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A DEEP LEARNING MODEL FOR PNEUMONIA DETECTION FROM X-RAY IMAGES

Abstract: The World Health Organization estimates that more than four million deaths occur annually due to pneumonia and other diseases associated with air pollution, and the latest COVID-19 virus has dramatically increased the percentage of pneumonia cases. Over 150 million people get infected with pneumonia on an annual basis, especially children under 5 years old. There's also a global shortage of radiologists in both developing and developed countries. Over 2/3 of people on earth do not have access to radiologists. According to the Association of American Medical Colleges, the U.S. is projected to have a shortage of 17,000 to 42,000 radiologists by 2033. Currently, the development of artificial intelligence and machine learning technologies, as well as the accumulation of large volumes of medical images, make it possible to create automated systems for analyzing medical images. The article presents a simple sequential model based on deep learning methods (convolutional neural networks) that helps detect pneumonia. X-ray images of the Women's and Children's Medical Center in Guangzhou were used for the model. The development of the pneumonia diagnostic program was carried out in Python. Training the neural network took 26 minutes and 12 epochs. The results obtained in the test data are: recall: 96%; precision: 92%; accuracy: 92%; and f1: 94% for pneumonia cases. This is no less than the result proposed in many popular works. The model significantly reduces the burden on radiologists, helps them make decisions and save time, allows them to evaluate the quality of their work, and reduces the likelihood of medical errors.
Keywords: neural network, deep learning, pneumonia, medicine, X-ray images.

Introduction

Pneumonia is an acute infectious disease of the lower respiratory tract that causes inflammation of the lungs. The World Health Organization (WHO) estimates that more than four million deaths occur annually due to pneumonia and other air pollution-related diseases [1]. To make an accurate diagnosis or check for the presence of diseases in the early stages, the patient is prescribed radiation and functional tests such as X-rays, computed tomography, etc.

One radiologist receives thousands of X-rays a year. In sparsely populated areas (both in developing and developed countries), there is a shortage of radiologists. In 2015, only 11 radiologists served 12 million people in Rwanda, while Liberia, a country with a population of four million, had only two radiologists [2]. In addition, pneumonia is a high-risk disease, especially in developing countries, where millions of people are poor and do not have access to health

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facilities. Hospitals in large cities carry a heavy burden on doctors, which is why random errors can reduce the quality of analysis. Even for very professional and experienced doctors, diagnosing pneumonia with X-rays is still a big challenge, since X-rays contain similar information about various diseases, such as lung cancer. Therefore, the diagnosis of pneumonia by traditional methods requires a lot of time and energy, and it is impossible to determine whether a patient is suffering from pneumonia using a standardized process.

Pneumonia poses a serious threat to the elderly, hospital-admitted patients, and the lives of patients with asthma. The majority (45%) of cases of pneumonia are in children under the age of five. Pneumonia kills more than 800,000 children under the age of five a year, with about 2,200 children dying every day. There are 1,400 cases of pneumonia for every 100,000 children each year globally. Statistics showing the total number of deaths worldwide [3] are shown in Fig. 1.

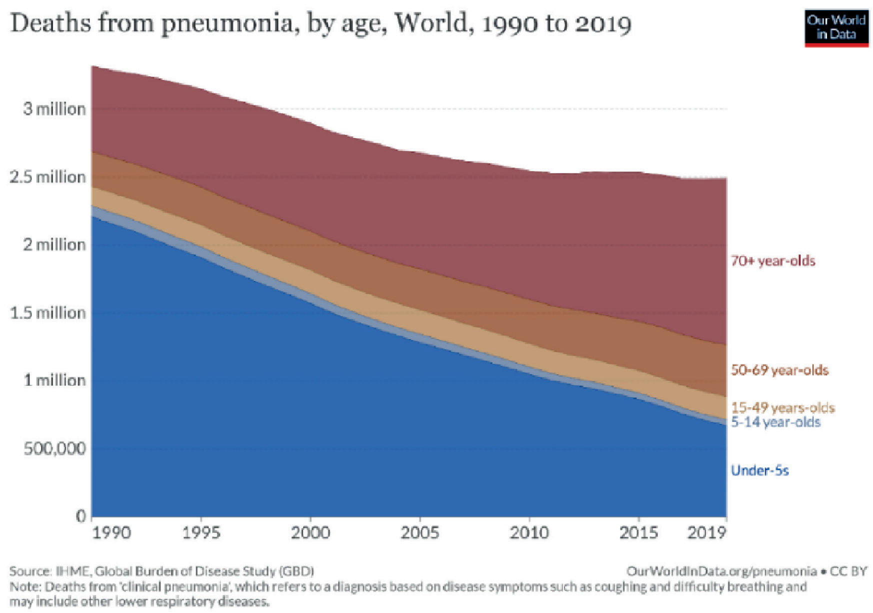

Figure 1. Dynamics of the number of deaths from pneumonia worldwide in the period from 1990 to 2019 and the ratio by age group [3].

