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THE USE OF ARTIFICIAL INTELLIGENCE ON COLPOSCOPY IMAGES AND SEGMENTAL VOLUMES, CONSTRUCTED FROM MRI AND CT IMAGES, IN THE DIAGNOSIS AND STAGING OF PRECANCERS, CERVICAL CANCERS AND THYROID CANCERS

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ABSTRACT

Aim of the study For the accurate diagnosis and staging of precancers and cervical and thyroid cancer, we aim to create a diagnostic method optimized by artificial intelligence (AI) algorithms and validated by the notable positive results of a randomized, controlled, 17-month trial.. **Materials and methods** The optimization of the method will involve the development and training of artificial intelligence models using convolutive neural networks (CNN) to identify precancers and cancers in colposcopic images. We will use topologies that have demonstrated strong performance in similar image recognition projects, such as VGG16, Inception, MobilNet, ROI, U-Net, and KiU-Net. Additionally, the research includes a comparative study of various algorithms and tools employed in segmental volumetric constructions to generate 3D images from MRI/CT data.
This study will also evaluate current advancements in DICOM image processing using techniques such as volume rendering, transfer functions for opacity and color, and shades of gray from DICOM images projected in a three-dimensional space. Validation of the proposed method will be achieved through a randomized, controlled clinical trial conducted over 17 months. Patients will be informed and recruited either via random presentation at the specialized medical centers participating in the trial or through a dedicated web platform. Selection criteria will adhere to inclusion and exclusion parameters defined in the clinical trial protocol, and all patient data will be handled ethically and in accordance with written and informed consent approved by the Ethics Committee.
. **Results** The optimized method, supported by AI algorithms and validated through clinical trials, aims to demonstrate concrete and favorable outcomes in the diagnosis, staging, and treatment planning for cervical and thyroid precancers and cancers.. **Conclusions** By implementing this AI-optimized diagnostic method, we seek to raise the quality standard in diagnosing and staging precancers and cancers, ultimately enhancing therapeutic decision-making and patient outcomes.

Key words: AI, deep learning, precancers and cancers of the cervix and thyroid

INTRODUCTION

Post-total thyroidectomy, the documented values of postoperative calcium in the two main categories, with reimplantation and without reimplantation, respectively, were close, the reimplanted category registering slightly lower values[1].

Thyroidectomy with radical neck dissection offers undeniable advantages in advanced thyroid cancer. Total thyroidectomy with radical or radically modified throat dissection has become a procedure of choice in advanced thyroid cancer (the best result is papillary thyroid cancer in females under 55 years of age) [2].

The entire cancerous lesion is surgically removed along with a small area of surrounding healthy tissue to ensure that all malignant cells have been removed. The goal of surgery is to remove all affected tissues

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without compromising the integrity of the structures in the surrounding areas [3].

We aim to increase the quality standard in the diagnosis and staging of cervical and thyroid precancers and cancers by developing an optimized and validated diagnostic method. Optimized and validated diagnostic method through the use of AI.

The main and secondary objectives set for the implementation of the project:

Main objective: To validate the method of optimizing the diagnosis and staging of cervical and thyroid precancers and cancers;

Secondary objectives: Accurate classification, identification and staging of precancer and cervical and thyroid cancer.

MATHERIALS AND METHODS

The methodology used to achieve the objectives

Description of the methods of achieving the objectives to be achieved:

a) development and pre-training of artificial intelligence algorithms for optimizing the diagnosis and staging of precancers and staging of cervical and thyroid cancer through optical and imaging investigations, digital colposcopy and, MRI, CT.

b) conducting a randomized, controlled, multicenter clinical trial over a period of 17 months, by validating the AI-optimized diagnostic method by obtaining optimal results.

a) In this project we address the problem of image pattern recognition by using a Convolutional Neural Network (CNN), as this approach has already proven to be a viable tool for this type of task [4]. As part of the broader field of deep learning, CNN is a deep neural network, which means that it contains multiple layers of neurons and is often used in image analysis. CNN is a regularized version of the classical multilayer perceptron (MPL), but it performs better [5]. Many times, MPL produces a phenomenon called overload, which means that it works very well in formation, but when new data is fed into the network in the prediction phase, the results are below the desired thresholds.

Classification (normal/abnormal) or multiclass (healthy/cervical cancer type 1/2/3) is not

having regard to the particularities of the problem in question. A naïve approach might be to use a pre-trained CNN using a generic image dataset such as ImageNet, Google Open Images, etc., in the hope that it will correctly classify cancers.

