Chest Pathologies Intellectual Analysis

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Abstract. **The paper addresses chest pathologies analysis problem. An algorithmic approach based on neural networks is proposed. An algorithm is implemented as a special software package.**

Keywords: **neural networks, X-Ray image, chest pathologies, medical screening, supervised learning**

I. Introduction

In the conditions of a pandemic, the primary task of medicine is to detect the disease at an early stage. The solution of this problem is carried out by mass screening of the population. Doctors usually use all kinds of (stationary and portable) equipment to obtain primary data about patients. However, the use of various types of medical devices makes analysis of the images obtained quite difficult. To increase radiologists' performance, in this case, a flexible software tool is necessary. It should be as independent as possible from the types of technical devices. The data processing and diagnosis making a diagnosis can be simplified to a greater extent by using an appropriate set of algorithmic tools that automate all its stages.

The report discusses one of the possible approaches to solving the problem based on intelligent image analysis [1, 2].

II. Problem Analysis and Problem Statement

Before proceeding to the solution of the problem, it is necessary to identify the main stages of obtaining and analyzing [3–5]. X-ray images and the problems associated with them.

The overall process of obtaining and analyzing radiographic images can be presented in the form of a sequence of the following main stages:

- Collecting data from various radiographic devices,
- Image preprocessing,
- Intellectual data analysis,
- Predictions calibration,
- The stage of diagnosis.

It is evident that the solution of a specific application problem is associated with each of these stages. In addition to that, it is necessary to take into account the specifics of the corresponding problem when solving them. Thus, at the data collection stage, it is necessary to support the transfer of images from various types of medical devices. At the image preprocessing stage, images of various devices must be brought to the common view. At predictions' calibration stage the specifics of the specific medical equipment should be taken into account. Finally, when making a final diagnosis it is necessary to diagnose not only the main, but also the accompanying diseases.

III. The Process of Solving the Problem

Let's first consider the stage of preprocessing a set of images X.

Let some transformation $g: X \to X'$ be given for performing image preprocessing. The resulting image X' has the following limitations: $x' \in \in [0 \dots 255]^{w \times h \times c}, \sim \forall x' \in X'$, where w and h are width and height of the image and c is the number of channels.

That is, the initial X-ray images are reduced to a common format with the same dimension, which simplifies their subsequent processing.

Let's consider the next stage of image analysis. Let $D = \{d_1, d_2, \dots, d_k\}$ be the set of possible pathologies. Notation $d_i \in x$ is used to show that pathology d_i is present at the image x. Since it is necessary to detect all diseases present in the image, then for each input image $x \in X'$ a k -dimensional vector $y = = \left(y_i \middle| y_i = 1(d_i \in x)\right)$ is assigned, where $1(x)$ is an indicator function.

Let $Y = \{y\}$ be the set of all possible pathologies. Thus, at the stage of image analysis, it is necessary to construct a transformation $C: X' \to Y$.

To solve this problem, a convolutional neural networks approach [6–8] is proposed. Inputs for the neural network are images $x \in X'$ and outputs are probability vectors $p(x) = p\left(p_i \middle| p_i = P(d_i \in x)\right)$.

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At the stage of converting the vector p into y, it is necessary to build an algorithm $I: P \rightarrow Y$. It is intended for results calibration and interpretation. At the same time, it is necessary to take into account the specifics of the X-ray equipment (the manufacturer, the shooting conditions and other factors). A simple threshold selection algorithm is proposed.

Let's assume that a vector of threshold values $T = (t_1, t_2, \dots, t_k), \sim t_i \in (0,1)$ is given for each specific device. Interpretation transform is defined as following: $I(p) = \left(\hat{y}_i | \hat{y}_i = 1(p_i > t_i)\right)$.

Thus, the process of chest pathologies analysis is described in general terms. The most interesting stage in this case is the image analysis stage, since the performance of the entire intellectual framework depends on the quality of its solution.

IV. DenseNet architecture

A well-known DenseNet architecture [9, 10] is chosen for image analysis. An image x of dimensionality $384 \times 384 \times 3$ is fed into the network. As a result of the transformation performed by the neural network, the resulting feature description of the image $f(x)$has dimensionality of $12 \times 12 \times 2048$.