The sudden outbreaks and uncontrolled spread of COVID-19, whose main symptom is also pulmonary pneumonia, have been one of the most serious global problems to date. COVID-19 is a rapidly spreading disease of a highly contagious nature caused by the SARS-CoV-2 virus from the group of coronaviruses. At the end of January 2020, the World Health Organization (WHO) declared a global health emergency and a pandemic in a month and a half. By March 4, 2023, there were 675 860 881 confirmed cases and 6 876 867 deaths [4]. From a public health perspective, early detection of COVID-19 and the isolation of patients have become critical due to the lack of adequate drugs. As the available resources were limited, hospitals experienced an exponential increase in the number of patients.

The model based on 22-layer convolutional neural networks presented in the work takes an X-ray image of the chest as an input and determines whether there is pneumonia in the lungs in a short time. In the test data, classification accuracy was 92.3%, and recall was 96%. This is much higher than the results obtained by traditional machine learning methods presented by other authors in this research area. In the future, automatic detection of pneumonia from medical images with this model will help radiologists make decisions and save time, greatly improving the quality of service. It is also invaluable for providing medical care to populations with little access to diagnostic imaging specialists.

Literature Review

In recent years, the role of deep learning in medical imaging has grown immensely, promising groundbreaking advances in various medical diagnostics. The deployment of deep learning models, particularly in the detection of pneumonia from X-ray images, is a notable area of exploration. The subsequent review aims to highlight the contemporary literature on this subject while identifying potential research gaps.

Historical Overview and Conventional Methods

Historically, radiologists have relied on their expertise and experience to diagnose pneumonia by interpreting X-ray images. Traditional image processing methods involved manual or semi-automated techniques that, while effective, could potentially introduce human error and were time-consuming [5]. The need for a faster, more consistent, and automated approach became apparent.

Introduction of Deep Learning in Medical Imaging

Deep learning, a subfield of machine learning inspired by the structure and function of the brain, has emerged as a powerful tool. Convolutional Neural Networks (CNNs), in particular, have shown substantial promise in image classification tasks, including pneumonia detection [6]. CNNs, with their inherent ability to learn image features automatically and hierarchically, led to significant improvements in accuracy and reduced reliance on manual feature extraction [7].

Achievements and Limitations

Multiple studies have showcased the potential of CNNs in pneumonia detection. For example, [8] implemented a deep CNN that achieved a diagnostic accuracy of over 92%, rivaling and sometimes even surpassing experienced radiologists. However, such results aren't universal. A challenge frequently highlighted is the lack of extensive and diverse training datasets, which can lead to overfitting and reduced generalizability [9].

Moreover, while deep learning models boast high accuracy, their "black box" nature poses a significant challenge. Interpreting why and how these models make specific decisions remains a significant concern, especially in a critical domain like healthcare, where interpretability is paramount [10].

Comparison with Other Modalities

Deep learning is not the only advanced approach to pneumonia detection. Studies have compared CNNs with other machine learning techniques such as Support Vector Machines (SVM) and Random Forests (RF). While deep learning consistently shows higher accuracy, SVM and RF models offer more interpretability, posing an essential trade-off to consider [11].

Research Gaps

Several research gaps are evident upon reviewing the existing literature:

Diverse Datasets: Many studies utilize limited datasets, often from single institutions. There's a pressing need for more diverse datasets that encompass variations in age, ethnicity, and disease severity to improve model robustness [12].

Model Interpretability: As noted, the black-box nature of deep learning is a significant concern. More research is needed to develop techniques or hybrid models that combine the accuracy of CNNs with the interpretability of traditional machine learning models [13].

Real-world Implementation: Most studies focus on model accuracy in controlled environments. Practical challenges like integrating these models into existing medical infrastructure,

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ensuring real-time processing, and handling imperfect or low-quality images remain relatively unexplored [14].