To pursue this goal, in our research we used various network topologies that has produced promising results in image pattern recognition activities such as VGG16, Inception or Mobilnet [4]. We have specialized them in the network by retraining the last layers with specific image domain in digital colposcopy. By using this mixed approach we will benefit from both the generic knowledge given by the pre-training of the upper layers of the network against the very large image datasets and the domain-specific training of the final layers, given the smaller colposcopy datasets that we have available from our own research, as well as from the public colposcopy [6].

Moreover, to get a better score, we will apply a preprocessing method to eliminate speculative reflection [7] and a segmentation technique to obtain a region of interest (ROI) to help our model focus only on the relevant areas of the images. U-Net will be used, an algorithm that has proven effective [8,9].

Each MRI and CT scan were sent for three-dimensional reconstruction at the volume of the application. Three-dimensional (3D) reconstruction of computed

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tomography/magnetic resonance imaging (CT)/(MRI) facilitates surgical planning by anatomically visualizing the relationships of lesions in all planes (arteries, veins, nerves, lymph nodes, etc.) and choosing the type of surgical approach.

The main analysis focused on the automatic diagnosis of the images collected using a three-dimensional MRI / CT reconstruction algorithm.

DICOM [10] is currently the most common standard for transmitting medical images and

other information about the patient. DICOM supports a wide range of medical images, including tomography (CT), magnetic resonance imaging (MRI), as well as medical images in the fields of radiology, cardiology, pathology, dentistry, and other fields. The DICOM standard provides for storage in a directory that contains several files in DICOM format and organizes them by patient, study and series[11].

We synthesize the theory underlying the volume rendering technique, listing some algorithms based on the discretization of the physical process that models the passage of light through permeable material. By using a so-called transfer function for opacity and color, the grayscales in DICOM images are projected into a three-dimensional space [11].

We followed a set of quantitative and qualitative parameters of software applications and libraries on the market, such as: minimum hardware requirements, licensing mode (e.g. open source vs commercial), portability between different operating systems, ease of installation and use, quality of volumetric interpretations, speed of interpretation, maintenance and support provided by the development team, extensibility through existing connectors or custom code, quality of documentation, and availability of training in the use of software products.

Finally, we studied a new approach that recognizes the challenges of setting up and using transfer functions to adjust the optical properties of 3D interpretation. The surgeon's goal is to understand the distinctive features of volumetric interpretation, which is not always possible by simply limiting ourselves to transfer functions, requiring a detailed inspection of these three-dimensional spaces. Artificial intelligence (AI) through the technique of generative adversaries networks (GAN) have proven to be effective in representing complex data distributions (4) since they do in the present study.

b) we conducted a randomized, controlled, multicenter clinical trial over a period of 17 months, by validating the AI-optimized diagnostic method by obtaining optimal results. We aim to demonstrate the efficiency of this method of diagnosis and staging by conducting a randomized, controlled, multicenter clinical trial (St. Spiridon Hospital Iasi - Surgery IV Department, Imaging Department, Endocrinology Department and Obstetrics-Gynecology Medical Office), opened for a period of 17 months.

Next, we will present and describe the U-Net-based architectures and then we will present the key elements that we considered important in the design, optimization and validation of the combined DL model, from the U-Net-based architectures, imagined by us.

1. U-Net-based architectures

1.1. Attention U-Net

One of the architectures investigated is Attention U-Net, developed in 2018. Typically, for a segmentation task there is only a part or a few parts of the image that are

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relevant to the problem.

However, the basic U-Net is not able to focus on a specific region of interest and over-processing irrelevant areas. Both the image and its description are taken from the original work[12]. The input image is progressively filtered and reduced by factor 2 at each scale in the encoding part of the network (e.g.,H4 = H1/8). Nc denotes the number of classes. Attention Gates (AGs) filter out the characteristics propagated through the skip connections. Feature selectivity in GA is achieved by using contextual information (gating) extracted at coarser scales.

Attention U-Net,

The Attention Gate Mechanism is an enhancement added to U-Net that: suppress irrelevant regions and highlight key features that are useful for segmentation, they do not add significant computational expenses when integrated into U-Net.

The authors of the architecture presented in [12] propose that the input characteristics of each layer be scaled with attention coefficients that are calculated in the attention gate. Each pixel at the input has its own attention quotient to enhance important regions and suppress irrelevant ones. The description is taken entirely from the original work [12].

