Pre-trained CNN models trained on general image datasets can be fine-tuned using ultrasound images containing artifacts. By leveraging the feature representations learned from diverse datasets, transfer learning enables the CNN to adapt to artifact-rich ultrasound images more effectively.

By training CNNs to recognize and process artifacts in ultrasound images, it can enhance the robustness and reliability of automated diagnostic systems, ultimately improving patient care and outcomes in ultrasonic diagnostic imaging.

Another difficulty is the structure of the organ itself. Although the thyroid gland was chosen as an example for research in this article as one of the easiest organs to analyze, it has its own characteristics. The thyroid gland consists of lobes. On both sides of the organ there are carotid arteries, in which there is an active blood flow, sometimes it looks pulsating on ultrasound. This may prevent the neural network from performing a high-quality analysis. Moreover, in the middle of the organ is the larynx, which also needs to be distinguished from pathology.

However, the thyroid gland is still an easy organ to diagnose. In comparison, for example, with abdominal organs, thyroid ultrasound rarely shows a nebula associated with a large amount of subcutaneous fat in the patient.

Figure 8: Thyroid gland ultrasonography example [11]

Due to the fact that every person has a larynx and carotid arteries, the neural network will learn to iso late them and accept them as normal thanks to a large training sample.

In the picture 6, the round blackouts on the sides of the thyroid gland are the carotid arteries. And the round gray area in the middle is the larynx.

VI. OSTIS Technology integration

Working with artificial intelligence is not limited to neural networks alone. One of the strong representatives

Figure 9: Thyroid gland ultrasonography in longitudinal projection example [12]

of symbolic artificial intelligence is OSTIS Technology. [13]

1) By integrating this technology into the described project, the following results can be achieved:

2) Thanks to the implementation of OSTIS, it is possible to additionally train the neural network not only on ongoing research, but also on feedback from medical experts.

3) An intelligent assistant system can be integrated into the application, which will determine not only the presence or absence of pathology, but will also

be able to analyze the general state of the patient's health and draw conclusions about what a particular problem in the body is related to.

4) The treatment regimen for some pathologies is described by protocols and is similar in different patients. Thus, the system integrated with OSTIS will be able not only to check for problems in the organ, but also to offer appropriate treatment. Thus, the doctor will not have to write it himself. It will only be enough to edit a ready-made treatment regimen.

5) OSTIS is based on a knowledge base. Therefore, the system takes all the information from there and draws conclusions based on it. Although neural networks are a fairly productive tool, they have a large percentage of error. OSTIS will help to minimize the number of incorrect answers and reduce the reliability of the system analysis to 99

VII. Conclusion

Medical ultrasonography, a widely-used diagnostic imaging modality, plays a pivotal role in healthcare by providing real-time images of internal organs and tissues. However, the manual interpretation of ultrasound images can be challenging and time-consuming, often requiring specialized expertise. In recent years, significant advancements in artificial intelligence (AI) and image

analysis techniques have revolutionized medical imaging, paving the way for the automation of ultrasonography interpretation through intelligent image analysis.

This article provides a comprehensive overview of the application of AI in medical ultrasonography and its potential to enhance diagnostic accuracy, efficiency, and patient care. It proposes one of the solutions which can help to minimize the number of errors associated with the human factor. After all, an ultrasound diagnostic doctor should be extremely attentive and focused throughout the entire work shift. However, the study may take place at night, the person may be in poor health, there maybe too many patients, the doctor may not have enough experience. These factors directly affect the quality of the study and the timeliness of diagnosis of life-threatening pathologies.

At the moment, artificial intelligence is rarely used on a large scale due to the fact that it cannot completely replace humans. Especially in such an area as medicine. This sphere doesn't forgive mistakes. The option proposed here is a compromise between using only artificial intelligence and only human power.

The article describes an algorithm for creating an intelligent system for determining thyroid pathologies using image analysis. During the work, the advantages and disadvantages of this approach were considered, and options for overcoming the difficulties that will have to be faced during the implementation of the project were proposed. The subject area was also analyzed, the process of ultrasound examination, the principle of operation of the ultrasound machine were described. Moreover, an analysis of existing publications and projects on related topics was carried out.

Integration of the system with OSTIS technology was also proposed.