Comparison with Emerging Imaging Modalities: The focus has been predominantly on X-ray images. However, other imaging modalities like CT scans and MRIs may offer additional insights. How deep learning models perform in comparison to or in conjunction with these modalities is a ripe area for exploration [15].

The advent of deep learning for detecting pneumonia from X-ray images has undeniably revolutionized the field. While achievements are noteworthy, significant challenges and research gaps remain. Addressing these will be crucial to fully realizing the potential of deep learning in this domain.

Many application-oriented papers, while presenting novel methods and architectures, have not adequately addressed the robustness of their approach. Notably:

Limited Validation Schemes: Cross-validation, stratified sampling, and out-of-sample validation are vital to ensuring a model's generalizability. The absence of such rigorous validation methods in many studies casts doubt on the real-world efficacy of the proposed models [16].

Lack of Comparative Analysis: For an application-driven approach to be considered superior, it must not only present its performance metrics but also juxtapose them against baseline or existing methods. The absence of such comparative analyses is glaring in numerous studies [17].

Over-reliance on Accuracy: As discussed, while accuracy is an essential metric, its overemphasis without considering other performance metrics (like F1-score, AUC-ROC, etc.) can be misleading, especially in medical applications.

Material and methods

The development of artificial intelligence and machine learning technologies, as well as the accumulation of large volumes of medical images, make it possible to create automatic analysis systems in the field of medicine. Deep learning algorithms based on CNNs (convolutional neural networks) are the standard choice for classifying medical images, although current methods constitute an embedded network architecture similar to a trial-and-error system. U-Net, SegNet, and CardiacNet are some of the outstanding architectures for medical image testing. In recent years, several methods, especially deep learning methods, have been introduced to describe the short process of pneumonia detection using chest X-ray images. Deep learning has been successfully applied to improve the performance of computer aided diagnosis technology (CAD), especially in the fields of medical imaging [18], image segmentation [19], [20], and image reconstruction [21], [22]. In 2017, Rajpurkar et al. [23] proposed a classic deep learning network called DenseNet-121 [24], which was a 121-layer CNN model to accelerate pneumonia diagnosis. Unlike the experienced doctors, it got a higher F1 score.

During training, models such as reinforcement learning (RL) are included to find the optimal hyperparameters of the network. However, these methods are computationally expensive and consume a lot of power. As an alternative, this study offers a conceptually simple but effective network model for solving the problem of detecting pneumonia.

The main stages of the model creation process are:

1. Importing data;
2. Data preprocessing;
3. Building the model architecture;
4. Model training;
5. Evaluation of model quality based on validation data;
6. Testing the model.

First, X-ray images in JPEG format with a total size of 1.16 GB were downloaded to the local computer. The data presented were preprocessed because they were highly unbalanced. This step included resizing the images to a single size of 150x150, normalizing pixel values (to the range 0-1), rotating the data, multiplying by zooming in and out, and finally dividing into train, test, and validation sets. Using the Keras Sequential API, a sequential network was created from convolution, batch normalization, flattening, dropout, and max pooling layers. Subsequently, the pre-processed data were passed through the network, and performance metrics were calculated from the validation data. A number of changes were made to the model until our target of 90% accuracy was achieved, the final version being the network revealed in section 1.2.2 below. Finally, the best-performing network weights were saved to a .h5 file.

Fig. 2 also provides information about CPU execution and component processes under each key stage. Since neural networks are parallelizable, computations on a GPU help a lot with efficient use of time.