With the help of linear layers composition feature description is projected into the vector $L = = (l_1, l_2, \dots, l_k | l_i \in \mathcal{R})$. Number of components k in that vector matches the total number of lung pathologies under analysis. To interpret the result in terms of probability, as required by the process, it is necessary to apply a sigmoid function to the vector L component-wise: $p(x) = \left(\sigma(l_1), \sigma(l_2), \dots, \sigma(l_k)\right)$, where $\sigma(x) = = \frac{1}{1+e^{-x}}$. DenseNet architecture is presented in Fig. 1.

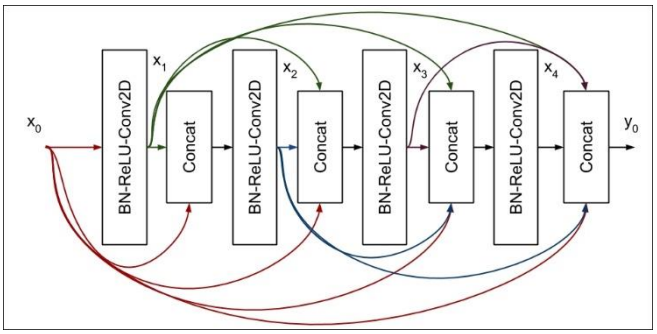

Fig. 1. DenseNet architecture

As a result of the intelligent image analysis, besides pathologies recognition, it is also vital to interpret the outputs of the neural network. That interpretation will be used later by the radiologist to validate or correct the diagnosis made by the algorithm.

To interpret the prediction, it is proposed to use a heat map constructed by the CAM algorithm.

Let $f(x)_{ij}^k$ be a pixel of k-th feature map of the resulting image vector description created by the neural network. The operation Global Average Pooling can be defined as follows: $F^k(x) = \frac{1}{144}\sum_{i=1}^{12}\sum_{j=1}^{12} f(x)_{ij}^k$. The heat map is defined by the equation $Y^c = \sum_{i=1}^{k} w_i^c F^i$, where c is the sequence number of the pathology under consideration, w_i^c is the weight of the connection between $k-$th feature map and c-th pathology inside the dense classification layer.

V. Experiments

To test the operability of the algorithmic solution, experiments were conducted using images from the NIH [11] and RSNA radiographic image databases.

The RSNA database contains X-ray images with annotations. The total amount of data is about 30,000 images. There are 3 classes available for recognition: *Normal*, *Lung Opacity*, *Not Normal/No Opacity*. To simplify the experiment, only the first 2 classes were used. In addition to the class labels, the annotation of the images contains the coordinates of the areas in the image that the experts considered important when making the final diagnosis. Such data are not used in this study. The results of evaluation on the test set are presented in Table I.

TABLE I. RSNA EVALUATION RESULTS

	Precision	Recall	F1
Normal	0.947	0.971	0.959
Pneumonia	0.956	0.919	0.937

The second data set (NIH) consists of 112 thousand images. 14 different lung pathologies are available for classification. A distinctive feature of the data set is that pathologies can appear simultaneously. The data set is very diverse, it contains images that differ in brightness and contrast. Some images have labels that indicate the orientation of the X-ray image.

The NIH database is not balanced by the number of classes which significantly complicates the process of training a neural network. To overcome this complexity, the following approach is proposed.

Each training sample x is assigned a vector w which is used to scale loss function for that training sample. For each unique pathology label $c \in T$ two weight coefficients w_c^+ and w_c^- are calculated. The first one is used for positive images relatively to pathology c, the second one - for negatives.

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$$w_c^+ = \frac{\alpha_c(N_c - N_c^+)}{\alpha_c(N_c - N_c^+) + N_c^+},$$

$$w_c^- = \frac{N_c^+}{\alpha_c(N_c - N_c^+) + N_c^+}.$$

In that equation N is the total number of training samples, N_c^+ - the number of samples with pathology c, α_c is a hyperparameter. The resulting weight w is calculated as $w = (w_i | i \in T), w_i = 1(i \in x) * w_i^+ + 1(i \notin x) * w_i^-$.

