Thyroid Gland Ultrasonography Automation Through Intelligent Analysis

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***Abstract*—This article proposes an algorithm for automating the process of medical ultrasound diagnostics using intelligent analysis. The actions are described using the example of a thyroid gland study. Additional verification of the result by the artificial intelligence allows novice doctors to feel more confident and minimize the influence of the human factor on the quality of diagnosis.**

***Keywords*—Ultrasonography automation; thyroid gland ultrasonography; artificial intelligence in medicine; intelligent image analysis; neural networks; deep learning; convolutional neural network; OSTIS; OSTIS Technology integration;**

I. Introduction

Currently, thyroid problems are widespread in the population of the Republic of Belarus. This is due to the disaster at the Chernobyl nuclear power plant in 1986. The Gomel and Mogilev regions of the country were the most affected. In the first 10 days after the accident, the concentration of radioactive iodine was increased in some territories of the republic, which led to an increase in cases of thyroid pathology.

According to the Ministry of Health for 2021, 3.8% of the population of Belarus has pathology of this organ. There is an increase in the incidence every year.

Therefore, improving the technique of ultrasound diagnostics of thyroid pathologies is an urgent issue of our time.

Neural networks are gaining more and more popularity. They are often used in medical diagnostics. For example, to process test results, improve the quality of magnetic resonance imaging, analyze large amounts of data, and even perform surgical interventions.

By connecting artificial intelligence to the research, it is possible to reduce the influence of the human factor on the quality of the diagnosis. The result of ultrasound often depends on the doctor's experience. After all, this type of diagnosis involves processing the results directly at the time of the study. In this regard, there remains a high risk of missing an important feature of the organ structure.

II. Domain analysis

Diagnostic ultrasound is a safe, non-invasive diagnostic technique used to image inside the body. Ultrasound probes, called transducers, produce sound waves that have frequencies above the threshold of human hearing (above 20KHz), but most transducers in current use operate at much higher frequencies (in the megahertz (MHz) range).

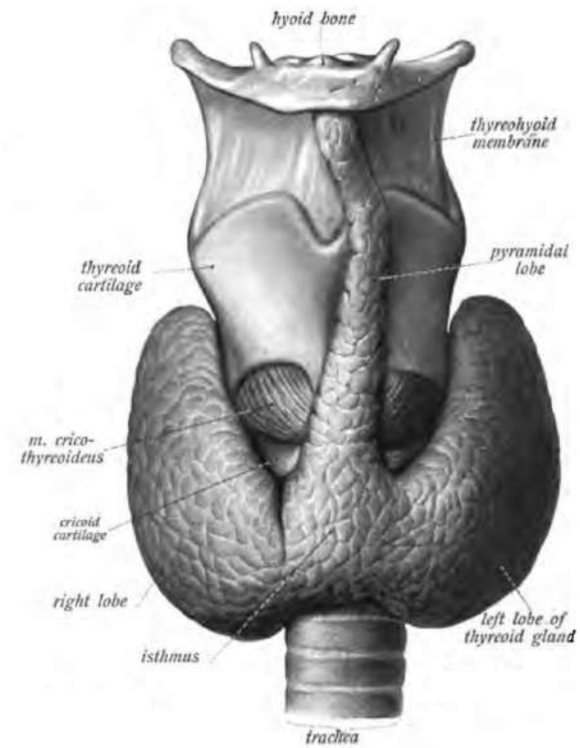

Figure 1. Thyroid gland scheme [1]

Ultrasound waves are produced by a transducer, which can both emit ultrasound waves, as well as detect the ultrasound echoes reflected back. In most cases, the active elements in ultrasound transducers are made of special ceramic crystal materials called piezoelectrics. These materials are able to produce sound waves when an electric field is applied to them, but can also work in reverse, producing an electric field when a sound wave hits them. When used in an ultrasound scanner, the transducer sends out a beam of sound waves into the body.

The sound waves are reflected back to the transducer by boundaries between tissues in the path of the beam (e.g. the boundary between fluid and soft tissue or tissue and bone). When these echoes hit the transducer, they generate electrical signals that are sent to the ultrasound scanner. Using the speed of sound and the time of each echo's return, the scanner calculates the distance from the transducer to the tissue boundary. These distances are then used to generate two-dimensional images of tissues and organs.