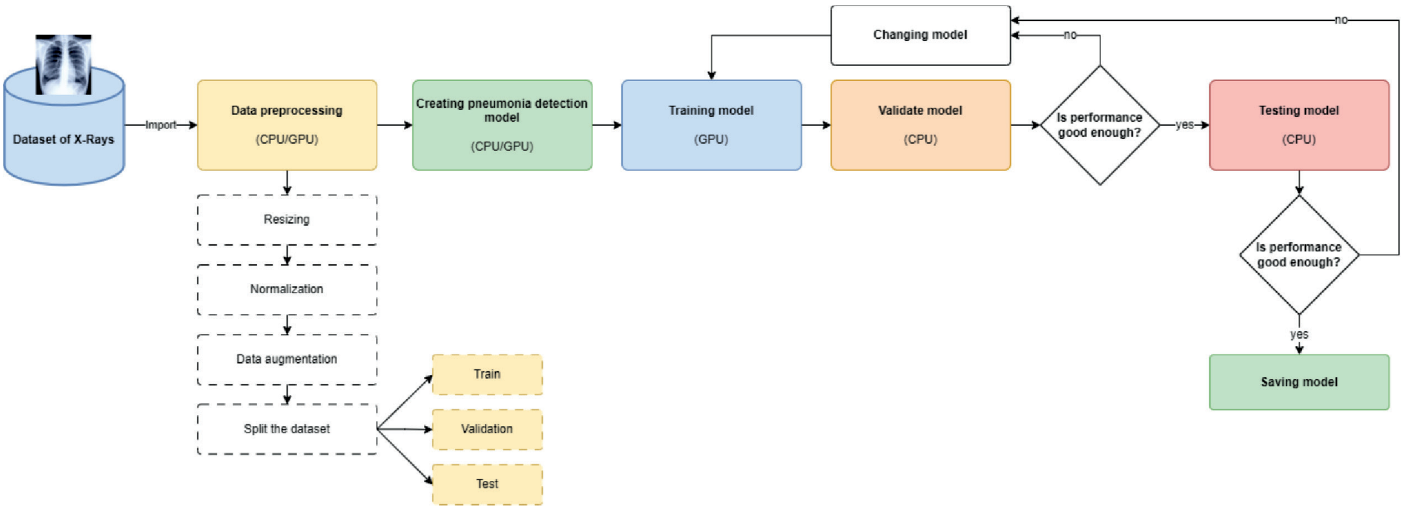

Figure 2. Diagram of the model building process.

Dataset

A Kaggle competition dataset [25] consisting of 5863 X-ray images in jpeg format from the Guangzhou Women's and Children's Medical Center was used for the model. All chest radiographs (anterior and posterior) were obtained from patients aged one to five years. The dataset is organized into three folders (train, test, and val) and classified into two categories each (normal and pneumonia).

All chest radiographs were performed as part of the patients' routine clinical care. For the analysis of chest radiographs, all chest radiographs were initially screened for quality control by removing all low-quality or illegible scans. Imaging diagnoses were evaluated by three expert physicians.

The data are unbalanced because the ratio of healthy people to pneumonia cases is large. It is shown in the histograms in Fig. 3.

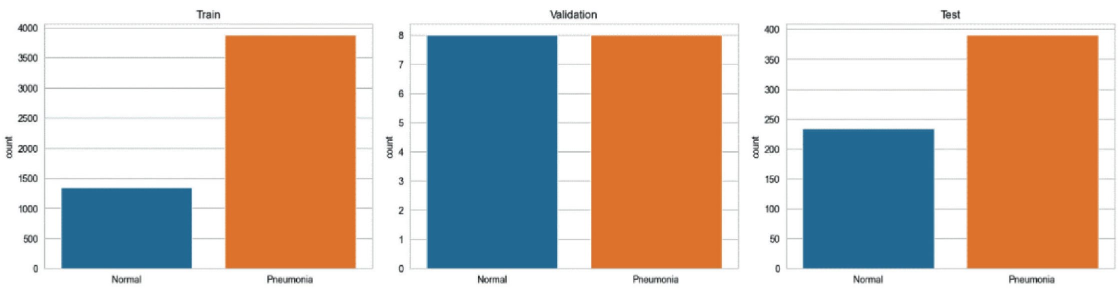

Figure 3. Class distributions in different datasets.

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Samples and labels from the dataset are shown in Fig. 4.

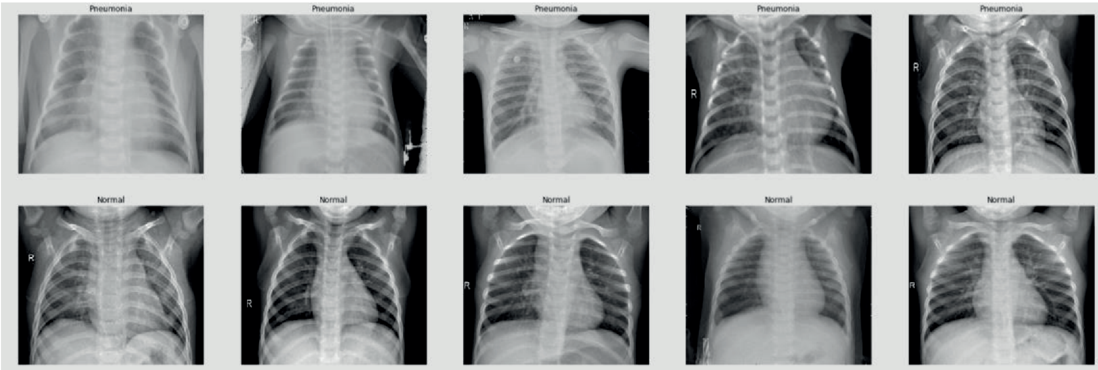

Figure 4. Random examples from class samples.

