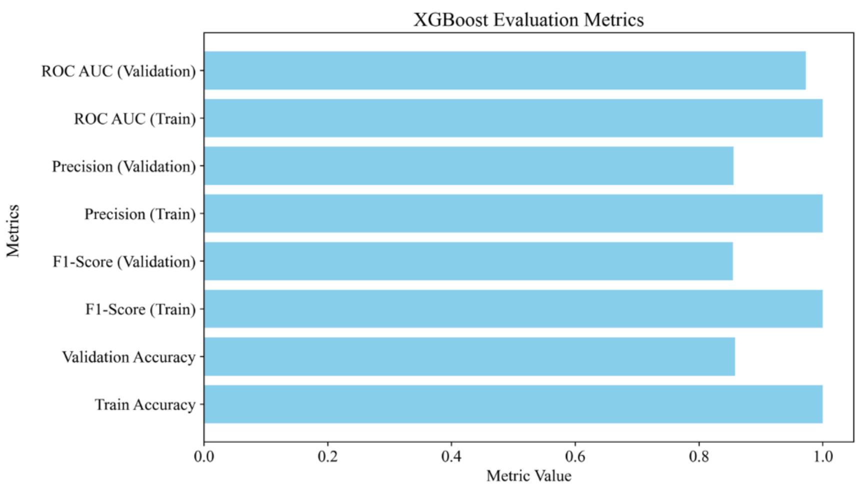

Figure 2. XGBoost model training accuracy results

Performance ResNet50 exhibited outstanding performance and handled the classification task with high accuracy. This model also achieved 100% accuracy on training data. Unlike XGBoost, ResNet50 showed significantly better results on the validation set: accuracy - 96.09%, F1-Score - 96.05% as shown in Figure 3. Its ability to extract high-level features from images allowed it to achieve high results without the need to manually define features.

It is important to note that both models showed high values of the ROC area under the curve (AUC) metric, which indicates their good ability to discriminate between classes. However, ResNet50's higher F1-Score and accuracy indicate its better performance, possibly due to a better balance between sensitivity and specificity. Having compared the performance of XGBoost and ResNet50 in the task of diagnosing pneumonia on fluorographic images, we can conclude that complex models specialized in working with images can show better results in such tasks. Data preprocessing, including segmentation and scaling, also has a significant impact on model performance. Despite this, overtraining remains an important aspect that requires further research and correction.

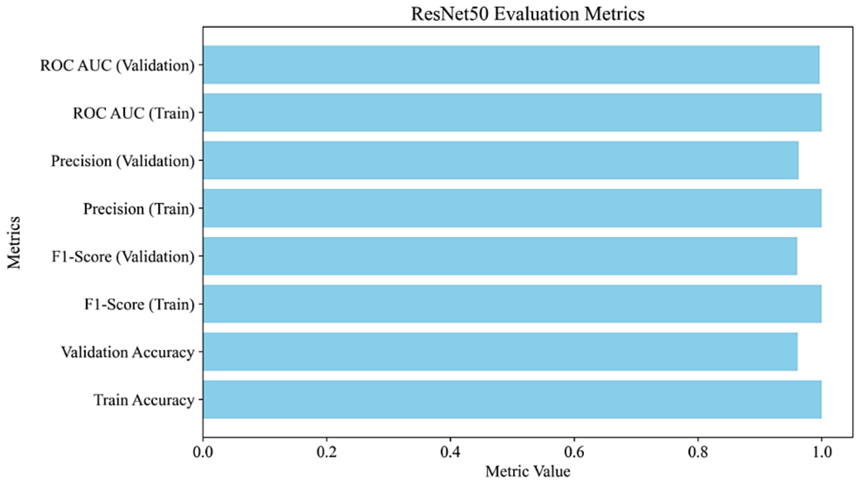

Figure 3. ResNet50 model training accuracy results

4. CONCLUSION

In this article, a study was conducted on the classification of pathologies in digital chest radiographs using machine learning methods, in particular, XGBoost and the deep convolutional neural network ResNet 50. The study confirmed that both the machine learning method and deep neural networks have the potential to successfully classification of pathologies on chest X-rays. Both methods achieved high precision and recall, but ResNet 50 showed more outstanding performance. Deep neural networks such as ResNet 50 have shown their ability to extract high-level features from images, which significantly improves classification accuracy. This makes them a powerful tool in radiology for automated diagnosis.

Future research could focus on improving data preprocessing techniques, as well as collecting larger datasets to improve model training and generalization. The results of this study may be useful for radiologists and medical specialists by providing them with tools to automate the process of diagnosing pathologies on radiographs. Overall, this study highlights the importance of machine learning techniques, especially deep learning, in the field of medical diagnostics and provides a basis for further research and development of intelligent systems for medical image analysis.

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