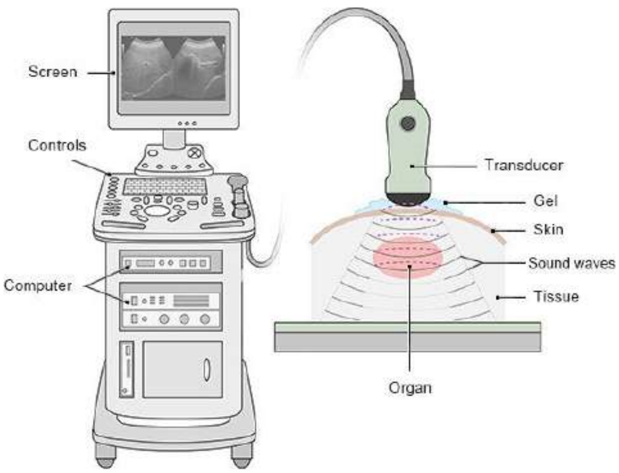

Figure 2. Ultrasound system scheme [2]

During an ultrasound exam, the technician will apply a gel to the skin. This keeps air pockets from forming between the transducer and the skin, which can block ultrasound waves from passing into the body. [3]

Ultrasound is a method of shadows. This study does not show a volumetric model of human organs, however, it allows to estimate the size, volume, density, correct location of the organ relative to the entire body, the presence of fluid in the area under study, as well as cysts, tumors and other formations. Moreover, minimally invasive operations are also performed under the control of an ultrasonic sensor. This allows the doctor to monitor the progress of the study without having to make large incisions on the human body.

During the ultrasound examination, the signal passes through the tissues of the human body and returns back. Solid dense organs reflect the sound signal well. Therefore, areas such as bones and stones look white on ultrasound.

Internal organs and soft tissues are usually represented by different shades of gray depending on the density of the organ.

Voids and liquid are shown in black on the screen, because in this case there are no obstacles in the signal path, and therefore it is practically not reflected at all.

Depending on the diagnostic areas, different types of sensors are used. The linear sensor has a rectangular image. The 2D sensor has a wide aperture, and its central frequency is in the range of 2.5-12 MHz (3D-4D is in the range of 7.5-11 MHz). Piezoelectric crystals in a linear sensor are located in the same plane, so such a sensor provides good visibility at close range. It is used for ultrasound of blood vessels, muscles, performing anesthesia under ultrasound control, examining mammary glands, thyroid gland and other superficial organs.

Figure 3. An example of an ultrasound made by a linear sensor [4]

In a convex sensor, piezoelectric crystals are arranged curvilinearly. Therefore, such a sensor visualizes deeply located structures well. The convexic 2D sensor has a wide aperture, and its central frequency is 2.5-7.5 MHz (3D, 4D — 3.5-6.5 MHz). With its help, ultrasound of the fetus, pelvic organs, and abdominal cavity is performed.

The sector phased array sensor is so named after the type of piezoelectric element device, which is called a phased array. The phased array sensor has a small aperture and a low frequency (the central frequency is 2-7.5 MHz). The shape of the scanning area is almost triangular. These sensors have poor resolution in the near field but give a good view at depth. They allow to observe structures through a narrow intercostal gap. With its help, ultrasound of the heart, abdominal organs, and brain is performed.

For ultrasound diagnosis of the thyroid gland, only a linear sensor is often used. However, it is possible to see a trapezoidal image on the screen of the device. This is due to the fact that the linear sensor has the function of a virtual convection, which allows to make the viewing plane wider and accommodate the entire organ there.

The convex sensor is used only when the thyroid gland is enlarged and the patient's body weight is too large.

Also ultrasound information can be displayed in several ways:

A-mode: As spikes on a graph (used to scan the eye).

B-mode: As a 2-dimensional anatomic images (used during pregnancy to evaluate the developing fetus or to evaluate internal organs).

Figure 4. An example of an ultrasound made by a linear sensor with virtual convex mode [5]

M-mode: As waves displayed continuously to show moving structures (used to evaluate the fetus's heartbeat or to evaluate heart valve disorders).

B-mode ultrasonography is most commonly done.