Methods

Data preprocessing

The process of creating and configuring a training object for an image recognition problem may include the following steps: data augmentation, scaling the image to the desired size, normalizing it, applying filters, and so on. It is not necessary to perform all the steps; rather, some steps may not be used at all, and others may be repeated several times.

Scaling is a change in the size of the image vertically and horizontally. In this work, scaling consisted of changing the vertical and horizontal size of the image by 150 x 150 pixels.

Data augmentation. When there is not enough data for training, overfitting occurs. One way to solve the data shortage problem is to increase the size and variability of the data. Multiplication is directly related to the use of various transformations of the source data. This method helps to increase the number of unique input instances that the model no longer sees. This, in turn, contributes to obtaining high accuracy in the testing data.

Using Tensorflow.keras, we can implement the changes and generation of new images using the ImageDataGenerator class. For this, it is enough to give the transformations that we want to apply to the images as parameters.

The image augmentation parameters are shown in Table 1.

Table 1. Data preprocessing parameters.

Parameter	Value
Resize	150x150
Normalization	(0, 255) → (0, 1)
Rotation Range	0, 30
Zoom Range	0.2
Width_Shift_Range	0.1
Height_Shift_Range	0.1
Horizontal_Flip	False
Vertical_Flip	False

Here is the reason for setting the horizontal and vertical flips to false (the last two rows in Table 1). Data augmentation should be close to real life and should not change the nature of the object being studied. If we switch the images completely oppositely, it leads to the displacement of other organs in the X-ray image (Fig. 5). In particular, the heart. If other diseases are studied together, this would give the wrong results because the heart is located on the right side of the disease. This can cause errors, especially in the classification of various diseases.

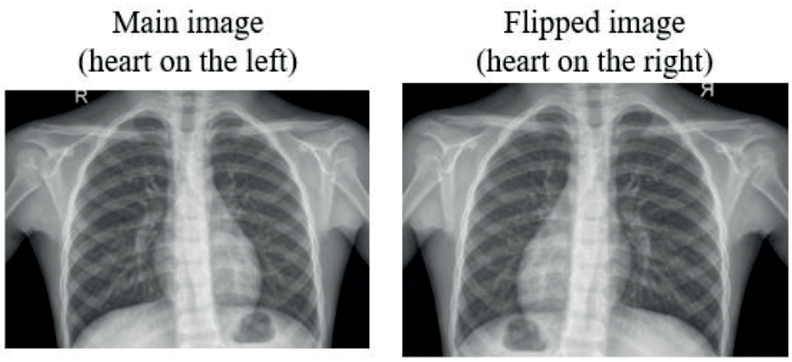

Figure 5. The result of contrast replacement of the X-ray image.

Proposed network

The architecture of the proposed deep neural network model presented in this paper is shown in Fig. 6. The proposed network uses several techniques, such as convolutional layer, batch normalization, max pooling dropout, and flatten layer.

