Chest Pathologies Analysis System Based On X-Ray Images Using Neural Network

Andrew Naumovich
Faculty of Applied Mathematics and Computer Science
Belarussian State University
Minsk, Belarus
andrew.naumovich@yandex.ru

***Abstract*—The paper deals with the problem of chest pathologies recognition based on images obtained from protable fluorographic devices. An approach based on the neural network technology is proposed. A complex algorithmic solution is delevoped. The algorithm is implemented as a specialized software package.**

***Keywords*—neural network, recognition, supervised learning, X-Ray image**

I. Introduction

The epidemiological situation in the country has revealed the necessity of population medical screening. This standard mean allows one to identify lung pathologies at an early stage quickly. Portable digital fluorography equipment is often used for medical screening. Such a type of the equipment makes it possible to obtain high-quality digital images with lung tissues visible. Therefore, the task of effective medical image processing technologies development is currently urgent [1], [2].

II. The problem of chest pathologies recognition

Algorithmic solutions to that problem exist [3], [4]. They are primarily based on X-Ray pathology classification using deep learning. Authors of the approach use DenseNet neural network for that purpose. The evaluation results are considered to be suitable for pratical usage.

However, during the analysis of existing solutions a few problems were discovered.

The first of them is that the algorithmic solution doesn‘t take into account the specifics of a particular medical device. Images taken with diverse devices can be very different and thus can be misclassified.

The second problem is purely technical in nature. Any medical device is a highly specialized device. Therefore, running e.g. a neural network on such a device is almost impossible.

The third one is connected with the interpretation of the recognition results. It is necessary for specialists-radiologists to validate their diagnosis. The implementation of that feature requires the development of specialized procedures for organizing effective medical image processing.

Thus, we can conclude that the existing algorithms actually perform the task of flourographic image analysis. However, this is not enough to make a final verdict.

III. Solving the problem

The development of the software package focused on portable equipment can be become a productive solution to the problem. It should not only increase the efficiency of the pathology diagnosis process, but also automate the entire process as much as possible [5]. The algorithmic solution should allow one to perform (in conditions of limited resources) image analysis quickly. In addiction to that, iterpretation and results visualization is required. Moreover, it is necessary to solve the non-trivial problem of technological compatibility of all heterogeneous components included in the software package.

The following architecture and composition of the software package is proposed. It is based on neural network data processing technology [6]. The complex consists of the following main modules:

- Algorithmic module.
- Database with reference images.
- Module for visualization and interpretation of results
- Calibration module.
- User interface.
- Expert advisor interface.

The overall architecture of the software package is shown in Fig. 1.

Due to the limited scope of paper, only the algorithmic module and database module of the software package will be considered.

IV. Algorithmic module

Let X be an input image and D - medical equipment information. As the result of the classification, each image X is assigned a vector of probabilities $P(X)$ of the presence of pathologies from the set T. With the help of the calibration module and the information D vector $P(X)$ is transformed into vector $P'(X)$ which, in turn, is used for a final conclusion. In addition to the probabilities of pathologies, the algorithmic module

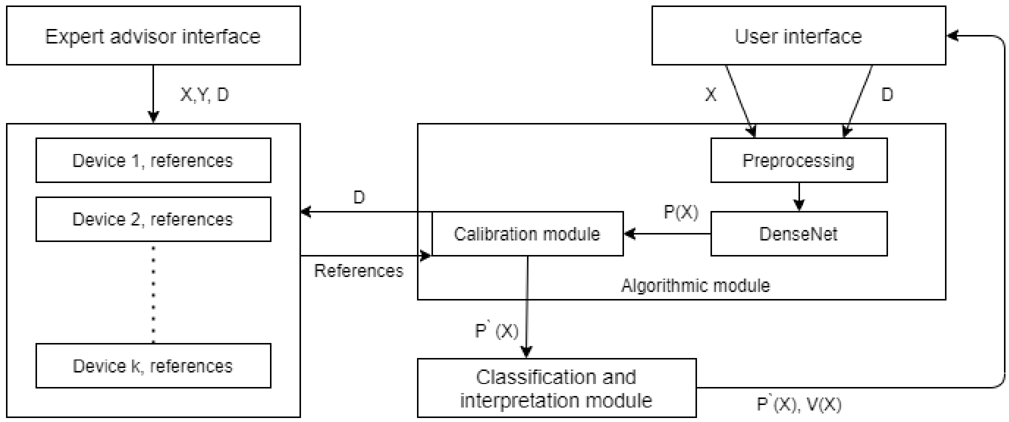

Figure 1. Software package architecture

should provide the user with the ability to interpret the predictions made.