Sonography can be enhanced with Doppler measurements, which employ the Doppler effect to assess whether structures (usually blood) are moving towards or away from the probe, and its relative velocity. By calculating the frequency shift of a particular sample volume, for example a jet of blood flow over a heart valve, its speed and direction can be determined and visualised. This is particularly useful in cardiovascular studies (sonography of the vasculature system and heart) and essential in many areas such as determining reverse blood flow in the liver vasculature in portal hypertension. The Doppler information is displayed graphically using spectral Doppler, or as an image using color Doppler (directional Doppler) or power Doppler (non directional Doppler). This Doppler shift falls in the audible range and is often presented audibly using stereo speakers: this produces a very distinctive, although synthetic, pulsing sound.

Doppler ultrasonography uses changes that occur in the frequency of sound waves when they are reflected from a moving object (called the Doppler effect). In medical imaging, the moving objects are red blood cells in the blood. Thus, Doppler ultrasonography can be used to evaluate.

It is used to evaluate how well the heart is functioning (as part of echocardiography), to detect blocked blood vessels, especially in leg veins, as in deep vein thrombosis, when veins are blocked by a blood clot. To detect narrowed arteries, especially the carotid arteries in the neck, which carry blood to the brain.

Strictly speaking, most modern sonographic machines do not use the Doppler effect to measure velocity, as they rely on pulsed wave Doppler (PW). Pulsed wave machines transmit pulses of ultrasound, and then switch to receive mode. As such, the reflected pulse that they receive is not subject to a frequency shift, as the insonation is not continuous. However, by making several measurements, the phase change in subsequent measurements can be used to obtain the frequency shift (since frequency is the rate of change of phase). To obtain the phase shift between the received and transmitted signals, one of two algorithms is typically used: the Kasai algorithm or cross-correlation. Older machines, that use continuous wave (CW) Doppler, exhibit the Doppler effect as described above. To do this, they must have separate transmission and reception transducers. The major drawback of CW machines, is that no distance information can be obtained (this is the major advantage of PW systems - the time between the transmitted and received pulses can be converted into a distance with knowledge of the speed of sound).

In the sonographic community (although not in the signal processing community), the terminology "Doppler" ultrasound, has been accepted to apply to both PW and CW Doppler systems despite the different mechanisms by which the velocity is measured.

Spectral Doppler ultrasonography shows blood flow information as a graph. It can be used to assess how much of a blood vessel is blocked.

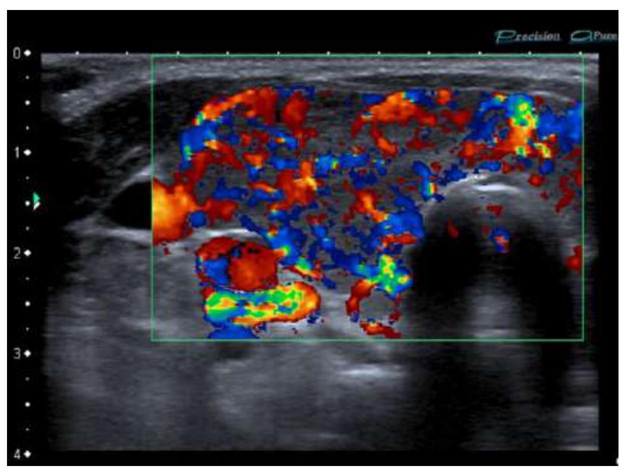

Figure 5. An example of thyroid dopplerography [6]

III. Overview of existing approaches

There are already a lot of scientific articles on the processing of ultrasound results using artificial intelligence. Some of them are even applied in practice. Moreover, there is a S-Detect (Samsung RS80A ultrasound system, Seoul, Korea). It is the first commercially available ultrasound CAD based on deep learning technology for thyroid imaging. [7]

S-Detect is a computer-aided detection (CAD) software developed by Samsung Electronics for use with their RS80A ultrasound system. It is designed to assist radiologists and clinicians in the detection and characterization of breast lesions during ultrasound examinations.

Figure 6. An example of Samsung S-Detect-system interface [8]

This system has a lot of pros: it provides real-time feedback to the clinician during the examination, enabling immediate assessment and decision-making regarding lesion characterization and management. More than that, the software provides standardized reporting templates that facilitate structured documentation of lesion characteristics, including malignancy probability scores and recommended management options. This promotes consistency and completeness in reporting. S-Detect seamlessly integrates with the RS80A ultrasound system's workflow, allowing for efficient and streamlined use within clinical practice. It is user-friendly and does not significantly disrupt the examination process.