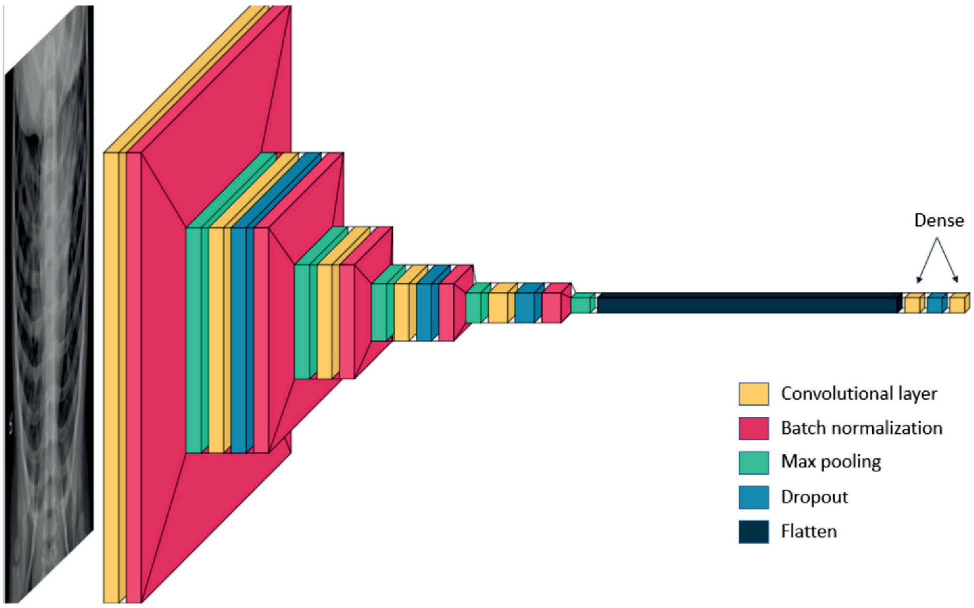

Figure 6. Proposed deep CNN architecture.

Total number of parameters: 1 246 401
Number of trainable parameters: 1 245 313
Number of untrainable parameters: 1 088

The Keras Sequential API was used. The first one is **a convolutional layer (Conv2D)**. This is a set of trainable filters. For the first Conv2D layer, 32 filters were set; for the next two layers-64, and for the last two layers-128, 256 filters. Each filter transforms a portion of the image (determined by the kernel size) through a kernel filter.

CNN extracts useful properties from these transformed images at all times. The second important layer in CNN **is the pooling layer (MaxPool2D)**. This layer simply acts as a compression

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filter. It looks at the adjacent 2 pixels and selects the maximum value. They are used to reduce computing costs and reduce the dimensions of the feature maps. By combining convolutional and pooling layers, CNNs can combine local properties and learn more global properties of an image.

Dropout is a method where the percentage of nodes in a layer is randomly ignored for each training model (by zeroing out their weight). This method improves generalization and reduces overfitting. The **"relu"** is used to add non-linearity to the network.

The **Flattening layer** is used to transform the final feature maps into a single 1D vector. This step is necessary to use fully connected layers after some convolutional or pooling layers. It combines all the local features found in previous convolutional layers. Finally**,** we used **two fully connected (dense) layers**, which are an artificial neural network (ANN) classifier. Activation: "sigmoid".

In the proposed model, to reduce the learning rate when encountering a plateau, in order to get at least a little closer to the global minimum keras.callbacks.ReduceLROnPlateau method was used. The parameters are shown in Table 2.

Table 2. Parametrs of the ReduceLROnPlateau method.

Parameter	Meaning	Value
monitor	controlled value	val_accuracy
patience	number of unimproved epochs, after which the learning rate decreases	2
factor	factor that reduces the learning rate new_lr = lr * factor.	0.3
min_lr	lower limit of learning rate	0.000001

Classification performance metrics

Four standard metrics were used to evaluate the proposed model in sets of pneumonia data: Accuracy, Precision, Recall, and F1 [26]. To define these metrics, let's first define the terms "true positive", "false positive", "true negative", and "false negative". For a binary classification problem, assume that two classes in the data set are called "positive" and "negative" classes. The above-mentioned terms can be defined as follows.

- True Positive (TP) refers to a sample that belongs to a positive class and is correctly classified by the sample.
- False Positive (FP) refers to a sample that belongs to a negative class that was mistakenly classified as belonging to a positive class.
- True Negative (TN) refers to a model that belongs to a negative class and is correctly classified according to the sample.
- False Negative (FN) refers to a sample belonging to a positive class that was mistakenly classified as belonging to a negative class.

The four estimated metrics can now be defined as follows:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall\ (Sensitivity) = \frac{TP}{TP + FN}$$

$$F1 = \frac{2}{\frac{1}{Precision} + \frac{1}{Recall}}$$

The accuracy metric provides a general measure of the number of correct model predictions. However, the high accuracy of the model does not ensure its ability to distinguish between different classes in the same way if the data set is unbalanced. In particular, the classification of medical images requires a model that can be generalized to all classes. In such cases, the Precision and Recall values give an idea of the model's performance. Precision shows the accuracy of the forecast of a positive model class. This provides a ratio of correct forecasts to the overall forecasts given by the model. In contrast, Recall measures the accuracy of predicting a true negative class correctly predicted by the model. These two estimators evaluate whether the model can reduce the number of FP and FN predictions. F1 provides a balance between Precision and Recall, taking into account both FP and FN.