Thus, the process of operation of the algorithmic module can be represented in the form of sequential execution of severals tages: pre-processing , classification of pathologies, calibration of predictions and interpretation of results. It is necessary to consider some of steps of the algorithm.

The key objective was to choose neural network architecture for image analysis. AlexNet, ResNet, EfficientNet and DenseNet architectures were considered. To measure their perfomance RSNA dataset was used and the results are presented in Table I.

Table I
MODEL SELECTION

	AlexNet	*ResNet50*	*EfficientNetB4*	*DenseNet121*
Accuracy	0.889	0.931	0.949	0.936

DenseNet121 was chosen for image encoding [7], [8] despite the fact that EfficientNet shows better results in classification. DenseNet121 has much fewer parameters and shows higher throughput capacity.

A grayscale image of size 384×384 is fed into the network. As a result of the network operation, two tensors are constructed. The first one is a vector of probabilities of pathologies. The second is the feature map of the last convolutional layer. This feature map is then used to visualize the results. A schematic architecture of the network is presented in Fig. 2.

The prediction calibration module is based on the threshold selection method. The appropriate threshold is selected for each pathology label (taking into account the information D). For this purpose, information about medical equipment and reference images is used, which is stored in the database module.

The interpretation and visualization procedure operates feature maps obtained from the last convolutional layer

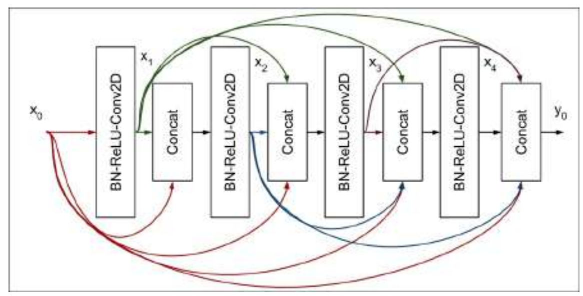

Figure 2. DenseNet architecture

of the network. Heatmaps of pathologies are constructed using the GradCAM algorithm.

V. DATABASE MODULE

The module is designed to store images from various devices and annotations for these images. Additionally, information about medical equipment must be stored.To ensure high speed of the algorithmic module, the images should be structured according to the medical equipment they belong to.

As medical screening is performed continuously, many new images appear with an unverified diagnosis made by the algorithm. Therefore, it is proposed to present the database module in the form of 2 databases: Hotbase and Warehouse. Warehouse stores data validated by an expert. Hotbase contains model's predictions that wait for validation. After validation completion data from Hotbase flows into Warehouse and can be used for model finetuning.

To organize the validation process, the expert interface is introduced.

Fig. 3 shows schema of the database module.

VI. IMPLEMENTATION DETAILS

The software package is implemented in Python using “tensorflow“ and “tensorflow.keras“ machine learning libraries. These libraries provide a framework for quick

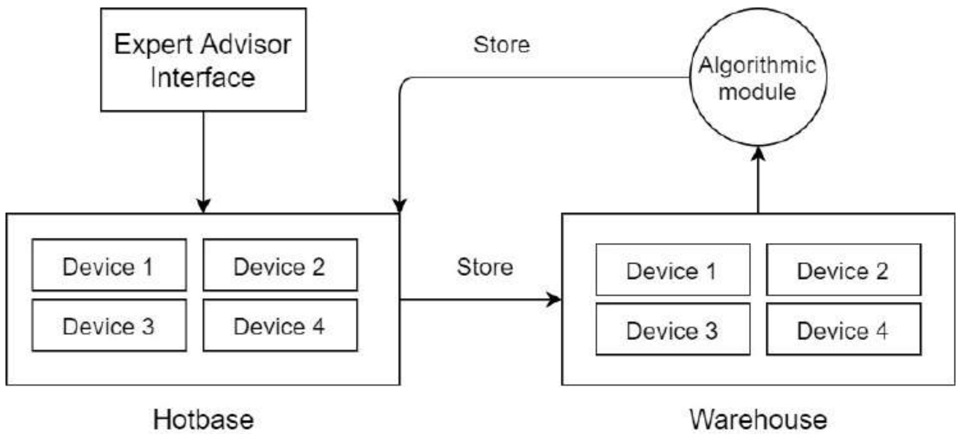

Figure 3. Database schema

building and training of the neural networks. For these purposes, "tensoflow" mathematical operations are represented as a computational graph with the possibility of their automatic differentiation.