But S-Detect is primarily designed for breast lesion characterization and may not be suitable for other types of lesions or organs. Its utility is limited to breast ultrasound examinations and may not address the full spectrum of diagnostic challenges encountered in clinical practice. While S-Detect is user-friendly, clinicians may require some time to familiarize themselves with the software's features and functionality. Training and ongoing education may be necessary to optimize its use and interpretation. Moreover, The implementation of S-Detect may incur additional costs associated with software licensing, training, and maintenance. Clinics and healthcare facilities must consider the financial implications before adopting the technology.

There are another people who have been automating ultrasound diagnostics of the thyroid gland using artificial intelligence. For example in 2021 scientists from Romania published their article "Intelligent Diagnosis of Thyroid Ultrasound Imaging Using an Ensemble of Deep Learning Methods".

They developed a CNN-VGG ensemble fused from two models: a pre-trained fined tuned model VGG-19 and an efficient lightweight CNN model. The proposed ensemble method proved to be an excellent and stable classifier with a good performance in terms of overall sensitivity (95.75%), specificity (98.43%), accuracy (97.35%), AUC (0.96), positive predictive value (95.41%) and negative predictive value (98.05%). [9]

Also there are scientists from China who published an "Artificial intelligence in thyroid ultrasound" article in 2023. Their research is more focused on the prevention and early detection of the thyroid cancer. They also used deep learning algorithms to achieve this goal. They tests different types of DL-based neural networks. [7]

The research of the above-mentioned scientists has been very successful. Their authors placed great emphasis on training the neural network to make diagnoses and look for pathology in ultrasound diagnostic images.

In the current work, a simpler and more global approach is considered: the neural network does not diagnose, but only assists the doctor. Their joint work makes it possible to minimize the errors of both the doctor and the software. The approach is described using the example of thyroid gland examination, but it can also be used in ultrasound diagnostics of other organs.

Also in this article, it is proposed to analyze not individual images, but a video recording of the entire research process.

Based on the approach described below, it is planned to develop a software product in the future and implement it into the work of a medical institution in a test mode.

Also, in the future, it is planned to develop the idea in such a way as to process not the final product of the work of some software: a visual representation of the ultrasound process, but the initial product, that is, ultrasonic signals. This will make the processing process faster.

IV. Proposed approach

Currently, artificial intelligence has been used in medicine for a long time. Integrating artificial intelligence into the ultrasound diagnostic process is not the easiest task. After all, software needs time to analyze. Many studies allow to process the result later: for example, MRI, X-ray and others. But a standard ultrasound examination involves the interpretation of the result by a doctor right at the time of the study. In this regard, the quality of the study directly depends on the experience and attentiveness of the doctor.

To do intelligent processing of MRI results, it is enough to simply install the appropriate program on your computer. Because the MRI is first fully performed and then interpreted. And due to the fact that the ultrasound examination is simultaneously performed and interpreted, a third-party computer is rarely used by a doctor for it. But connecting the software directly to the ultrasound machine is almost impossible, for two reasons. Firstly, devices from different manufacturers with different software are used for diagnostics, which is written in low-level languages and can be difficult to integrate with other more modern technologies. Secondly, as mentioned earlier, the software needs time to process the data.

After numerous consultations with specialists in the medical field, analyzing the situation and finding the best way to introduce artificial intelligence into the ultrasound diagnostic process, it was decided to record the research process in a video format file. Then the data is transferred to the computer. The video is divided into frames of 0.5 seconds of research. It is this time interval that will allow not to process the same images several times, but at the same time not to miss important changes. The frames are then processed by a neural network. At the end of processing, the software generates its own, it will highlight a suspicious area and comment on it. In this case, the doctor can either ignore the prompts of artificial intelligence, if he has already paid attention to this pathology, or put a sensor and review the moment of interest again.

Training a neural network for the automated analysis of thyroid gland ultrasonography images involves several key steps.