To increase the variety of images and combat the retraining of the neural network, the augmentation of input data is conducted. The following operations are considered: *Center Crop*, *Random Horizontal Flip*, *Random rotation*.

VI. Practical implementation and the examples of operation

A software package has been developed based on the algorithmic solution of the problem. This complex automates the process of diagnosis, which greatly simplifies the work of radiologists.

The software package consists of the following modules:

- Algorithmic module,
- A database with verified images and diagnoses to them,
- Module for visualization and interpretation of results,
- Calibration module,
- User and Expert Interfaces.

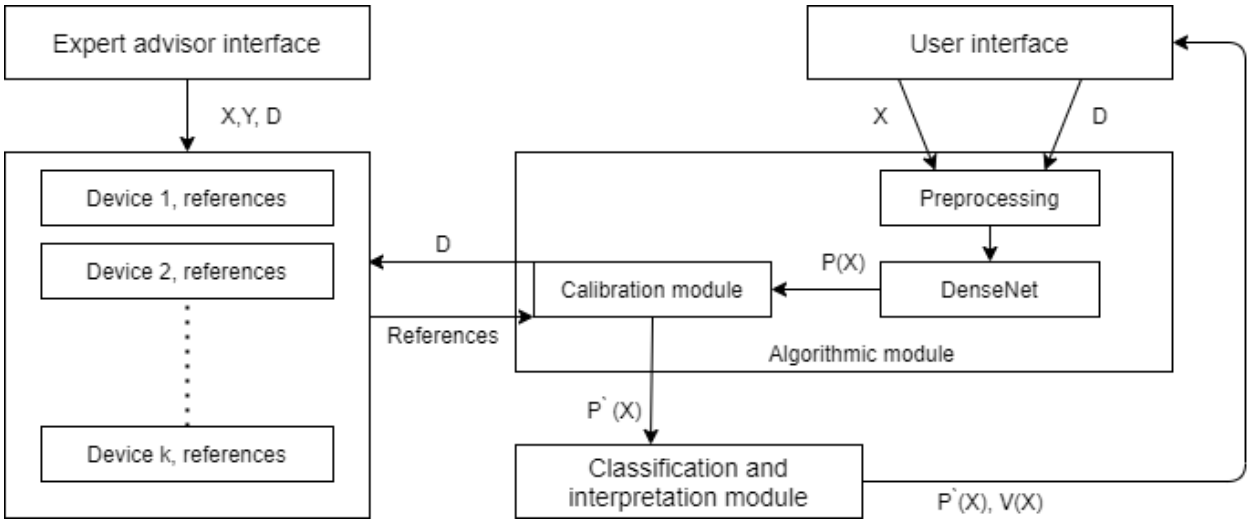

Fig. 2. Software package architecture

The results of the evaluation are presented in Table II. They confirm the efficiency of the proposed algorithm for its use in practice.

TABLE II. NIH evaluation results

	AUC-ROC	**F1**	**F1(calibrated)**	**Threshold**
No Finding	0.792	0.740	0.770	0.001
Atelectasis	0.816	0.397	0.420	0.7994
Consolidation	0.797	0.207	0.219	0.9790
Infiltration	0.708	0.387	0.426	0.001
Pneumothorax	0.885	0.383	0.422	0.959
Edema	0.883	0.237	0.237	0.9590
Emphysema	0.896	0.287	0.347	0.979
Fibrosis	0.799	0.092	0.110	0.979
Effusion	0.883	0.556	0.555	0.599
Pneumonia	0.791	0.068	0.096	0.979
Cardiomegaly	0.891	0.301	0.351	0.979

The architecture of the software package is presented in Fig. 2.

VII. Conclusion

The article addresses the problem of chest pathologies intellectual analysis. The process of the analysis is carried out using X-ray images. That images are obtained from different types of technical devices. An approach to solving the problem is proposed, including preprocessing of source images, interllectual analysis, calibration of results and diagnosis. Experiments have been conducted to confirm the efficiency of this approach. Based on the results of theoretical research, a software technology has been developed that provides an effective solution to the problem.

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