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Cancer Diagnosis With the Aid of Artificial Intelligence Modeling Tools

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ABSTRACT Cancer is one of the deadliest diseases in the present days. Its survivability is mostly corelated to early detection and treatment, which means that it is of utmost importance to successfully diagnose the patients. Unfortunately, even with years of experience human errors can happen which leads to the death of many individuals being misdiagnosed. Throughout the years there have been several applications created which could possibly aid doctors in the diagnosis. Neural Networks have always been a powerful tool which can be used in different applications that require an accurate model and the complexity of these models exceeds a human's computational capabilities. In image processing for example, a convolutional neural network can analyze each particular pixel and determine through the convolution function the common properties of different pictures. The objective of this study is to analyze different types of cancer diagnosing methods that have been developed and tested using image processing methods. The analyzed factors are training parameters, image processing technique and the obtained performances. This survey/review can be of significant value to researchers and professionals in medicine and computer science, highlighting areas where there are opportunities to make significant new contributions.

INDEX TERMS Cancer diagnosis, image processing, neural networks.

I. INTRODUCTION

In the present days the number of cases of cancer patients is rising steadily, mainly caused by overdiagnosing and overtreating patients. These mistakes are caused by the poor decisions the doctors make when they analyze the imaging. The highest survival chances, on any type of cancer appear when the cancer is detected in its early stages [1]. This can be an explanation for the increase in the number of deaths since time is one of the more important factors to be considered. Due to the increase in numbers artificial intelligence in diagnosis has been more and more popular in recent years. The properties of neural networks and the results that can be obtained solidify its use in many aspects. For a doctor it takes years of studying and experience in order to make the right calls when their patients test results are known and even then, there is a chance for the doctor to make mistakes. When the doctor makes his decision there are some key features in the images that he has to verify, but when comparing an ultrasound imaging with a colonoscopy it is much harder to determine when a patient has or does not have thyroid cancer as to when a person is having colorectal cancer. These key features found in the ultrasound imaging can be found by artificial intelligence (AI). With the use of a high number of images, for which the results are already known, an AI can determine much easier if the patient has cancer, or if the cancer is malign or benign [2]. In case of malign cancer, the chance of survival is low, due to its capacity to relocate via the blood vessels in other areas in the body [3]. Cancer can be caused by many factors, the most relevant ones are exposure to radiation, having an unbalanced diet, living in a stressful environment and even excessive drinking of alcohol and smoking. Due to this a healthy lifestyle is recommended in order to reduce the chance of developing cancer [4].

Doctors can make their decisions earlier if they can get the necessary information from screening. The main disadvantage of neural networks, and AI in general, is that it does not really work in a home environment, which means that it can

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be used as a tool for diagnosis by the doctors, but it shouldn't be used by people who cannot interpret the ultrasounds, CT or any other image types properly.

The main purpose of the current paper is to analyze the different AI tools which could aid in the detection of the most frequent cancer types.

The paper is structured in four parts. After this short introductory section, section II presents the main ideas of artificial intelligence in medical diagnosis. Section III analysis the developed diagnosis system, highlighting the advantages. The work ends with concluding remarks.

II. ARTIFICIAL INTELLIGENCE IN DIAGNOSIS SYSTEM

There are multiple types of neural networks which can create models by training a certain type of input and output data. In most cases Artificial neural networks can be used to determine a model for a certain application. There are many studies in which different techniques are used for different fields, ranging from chemistry, physics, biochemistry and even medical applications, just to name a few. At its core the principles do not change, even in the case of the perceptron, which is the first neural networks ever created, it uses a number of inputs and outputs to determine a model for logic gates. In the case of convolutional neural networks, however the inputs are images which can be represented as matrices with certain values depending on the color it needs to represent. Images depending on their format can be either gray or colored and even then, the extension of the file might matter because the color codes might differ. Before training a convolutional neural network, the images need to go through a process called processing or preprocessing in some cases. Usually training the network takes a certain amount of time, which may vary depending on the computers processing power and the data stored in the image. If there are a lot of pixels to work with, or the image is colored for example, the training may take longer. Depending on the application it may or may not need to take that long. The main drawback is that if the image is resized or its format needs to be changed, from RGB to gray for example, certain information may be lost and either more images are required to obtain a good model, or the model itself meets certain criteria set by the user and it is an acceptable result. However, a problem that may occur in some cases is that the training will not start due to the high number of variables from the images. In order to prevent this from happening the images can be resized to a more favorable number of pixels which the user can choose [5].

The ultrasound imaging itself is usually already on a gray pallet color, meaning that using a format that supports only gray colors can be an option. As default a JPEG image is usually loaded in a RGB format, meaning that 3 matrices are needed to represent the image, for a gray image one single matrix is sufficient.