The first step is to gather a large dataset of thyroid ultrasound images. These images should cover a wide range of thyroid conditions, including cysts, tumors, nodules, and other pathologies. The dataset should be diverse and representative of the population being analyzed.

Once the dataset is collected, it needs to be preprocessed to ensure consistency and quality. This may involve resizing the images, standardizing the brightness and contrast, and removing noise or artifacts. Each image in the dataset needs to be labeled with the corresponding thyroid pathology, such as cyst, tumor, or normal. This step is crucial for supervised learning, where the neural network learns from labeled examples.

Then it is need to choose an appropriate neural network architecture for the task. Convolutional Neural Networks (CNNs) are commonly used for image classification tasks due to their ability to capture spatial hierarchies in data.

A Convolutional Neural Network (CNN) is a type of deep learning algorithm specifically designed for processing and analyzing visual data, such as images. It is inspired by the structure and function of the human visual cortex and is well-suited for tasks such as image classification, object detection, and image segmentation.

CNNs can not only classify images but also localize the regions within the image that contain abnormalities. This is crucial in medical imaging tasks, as it allows clinicians to pinpoint the location of cysts or tumors within the thyroid gland. CNNs can be trained to output bounding boxes or segmentation masks that delineate the boundaries of detected abnormalities.

CNNs consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers.

Convolutional layers are the building blocks of CNNs. They apply convolution operations to input images, using learnable filters (also called kernels) to extract features

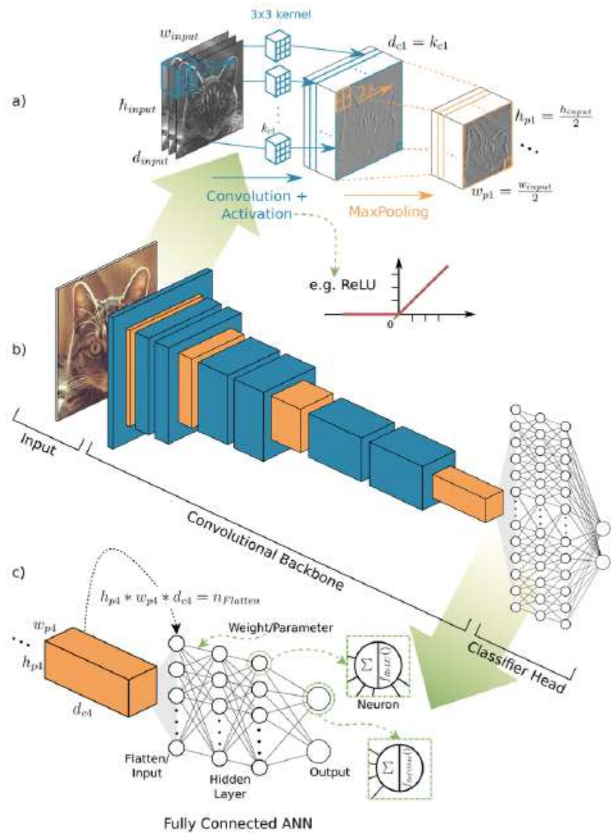

Figure 7. Overview and details of a convolutional neural network (CNN) architecture for image recognition [10]

such as edges, textures, and patterns. These filters slide over the input image, computing dot products between the filter weights and the input pixels to produce feature maps. Multiple filters are used in each convolutional layer to capture different features.

Pooling layers downsample the feature maps produced by the convolutional layers, reducing their spatial dimensions while retaining the most important information. The most common type of pooling operation is max pooling, where the maximum value within each region of the feature map is retained, effectively reducing the size of the feature maps.

Fully connected layers, also known as dense layers, are traditional neural network layers where every neuron is connected to every neuron in the previous and subsequent layers. These layers are typically used at the end of the CNN to map the extracted features to the output classes or labels.

As for the size of the training sample, it depends on various factors such as the complexity of the task, the diversity of the dataset, and the chosen neural network architecture. In general, larger datasets tend to yield better-performing models, especially for deep learning tasks. However, the minimum size of the training sample required for effective model training can vary significantly depending on the specific problem being addressed. It is essential to strike a balance between dataset size, computational resources, and model performance when designing the training pipeline. In the case of medical imaging tasks like thyroid ultrasound analysis, larger datasets with thousands to tens of thousands of labeled images are typically required to train accurate and robust models.