An important indicator that combines these estimates and gives an overall picture is the **confusion matrix**. In the case of binary classification, it has the form:

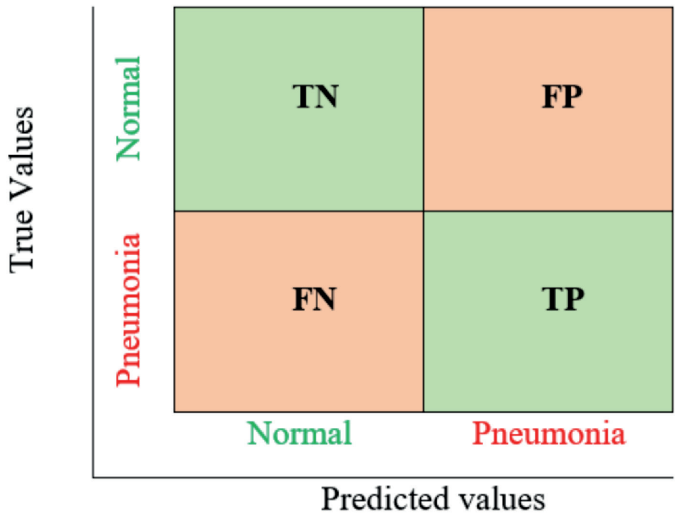
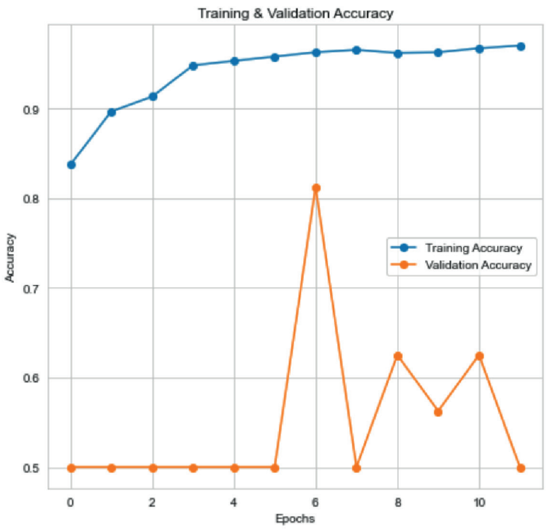


Figure 7. Confusion matrix.

Results

The training process lasted 12 epochs and took 26 minutes. Accuracy and loss in the training data and validation data changed during the process as follows:



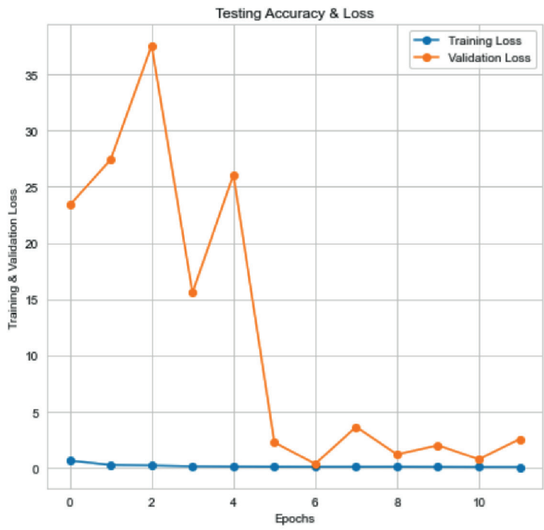


Figure 8. The training process.

The model quality indicators in the test data are shown in Table 3. In the test data, the model showed an accuracy of **92.3%**. The values of **precision = 91.7%, recall = 96.4%, and F1 = 94%** for detecting pneumonia are quite good indicators. The most important indicator here is recall, because detecting pneumonia is more important than giving us a false positive for pneumonia in a healthy lung.

Table 3. Report of the model result.

	Normal	Pneumonia	Accuracy	Macro avg	Weighted avg
Precision	0.935	0.917	0.923	0.925	0.924
Recall	0.855	0.964	0.923	0.909	0.923
F1-score	0.893	0.94	0.923	0.916	0.922
Support	234	390	0.923	624	624

Fig. 9 shows the confusion matrix. Of the 624 X-rays, 200 of the 234 healthy lungs were correctly identified by the model, and 34 were incorrectly identified as having pneumonia. Of the 390 examples of pneumonia, 376 were correctly identified and 14 were falsely labeled as having healthy lungs, which is equivalent to TP = 376, FP = 34, TN = 200, FN = 14.