The architecture was trained on two 3D datasets, one for which the task was multi-class segmentation (pancreas, spleen, kidneys) and another for single-class segmentation (pancreas only). Both datasets contain CT scans and can be found in the publicly available NIH-TCIA dataset.

Table 1. Comparison of Metric Quantitative Coefficient of Dice Score for Pancreas, Spleen, Renal Data Set, and Pancreas Data Set Between U-Net and Attention U-Net

	U-Net	Atenție U-Net	Number of CT scans in the dataset
Pancreas CT (3D)	0.814	**0.840**	150
Spleen CT (3D)	0.962	0.965	
Kidney CT (3D)	0.963	0.964	
Pancreas2 CT (3D)	0.820	**0.831**	82

1.2. Kiu-Net

The classic U-Net performs poorly in detecting small structures and does not segment the boundaries of regions precisely. This is because the deeper we go into the layers of the network, the larger the receptive field, and this leads to little attention to detail. A solution to this drawback came with the development of KiU-Net in 2020 in [13]. The architecture consists of two networks, a Kite-Net and a U-Net running in parallel, with the combined results.

Kite-Net can be thought of as an opposite of U-Net. While U-Net reduces the size of the

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image in the encoder and reconstructs it in the decoder, the Kite-Net up samples the image in the encoder and reduces it back in the decoder. In this way, the receptive field will not increase in the deep layers as in the U-Net and therefore the desired fine details are obtained. Since Kite-Net Only focuses only on extracting small structures, and the dataset could have both large regions and small regions to be segmented, it was put together with U-Net, which performs well at segmenting high-level features, i.e., large regions. Their outputs are concatenated, matching their dimensions accordingly, with the help of a cross-residual fusion block [13].

The architecture was trained on different data sets, with both 2D and 3D images, to prove the independence of the data type. The results are presented in Table 2 below in terms of the Dice score coefficient.

Table 2: Comparison of Metric Quantitative Coefficient of Dice Score for Brain US, GLAS, RITE, BraTS, and LiTS datasets between U-Net and KiU-Net

	U-Net	Kiu-Net	Numărul de imagini 2D/scanări 3D în setul de date
Segmentarea anatomiei creierului (SUA) (2D)	0.853	**0.894**	1629
Segmentarea glandelor (microscopice) (2D)	0.797	**0.832**	165
Segmentarea nervului retinian (Fundus) (2D)	0.552	**0.751**	40
RMN segmentare tumorală cerebrală (3D)	0.808	**0.876**	335 (155 felii în fiecare scanare)
Ct de segmentare hepatică (3D)	0.844	**0.942**	200

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1.3. U-Net with context aggregation blocks

Another improvement of the classical U-Net was proposed in [14] and consists of replacing some convolutional layers in the U-Net with context aggregation blocks. These blocks contain dilated convolutional layers and normal convolutional layers. Convolution dilation helps detect features in large receptive fields without increasing computational costs. However, this type of convolution has been reported to cause "gridding artifacts," which can affect model performance. To overcome this, expansion convolutions are combined with normal convolutions, and their output characteristics are aggregated. The task performed in [14] is multi-class segmentation, as the images are multi-channeled – each channel corresponds to an organ. After applying context aggregation blocks, a squeeze-extract block is used to assign different weights to each channel for reweighting the importance of each organ mask. The images and descriptions are taken entirely from the original paper [14].

The proposed architecture was trained on a dataset containing abomenal CT scans, and the task consisted of multi-class segmentation (segmented parts: bladder, bone marrow, left femoral head, right femoral head, rectum, small intestine, spinal cord). The results are presented in Table 3 below in terms of the dice score coefficient.

Table 3. Comparison of the metric quantitative coefficient of the dice score for the abdominal dataset between U-Net and U-Net with context aggregation blocks

	U-Net	U-Net cu CAB	Number of CT scans in the dataset
Bladder CT (3D)	0.902	**0.924**	105 (from 71 to 119 slices in scanning)
Bone marrow CT (3D)	0.846	**0.854**	
Left femoral head CT (3D)	0.893	**0.906**	
Right femoral head CT (3D)	0.897	0.900	
Straight Ct (3D)	0.778	**0.791**	
CTof the small intestine (3D)	0.813	**0.833**	
Spinal cord CT (3D)	0.823	0.827	

1.4. HarDNet-MSEG

This architecture was described in [15-18] and has reached the current state of the two datasets to date. It emerged as a solution to the failure of U-Net to segmenting small blurry areas, to the lack of coverage for broken image areas and time-consuming training. It consists of a HarDNet encoder and a partial decoder, which reduces training time. The encoder is based on a DenseNet, but has significantly smaller connections to reduce computational costs and lower channel width to recover the accuracy lost from cutting the connection. The HarDNet block used in the encoder, as an evolution of the DenseNet Block [12-18].