NNs can be trained effectively even with limited labeled data by employing data augmentation techniques. These techniques involve applying transformations such as rotation, scaling, flipping, and cropping to the input images, thereby augmenting the training dataset and improving the model's generalization ability.

Pre-trained CNN models, which have been trained on large-scale datasets such as ImageNet, can be fine-tuned for medical image analysis tasks with relatively small datasets. By leveraging the feature representations learned from generic image data, transfer learning enables CNNs to achieve better performance and faster convergence when applied to medical image datasets, including thyroid ultrasound images.

CNNs can provide insights into the decision-making process by generating heatmaps or saliency maps that highlight the regions of the image that contribute most to the model's predictions. This interpretability is valuable for clinicians, as it helps them understand why a particular diagnosis or classification was made by the CNN.

In summary, Convolutional Neural Networks offer powerful capabilities for automatically detecting and localizing cysts, tumors, and other abnormalities on thyroid ultrasound images. By learning complex patterns and structures from labeled data, CNNs can assist radiologists and clinicians in diagnosing thyroid pathologies more accurately and efficiently, leading to improved patient outcomes.

The expected result of the implementation of the approach should be a web application with artificial intelligence inside. Between the desktop and the web application, the choice fell on the second option. This is due to the fact that the neural network is able to independently learn additionally in the course of its work. To do this, she needs to have access to the results of working with the application of other users. It is more convenient to do this in a web format. It is also necessary to be able to refine the application. By updating web applications, the added changes will quickly appear to all users, unlike the desktop application, where each user will have to update it.

V. Overcoming obstacles

However, there are some serious pitfalls here.

With the web approach, a single server will have access to all application data. This violates the privacy policy and the protection of the user's personal data. The solution to this problem was found in having a separate server for each medical facility. And also not to transfer user data to the application. Based on the specifics of this software, it can process anonymous data and this will not affect the result.

The second difficulty encountered along the way is the presence of artifacts in the research process. The neural network must learn how to process them.

Artifacts in ultrasonic diagnostic imaging refer to misleading features or distortions present in the ultrasound image that do not accurately represent the anatomical structures being examined. These artifacts can arise due to various factors, including the properties of the ultrasound beam, the interaction of ultrasound waves with tissues, equipment settings, patient characteristics, and operator technique. Understanding and mitigating artifacts are essential for ensuring the accuracy and reliability of ultrasound diagnoses.

There are different types of artifacts. Reverberation Artifacts occurs when sound waves bounce back and forth between two strong reflectors, creating multiple, evenly spaced echoes on the image. It can give the appearance of additional structures or false boundaries within tissues.

Shadowing occurs when sound waves are attenuated by highly reflective or dense structures, resulting in a hypoechoic or anechoic region behind the structure. This can obscure underlying structures and limit visualization.

Edge artifacts occur at the interfaces between tissues with different acoustic properties. They manifest as bright or dark lines along tissue boundaries and can distort the appearance of adjacent structures.

Noise in ultrasound images can result from electronic interference, acoustic reverberations, or random fluctuations in signal intensity. It can degrade image quality and reduce diagnostic accuracy.

Motion artifacts occur when there is movement of the patient or probe during image acquisition. This can lead to blurring or ghosting of structures and compromise image clarity.

Teaching a CNN to process artifacts in ultrasound images is not an easy task. But there are some ways to overcome it.

Adversarial training involves training the CNN simultaneously with a generator network that generates realistic artifacts and a discriminator network that distinguishes between real images and artifacts. This helps the CNN learn to discriminate between artifacts and true structures.

Constructing a dataset that includes annotated examples of various artifacts encountered in clinical practice can facilitate CNN training. Annotating images to identify regions affected by artifacts allows the CNN to learn to ignore or compensate for them during analysis.

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 isolate 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]

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

1) 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.

2) 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.

3) 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.

4) 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 may be 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 improving 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 technologists 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 процесса медицинской ультразвуковой диагностики с помощью интеллектуального анализа. Действия описаны на примере исследования щитовидной железы. Дополнительная проверка результата со стороны нейронной сети позволяет начинающим докторам чувствовать себя более уверенно и минимизировать влияние человеческого фактора на качество диагностики.

Received 02.04.2024