In most cases the images obtained need to be processed before they can be used for training. Usually, this is done by applying a filter on the input images. Since MATLAB can be used to work on and save the images this process can be automatically done. A technique widely used is to apply a filter that enhances the image contours, and it is combined with the original image. The key features relevant to a correct diagnosis can be easier to spot and improve the accuracy of the models. Feature extraction is an important part of diagnosis. The features can be divided into geometric, statistical, texture and color. For each of these categories there are several subcategories that can be used. For example, in the case of color features there are:

- Color Moments which differentiate images by their own color features and are interpreted as a probability distribution;
- Color Histogram which is widely used due to its ease of use and extraction while containing more important information;
- Average RGB mostly used for image filtering and uses smaller number values represented by vector parameters;

Texture features are considered the most important types of features especially in medical imaging. There are two main subcategories in this case:

- Gray Level Co-occurrence Matrices (GLCM) which uses histograms to measure the gray levels and introduce an offset. Some of the features computed in this category are entropy, contrast, correlation, energy and homogeneity;
- Tamura which is used with contrast, directionality, coarseness, roughness, line-likeness and regularity.

Statistical features represent the textures in a more indirect approach by using the properties of distributions and the relationships between the gray levels of the input images. The possible features are contrast, entropy, RMS, energy, kurtosis, correlation, variance, smoothness, mean and standard deviation, fifth and sixth central moment.

The following are considered geometry features: area, slope, perimeter, centroid, irregularity index, equivalent diameter, convex area and solidity.

In cancer recognition all the feature extraction categories can be used, but the most relevant one is the texture feature [6].

Some of the images from the used database have black backgrounds and, in that case, to reduce the number of pixels cropping can be a solution. This can be manually done if the number of images is low, but for a neural network to obtain an accurate model using bounding boxes the process can be automated.

Neural networks are powerful artificial intelligence tool that can be used to create accurate models of complex systems or functions. There are many papers in which neural networks are used to model different types of biochemical processes, which mathematically are hard to obtain, without the help of such tools [7], [8]. In medical applications and diagnosis, neural networks can be used to determine or search for certain irregularities in imaging and other biological parameters, such as blood pressure, certain hormone and enzyme levels or even vitamin deficiencies. These parameters can be used to identify possible causes for the present symptoms in a patient.

There are different types of diseases that can be discovered in a patient by using its specific type of imaging. In the case of colorectal cancer, for example, colonoscopies are performed to increase the chances of discovering it early. For thyroid cancer an ultrasound imaging is performed and by identifying key features from the images, the doctor can make a decision on whether the patient is ill and in what situation the person is. In some cases, the cancer might already be in its metastasis, for which it is harder to determine the patient's survival chance [9].

There are multiple types of neural networks that can be used, Artificial neural networks are used if as input, and in some cases output, only numbers are used, like blood pressure or other vital characteristics. However, for imaging it is much better to use convolutional neural networks, which at its core work similarly, but use images as input.

The workflow for training neural networks is as follows. Firstly, the input data is required and, in some cases, it needs to be preprocessed or the training will not end in an accurate model. Usually, it is important to choose input variables that can influence directly the output, some input and output variables do not corelate in any way. If that happens new input data is required. Before training a network a certain number of parameters must be chosen, such as the number of neurons and layers which determine the complexity of the mathematical model to be obtained after the training process ends. The dimensions of the matrices which contain the weights and biases of the model are reflected in these values. Overfitting is a phenomenon that may occur when choosing the number of layers and neurons. It occurs when these numbers are too big, and it reduces the accuracy of the model. The activation function is required to choose in order to obtain good models. Choosing the function is hard, but usually the sigmoid and the linear functions are feasible. Other parameters which can be changed are learning rate, number of echoes, gradient and validation checks. These variables have default values and influence when the training of the networks stops. The values can be changed if the user decides to do so, which might increase the accuracy of the model, but are not required to be modified. Also, some parameters like learning rate can be modified, but usually that is not necessary to obtain an accurate model. When training the network there are certain training methods or algorithms that can be used, but usually the Levenberg-Marquadt method is used [10].

Convolutional neural networks have more layers, which have different roles, Figure 1.