A separate problem is the organization of effective interaction between the user and the neural network. To solve this problem, we suggest using Tensorflow Serving. To call the model and get the results, we propose an approach based on the joint use of containerization and the HTTP protocol.

VII. Experiments and evaluation

The effectiveness of the approach proposed is confirmed by the results of experiments. Two X-Ray images datasets are used: RSNA and NIH [9].

RSNA dataset is a collection of annotated X-Ray images. The total size of the dataset is around 30000 samples. There are three classes available for classification: Normal, Lung Opacity, Not Normal / No Opacity. For simplicity only the first two classes were used. In addition to anomaly labels dataset's annotation provides bounding box for a pathology region which were not used in our research.

Evaluation results for the RSNA dataset are shown in Table II. The overall classification quality is 0.950. The test set includes 6045 samples, classes are balanced.

Table II
RSNA evaluation results

	Precision	***Recall***	***F1***
Normal	0.947	0.971	0.959
Pneumonia	0.956	0.919	0.937

NIH Chest X-Ray dataset is comprised of approximately 112 thousands of images from over 30 thousands of patients. The dataset contains 14 different lung patholigies that may occur at the same time. However, some pathologies were not actually found in the dataset (no samples of that class) and therefore excluded from the classification report.

The main difficulty we faced with that dataset is images diversity (different brightness, contrast, labels at the image). Moreover, the dataset is highly imbalanced which makes the training process more complicated.

To prevent the neural network from overfitting and to expand input data distribution artificially an extensive data augmentation is used. It includes the following transformations:

- Center crop.
- Random horizontal flip.
- Random rotation.

DenseNet network has been training for 10 epochs, 4500 steps each with batch size 8. Adam optimizer was used with default parameters $\alpha = 10^{-4}, \beta_1 = 0.9, \beta_2 = 0.999$.

The evaluation results on NIH test subset (22420 samples) are shown in Table III. As a calibration mechanism for this data set, we use threshold selectionmethod performed at the validation part of the dataset.

Table III
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	0.222	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

An example of a pathology heatmap produced by GRAD-CAM algorithm is shown in Fig. 4.

Figure 4. Heatmap example

VIII. Conclusion

The paper presents a software package for X-Ray image processing from portable fluorographic devices. A complex algorithmic solution is proposed, which makes it possible to automate the process of image analysis. At the same time, it shows a good quality of prediction. In addition, it provides the ability to interpret the received predictions and has a high speed of operation. In view of the above, we can assume that the approach proposed in this paper has good practical prospects.

One of the problems mentioned is still unsolved. It is connected with the diversity of X-Ray images retrieved from different medical devices. To address that problem Domain Adaptation techniques can be used.Finally, the neural network can benefit from using bounding boxes for pathology regions. For that purpose Visual Image Transformer and Mask-RCNN architecture can be used.

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Система анализа патологий грудной клетки на основе рентгеновских изображений с использованием нейронной сети

Наумович А.И.

В условиях пандемии для раннего обнаружения патологии легких часто используют портативные флюорографические устройства. Из-за высокой загруженности специалистов-рентгенологов актуальной является задача разработка эффективных технологий обработки и анализа изображений, ориентированных именно на такие устройства. В рамках работы предлагается программная система, архитектура и состав позволяет эффективно решать поставленную задачу. Она состоит из 6 основных модулей: алгоритмического модуля, базы данных, модуля визуализации и интерпретации, а также модуля калибровки. Алгоритмическое решение основано на нейросетевой технологии обработки данных с использованием фреймворка DenseNet. Прототип программной системы реализован на языке Python с использованием библиотек машинного обучения Tensorflow и Keras. Эффективность предложенного подхода демонстрируется на наборах рентгенографических снимков из базы данных RSNA и NIH.

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