Speaking of decoder, the classic U-Net decoder produces in the shallower layers low-level high-resolution characteristics, therefore, they require high computational costs. The good thing is that the high-level features produced by the deep layers also include some sort of low-level structure, so it followed that

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the surface layers in the encoder could be removed when connecting with the decoder layers, resulting in a partially cascading decoder. Its architecture was taken entirely from [16] and consists of: (a) the traditional encoder decoding framework, (b) the proposed partial cascade decoding framework. We use VGG16 as our backbone network. The traditional frame generates the S saliency map by adopting the complete decoder that integrates all level features. The proposed framework adopts partial decoder, which integrates only features of the deeper layers and generates an initial saliency map Si and the final saliency map Sd [15].

The architecture has been trained on several datasets containing 2D colonoscopy images. Table 4 below contains details of the dice coefficient score results for Classic U-Net and HarDNet-MSEG. The Kvasir-SEG and CVC-ClinicDB dataset scores are currently SOTA in biomedical image segmentation.

Table 4: Comparison of the metric quantitative coefficient of the dice score for the Kvasir-SEG, CVC-ColonDB, ETIS-Larib Polyp DB and CVC-ClinicDB datasets between U-Net and HarDNet-MSEG

	U-Net	HarDNet-MSEG	Data Dimensions
	0.818	**0.912**	900
Polip Gastrointestinal polyps – Kvasir-SEG (2D)i de colon – CVC-ColonDB (2D)	0.512	0.731	unknown
Colon Polyps – CVC-ColonDB (2D)	0.398	0.677	unknown
Colon Polyps – ETIS-Larib Polyp DB (2D)	0.823	**0.932**	550

2. Design, optimization and validation of the DL combined model

2.1. Design and optimization of the DL model

We have analyzed some of the most interesting and powerful architectures, suitable for biomedical image segmentation with the objective of creating a high-performance, combined model of deep learning (DL) architectures aiming to segment the medical medical image that is independent of organ/tissue type, size or image type (2D/3D).

The performance of the model will also depend on the size, annotation, and labeling of the images in the datasets we'll be using:

· datasets containing 2D colonoscopy images – Kvasir-SEG, CVC-ColonDB, ETIS-Larib Polyp DB and CVC-ClinicDB datasets;

· dataset containing abomenal CT scans, and the task consisted of multi-class segmentation (segmented parts: bladder, bone marrow, left femoral head, right femoral head, rectum, small intestine, spinal cord);

· datasets, with both 2D and 3D images

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– Brain US, GLAS, RITE, BraTS and LiTS datasets;

· two 3D datasets, one for which the task was multi-class segmentation (pancreas, spleen, kidneys) and another for single-class segmentation (pancreas only). Both datasets contain CT scans and can be found in the publicly available NIH-TCIA dataset.

The DL model imagined by us combines the following DL architectures: Kite-Net, Attention U-Net, HarDNet-MSEG [12-14].

The combined Mr. model we designed taking into account the key features that each of the architectures mentioned as follows have:

U-Net has been enhanced by having an encoder with context aggregation blocks, and we will still retain the low-level image features that result from U-Net, but we will have a slightly finer segmentation of them, without adding costs due to context aggregation blocks;

The Kite-Net has a unit with attention gates and a Kite-Net decoder, in this way we add a benefit of attention to detail of the Kite-Net;

A partial decoder like the one in the HarDNet-MSEG architecture is used as the new U-Net decoder to reduce training time.

2.2. Validation of the DL model

In addition to comparing the performance of our model in terms of quantitative evaluation measurements, we also wanted to have an overview of the qualitative results. To do this, we compare the results obtained by the imaging model with the evaluation by a specialist of the images (raw, non-segmented), in terms of the diagnosis and colposcopic staging of cervical precancers and also the diagnosis and staging of cervical and thyroid cancers. We validated the qualitative results through a randomized controlled clinical trial over a period of 17 months.