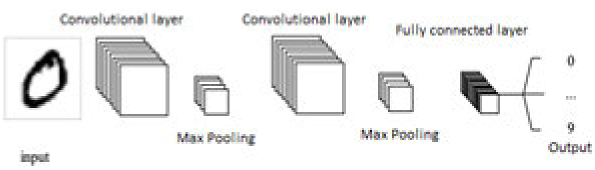

FIGURE 1. **Convolutional neural network structure.**

The first layer is the input layer which in this case is going to be an image. In figure 1 the network is fed pictures of digits and it has to recognize the digit found in those pictures. The image can be in different format and in different resolution. The next layer is the convolutional layer. It has the role of convolving the picture using trainable filters. It uses the convolution function between two matrices and one of them is a filter. It is considered a filter since its role is to either highlight certain features of an image, or entirely block some off. Usually, the use of this layer ends up with the image changing in size, which can be averted by using the next layer. The pooling layer can be considered a complementary layer of the convolution layer, since the two usually come in pair. The pooling layer selects a group of pixels and depending on its type it will choose a value depending on the type of pooling layer and decrease the size depending on the size of the layer. Often 3×3 pooling layers and mean pooling layers can be considered. The mean pooling does not choose a certain value, it computes an arithmetic mean from the pixels and that value is chosen after the layer. This group of layers can be used multiple times. The flattening layer comes next which transforms the matrices which are obtained after the convolutional and pooling layers into a 1D vector which can be processed by the following layer. The fully connected layer or dense layer behaves like an artificial neural network (ANN). Using the processed values from the images it will choose the appropriate output, which can be a choice between some limits or a yes or a no or depending on what the application strives to achieve. An important layer to be specified is the dropout layer which is not mandatory to use, but can help with networks that have a high number of computations. It has the role of removing certain neurons out of the layers if they do not have any involvement in the computation of the final value. It can prevent overfitting, which can usually affect performance [1].

III. DEVELOPED DIAGNOSIS SYSTEMS

A. AI DIAGNOSIS FOR THYROID CANCER

Many types of growths and tumors can develop in the thyroid gland. Most of these are benign (non-cancerous) but others are malignant (cancerous), which means they can spread into nearby tissues and to other parts of the body.

Lumps or bumps in the thyroid gland are called thyroid nodules (TNs). Most thyroid nodules are benign, but about 2 or 3 in 20 are cancerous. Sometimes these nodules make too much thyroid hormone and cause hyperthyroidism. Nodules that produce too much thyroid hormone are almost always benign. In figure 2 such thyroid nodule can be seen; the detection may be done due to the darker color (hypo-echogenicity) and the irregular contour in the ultrasound images. As comparison, in Figure 3 is presented a healthy thyroid ultrasound image.

People can develop thyroid nodules at any age, but they occur most commonly in older adults. Fewer than 1 in 10 adults have thyroid nodules that can be felt by a doctor.

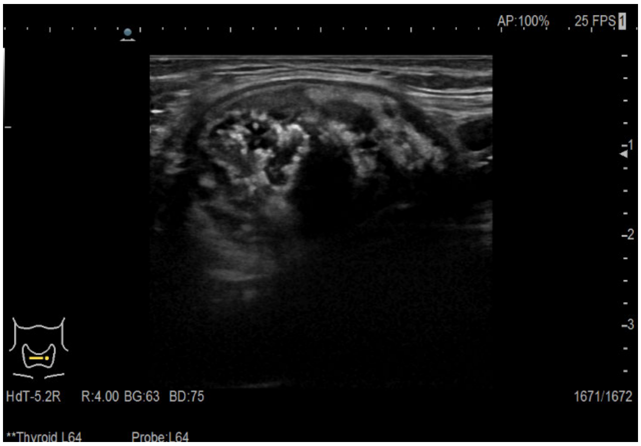

FIGURE 2. Thyroid ultrasound image with suspected malignant features of the tumor.

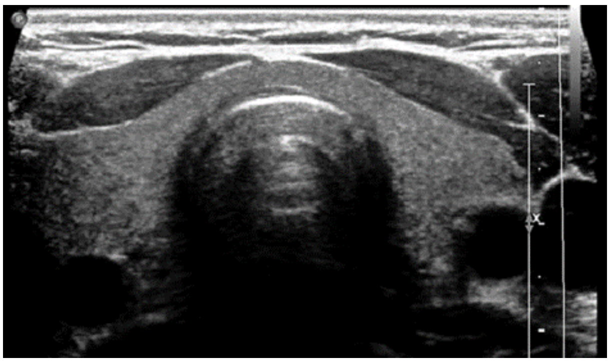

FIGURE 3. Healthy thyroid ultrasound image.

But when the thyroid is looked at with an ultrasound, many more people are found to have nodules that are too small to feel and most of them are benign.

Most nodules are cysts filled with fluid or with a stored form of thyroid hormone called colloid. Solid nodules have little fluid or colloid and are more likely to be cancerous. Still, most solid nodules are not cancerous. Some types of solid nodules, such as hyperplastic nodules and adenomas, have too many cells, but the cells are not cancer cells.