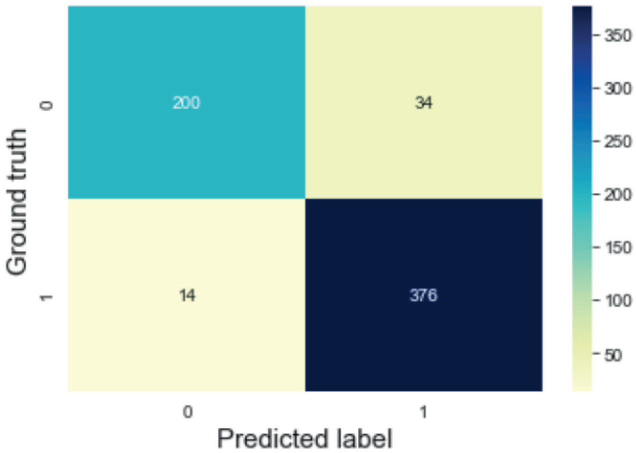


Figure 9. Confusion matrix.

Fig. 10 shows the correct and incorrect examples identified by the model. Images a and b are correctly identified, and c is a radiograph incorrectly identified by the model. In this example, the white infiltrates that distinguish pneumonia from healthy lungs are confusing the model. Such conditions can make diagnosis difficult even for an experienced radiologist, and chest X-rays for detecting pneumonia are prone to subjective variability [26].

a (correct normal)

b (correct pneumonia)

c (incorrect normal)

Figure 10. Results of model classification.

Until now, significant works have been presented in the research area. A comparative analysis of the accuracy indicators obtained by other authors with the accuracy of our network is shown in Table 4. As we can see, traditional machine learning algorithms like SVM, KNN, k-means clustering, etc. In comparison, the indicators for algorithms based on neural networks are high.

Advantages of the network presented in this work:

- time-saving (the training process took only 26 minutes);
- relatively high accuracy in detecting pneumonia (accuracy – 92.3%, recall – 96.4%);
- a simple model that doesn't require a lot of computing power.

Submitted works are evaluated in small databases and cannot be used on a commercial scale. In this regard, the use of large volumes of quality data validated by several highly specialized independent radiologists can lead to great progress, given the current pace.

It is planned in the future to create a learning process and expand the database, which will be accumulated using trends such as transfer learning in deep learning. This is because, although the accuracy obtained is relatively high, even 99% accuracy may not be enough because the area under study is related to human life.

In the future, accurate automated analysis of radiographs will increase the efficiency of the radiologist's workflow, which is important for reducing costs and response times and improving the quality of medical care. It also has great potential for spreading the experience to underserved areas.

Table 4. Comparison of the obtained result with the results of other studies.

Research	Used methods	Dataset	Results (accuracy)
Proposed model in this work	CNN	Pediatric chest X-rays model	92,3%
Comparative performance analysis of machine learning classifiers in detection of childhood pneumonia using chest radiographs [27].	SVM (Support Vector Machine), KNN, NB (Naive Bayes)	PneumoCAD	77%, 70%, 68%,
Detecting Pneumonia in Chest X-Rays with Supervised Learning [28].	k-means clustering	Chest X-ray14	60%
Learning to diagnose from scratch by exploiting dependencies among labels [29].	LSTM (Long Short-Term Memory)	Chest X-ray14	76%
Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images for Classification [30].	Variable training	Pediatric chest X-rays	90.7%
Deep Convolutional Neural Networks for Chest Diseases Detection [31].	CNN, CpNN (Competitive probabilistic neural network), BpNN (Back Propagation Neural Network)	Chest X-ray14	92%
Pneumonia Classification Using Deep Learning from Chest X-ray Images During COVID-19 [32].	Transfer learning	various datasets	91,43%

Conclusion

The realm of medical imaging is undergoing a transformative phase with the integration of advanced computational techniques, and this study has significantly contributed to this evolution. Through our exploration of a deep learning CNN model for pneumonia detection from X-ray images, we've demonstrated the potential of harnessing sophisticated neural network

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architectures in diagnostic processes. The results underscore the CNN model's prowess in not only improving detection rates but also potentially minimizing human diagnostic errors, thus streamlining clinical workflows. However, like all pioneering endeavors, there are inherent challenges. The need for more diverse training datasets, addressing model interpretability, and real-world implementation nuances are crucial areas demanding further investigation. It is also imperative to consider the ethical and practical implications of integrating such models into standard medical practice. As we move forward, the confluence of medical expertise and advanced computational models, such as the one presented in this study, promises a new frontier in medical diagnostics. Yet, it beckons a collaborative approach, ensuring that technology complements, not supplants, the human touch in patient care.

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