2.3. Materials and methods

Patients were informed and recruited by random presentation to the specialized medical centers nominated in the clinical trial. Patients with precancer and cervical and thyroid cancer will be included in the clinical trial. We included 60 patients with cervical precancer, 60 cervical cancer patients and 60 thyroid cancer patients in the clinical trial. A diagnostic batch was defined by the AI model, (G1), with two branches (G1c and G1t) and a training batch for the AI model, study group (G2), with two branches (G2c and G2t), both batches were investigated, explored and diagnosed by physicians,. We will differentiate the cervical study groups called G1c and G2c and for thyroid G1t and G2t, respectively.

Inclusion criteria: in the study groups (G1c and G2c) for the cervix, patients with diagnosis – precancerous staging and cervical cancers stages 0-IVB; in the control and study groups (G1t and G2t) for thyroid, patients with diagnosis - staging of thyroid cancer stages 0-IV. Exclusion criteria: in batches G1c and G2c we exclude virgo patients, total hysterectomy A.P., trachelectomy A.P., pregnancy, comorbidities incompatible with the clinical trial; in groups G1t and G2t we exclude benign pathologies, thyroidectomy patients, comorbidities incompatible with the clinical trial. We propose the diagnosis and staging of precancers and cancers of the cervix and thyroid through pre-trained algorithm models in the comparison of colposcopic images and 3D reconstruction, segmental volumetry with adjustment of optical properties.

We defined the parameters assessed by the evolutionary stages of precancers and cervical and thyroid cancers. Diagnosis and staging was performed by interpreting colposcopic

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images, MRI, and CT. Amt use the Bethesda 2001 system and the FIGO system for the classification of precancers and cervical and thyroid cancers. Colposcopic images and MRI and CT represent by their interpretation, the diagnosis - clinical staging of precancers and cancers of the cervix and thyroid cancers.

Sistem Bethesda	Sistem Bethesda	Sistem Bethesda	Sistem Bethesda	Sistem Bethesda	Sistem Bethesda	Sistem Bethesda	Sistem Bethesda
ASC-US ASC-H NOS	ASC-US ASC–H LSIL	ASC–US ASC–H HSIL	ASC–US ASC–H CA	III	IV	V	VI
Colposcopy	Colposcopy	Colposcopy	Colposcopy MRI (CA) CT (CA)	FNA	MRI CT	MRI CT	MRI CT
Cervix	Cervix	Cervix	Cervix	Thyroid	Thyroid	Thyroid	Thyroid

Cervical cervix: Legend[14,15].Bethesda system for reporting cervical cytology, AUC – US = atypical squamous cells of undetermined significance; AUC – H = atypical squamous indices, HSIL, ASC – US and ASC – H overlap with several categories cannot be excluded, which underlines the non-hierarchical character of these categories; Figo System for Reporting Cervical Cancer, Stage 0 = carcinoma in situ, CIN, stage I = invasive carcinoma limited to the cervix, stage IA diagnosed by microscopy only (IA1 and IA2), stage IB = clinically or microscopically visible lesion > IA2, stage II = extension beyond the cervix but not to the side wall (IIA and IIB), stage III = extension to the pelvic wall and/or lower third of the vagina: hydronephrosis (IIIA and IIIB), stage IV = extension beyond the pelvis or involving the bladder or rectum (IVA and IVB).

Thyroid: Legend [17].Bethesda System for Reporting Thyroid Cytopathology: Class III = Smear of Unclear Significance or Follicular Lesion of Uncertain Significance; class IV = smear with a defined appearance of follicular neoplasm or a suspicious appearance of follicular neoplasm / Hurthle cells; class V = smear with a suspicious appearance of papillary, medullary, anaplastic carcinoma, lymphoma; class VI = malignant smear.

Cervical cervix, precancer – colposcopy – AI; Uterine and thyroid, Cancers - AI

Patients:

The study used anonymized patient data and was approved by the Ethics Council of the University of Mdedicina and Pharmacy Gr. T. Popa Iași, (approval no. 97/24.06.2021). Patients received information and explanations about this study. Patients did not receive previous treatment for cervical or thyroid injury during the grant, prior to specific explorations. In the case of cervical lesions, precancers, HPV tests were performed prior to colposcopy, as a result of medical indication, of necessity and not for the special purpose of this study. Cervical biopsy was performed for patients with abnormal cervical lesions of ASC-US, LSIL, HSIL, atypical squamous cells cannot exclude HSIL (ASC-H), as well as for patients with LSIL/CIN1, HSIL/CIN2 and HSIL/CIN3. HPV types that were tested: High-risk HPV genotypes, such as 16, 18, 31, 33, 35, 39, 45, 51, 52, 56, 58, 59, 66, and 68.