The automation of medical ultrasonography through intelligent image analysis holds great promise for im- proving diagnostic accuracy, efficiency, and patient outcomes. By harnessing the power of AI and deep learning techniques, clinicians can leverage advanced tools to enhance their diagnostic capabilities and provide better patient care. However, further research, validation, and collaboration between clinicians, researchers, and tech- nologists are essential to overcome challenges and realize the full potential of AI-driven automatization in medical imaging.

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АВТОМАТИЗАЦИЯ УЛЬТРАЗВУКОВОГО ИССЛЕДОВАНИЯ ЩИТОВИДНОЙ ЖЕЛЕЗЫ С ПОМОЩЬЮ ИНТЕЛЛЕКТУАЛЬНОГО АНАЛИЗА

Черкас Е. О.

Эта статья предлагает алгоритм автоматизации про- цесса медицинской ультразвуковой диагностики с по- мощью интеллектуального анализа. Действия описаны на примере исследования щитовидной железы. Допол- нительная проверка результата со стороны нейронной сети позволяет начинающим докторам чувствовать себя более уверенно и минимизировать влияние человеческого фактора на качество диагностики.

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Chest X-ray Image Processing Based on Radiologists' Textual Annotations

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Abstract—More than 11,000 chest x-ray images and their corresponding text annotations were analyzed, and the first pilot studies on image processing tailored to text annotations of radiology specialists were conducted. An image processing pipeline for a database and for a neural network has been developed. The prediction of the parameter "Overall percent of abnormal volume" was performed and the mean absolute error (MAE) for the InceptionResNet50V2 neural network model was 11.073. **Keywords—medical image processing, medical image analysis, deep learning, computer-aided diagnosis, chest x-ray, textual annotations of lung lesions**

XIII. Introduction

In this article the main efforts are made to analyze and prepare Chest X-ray (CXR) images and corresponding text data annotations. A total of 11,493 non-empty CXR images were downloaded (in fact there are 13,521 instances, however 2,028 of them were empty and not downloaded from TB Portals [1] website).

On the CASE BROWSER [2] website CXR text annotation can be viewed as in Fig. 1 along the following path:

Patient: № → Case → View Imaging Study → Diagnostic Report.

All CXR textual data in corresponding JSON files as well as on the CASE BROWSER [2] 1 and TB DEPOT [3] websites are divided into three blocks of information (Fig. 2):

Figure 1: CXR textual annotation on the CASE BROWSER [2] website.

- anonymized patient information (gender, age, country, diagnosis, etc.);
- CXR radiologists' textual annotations, which is currently being analyzed in this article;
- reatment history, which includes medications and treatment days.

Second data block in Fig. 2 or "CXR annotations" can also be roughly divided into three groups:

- CXR annotations, as if it were a computed tomography (CT) scan, in total 106 images
- CXR annotations of the six lobes of the lung (sextants) with twenty parameters for each sextant, in total 546,364 non-empty text annotations in 9,154 CXR images;

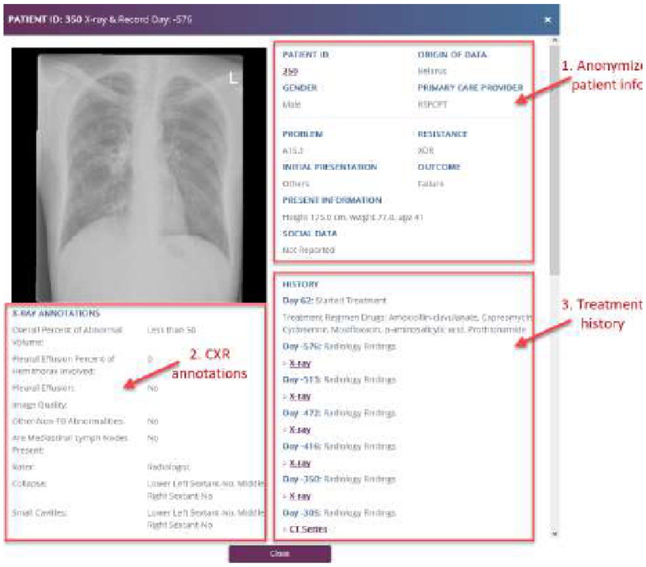

Figure 2: CXR case information on the TB DEPOT [3] website.

- CXR annotations of the lung as a whole using six parameters, see "Overall Characteristics" tab in Fig. 1, in total 11,387 CXR images.

For clarity, the image categories are shown in the diagram below, Fig. 3.

The results of the analyses of the annotations of these groups are summarized below. Further, after the data