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Study design:

The study design was based on routine practice: a total of 60 patients with HPV-positive precancerous cervical lesions and pathological colposcopy imaging, 60 patients with cervical cancer and 60 patients with thyroid cancer, were enrolled in this study.

Images:

Colposcopic images of lesions processed with 3% acetic acid were captured, cropped, and saved. Image data has been introduced for deep learning. Also, 2D CT and MRI imaging data have also been introduced into the deep learning module.

AI Preparation:

The anonymized images saved offline were transferred to the AI system. For the test dataset, 20 of the images were randomly selected for diagnosis and 40 images were used for training in the AI classifier. This way we didn't overlap the data sets. The AI was trained on the test set and validated. Since colposcopic images have arbitrary degrees of rotation, the resulting images have variable vector data, as a result, they have been captured, cropped, and saved. 2D CT and MRI imaging data were introduced as such.

Classifier IA:

The AI module used supervised deep learning with a convolutional neural network architecture (12,14) tested for different image sizes, in the case of colposcopy images (50×50, 75×75 and 100×100 pixels), L2 regularization (15,16,) and architectures consisting of a combination of convolution layers with nuclei (17-19), clustering layers (20-23), flattened layers (24), linear layers (25,26), rectified linear unit layers (27,28), chained layers, batch normalization layers (29), and a softmax layer (30,31) that demonstrated the probability of LSIL or HSIL in an image.

The architecture of the colposcopy image classifier consisted of:

1.Input Image: Convolutional Layer, Rectified Linear Unit Layer, Grouping Layer, Convolutional Layer, Rectified Linear Unit Layer, Grouping Layer, Flattening Layer, Linear Layer, Rectified Linear Unit Layer, Linear Layer

2.HPV Type: Catenary Layer, Batch Normalization Layer, Linear Layer, Softmax Layer

Architecture of the CT and MRI image classifier:

The 2D, MRI and CT images were sent for three-dimensional reconstruction at the volume of the application. The main analysis focused on the automatic diagnosis of the collected images using a three-dimensional MRI/CT reconstruction algorithm by processing the images in DICOM format through the volume rendering technique.

Output:

We used cross-validation for selection and proceeded to use an optimal number of images for training and validation.

RESULTS AND DISCUSSIONS

Statistical analysis and results:

Number of patients with pathological lesions: HSIL, 20; LSIL, 15; AUC-US, 10; ASC-H, 4; AIS; 1. The mean ± standard deviation, median HSIL vs. LSIL were 31.66±5.01 vs. 33.75±8.94, 32 vs. 33 and 19–

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46 vs. 19–62, respectively.

Laboratory and AI Classification data compared with the results of medical investigations indicated a statistically significant $P<0.05$ for both cervical precancers and cervical and thyroid cancers.

Discussion:

For the diagnosis of HPV-positive precancerous cervical lesions, the accuracy for the test dataset obtained by the classifier versus gynecologist was 0.841. The number of accurate HSIL and LSIL diagnoses by conventional colposcopy for the test dataset was 52 out of 60. The comparison with the diagnosis given by the gynecologist is very similar.

For the diagnosis of cervical and thyroid cancers, the diagnostic accuracy was 0.891. The number of accurate diagnoses of cervical cancer and thyroid cancer for the test dataset was 53 out of 60. For cervical precancers, the biopsy is necessary and important because it guides and certifies the therapeutic conduct. AI can use imaging data but also clinical data, this aspect can improve diagnostic performance and accuracy.

CONCLUSIONS

1. We have reviewed the best U-Net-based architectures suitable for biomedical image segmentation. We have specified their most important features that we have brought together in a new, high-performance model. In this regard, we have created a comprehensive AI-assisted diagnostic methodology validated by a randomized, controlled clinical trial. The model will be a highly automated tool for diagnosing and staging precancer and cervical cancer and thyroid cancers.
2. This would help drastically minimize the time and effort that specialists put into analyzing medical images, help make a better treatment plan, and can provide a computer-aided "second opinion" diagnosis

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