Types of thyroid cancer:

There are 4 main types of thyroid cancer:

- Papillary carcinoma – the most common type, accounting for about 8 in 10 cases; it usually affects people under 40, particularly women;
- Follicular carcinoma – accounts for up to 1 in 10 cases and tends to affect middle-aged adults, particularly women;
- Medullary thyroid carcinoma – accounts for less than 1 in 10 cases; unlike the other types, it can run in families;
- Anaplastic thyroid carcinoma – the rarest and most serious type, accounting for around 1 in 50 cases; it usually affects people over the age of 60;

There are several main steps in how thyroid cancer can be found / diagnosed:

1) LABORATORY TESTS

A blood test called a thyroid function test is used to check the levels of thyroid hormones in your blood. Abnormal levels could mean that you have an overactive thyroid or an underactive thyroid, rather than cancer. Positive correlation of rising thyroid-stimulating hormone (TSH) values and thyroid malignancy risk has been established [11]. Further tests, such as an ultrasonography, will be needed if the laboratory tests show that the TSH level is normal or elevated. Calcitonin is the specific serum marker for medullary thyroid cancer [12].

2) THYROID ULTRASOUND

An ultrasound examination (sonography) uses sound waves to create an image of the inside of your body. Ultrasound imaging of the neck may identify thyroid nodules, helping to determine which nodules demonstrate suspected malignant features and which of them should or should not be biopsied [13]. If a potentially cancerous nodule is found, a further evaluation of the nodule by fine needle aspiration biopsy will be required [14].

3) THYROID CYTOLOGY

The fine needle aspiration biopsy (FNAB) is considered the gold standard to determine whether a nodule is benign, what are its chances of malignancy and whether it will require possible thyroid surgery for final pathological diagnosis. A biopsy of the thyroid is usually done by inserting a thin needle into the nodule and a small sample of cells are removed and studied under a microscope. An ultrasound evaluation may be done at the same time to guide the needle into the right place. This is usually done as an outpatient procedure, which means the patient will not have to spend the night in hospital [15].

4) FURTHER TESTS

If a FNAB identifies the presence of thyroid cancer, further tests may be needed to check whether the cancer has spread to another part of your body. The main tests used for this are:

- A CT scan – a type of scan that uses a series of X-rays and a computer to create detailed images of the inside of the body
- An MRI scan – a type of scan that uses strong magnetic fields and radio waves to produce detailed images of the inside of the body

Detection of TNs has significantly increased over the past two decades with many more nodules now being incidentally detected. As the majority of these nodules are benign or behave indolently, accurate determination of whether thyroid nodules are benign or malignant could reduce patient risk and reduce the significant medical health care costs with FNAB/or surgery. The workup of these incidental thyroid nodules typically includes sonography [16].

Radiologists have identified a few sonographic characteristics of thyroid nodules as suggestive features of malignancy, including hypo-echogenicity, absence of a halo, micro-calcifications, solidity, intranodular flow and taller-than-wide shape. Based on these characteristics, a dedicated Thyroid Imaging Reporting and Data System (TI-RADS) to categorize thyroid nodules and stratify their malignancy risk has been developed for use by radiologists. TI-RADS scores of 2, 3, 4a, 4b, 4c and 5 are denoted as ''not suspicious'', ''probably benign'', ''one suspicious feature'', ''two suspicious features'', ''three or more suspicious features'' and ''probable malignancy'', respectively [13], [17].

However, the assessment of TNs using TI-RADS is time consuming and often not robust. The accuracy is often based on radiologist's personal experience, as current sonographic criteria to identify malignant nodules are imperfect with the variations in echo patterns of thyroid nodules limiting the judgement capability of radiologists.

Introduction of a TI-RADS reporting scheme that is validated would allow clinicians to be able to stop regular thyroid ultrasound evaluation with confidence that they are unlikely to be missing a malignancy. Moreover, utilizing TI-RADS scores allows the radiologists to be aware of how the machine is classifying the image because the sonographic characteristics are contained in the ultrasound images that can be digitized and sent to a machine learning scheme. Therefore, an automatic or semi-automatic classification system based on image features would be possible and very helpful to report TI-RADS scores and classify the thyroid nodule ultrasound images.

Many works utilizing different hand-crafted features extracted from thyroid ultrasound images have been recently proposed. These include the use of extracted features to perform supervised classification through existing machine learning classifiers. Most works used texture-based features in combination with a Support Vector Machine (SVM) classifier in order to accomplish the tasks of identification of nodules, classification of nodules based on their malignancy risk and characterization of the type of malignancy in a nodule. The advantage and importance of computer-determined image features have been established in a recent study where the authors concluded that non-clinical features such as tissue stiffness scores, texture and discrete-wavelet-transform-based features resulted in significantly higher classification accuracies compared to those obtained by clinical features alone such as vascularity, margins, shape, micro-calcifications [18].

Image features extracted from deep convolutional neural network (DCNN) have proven effective in image classification, segmentation or retrieval. Compared to the traditional feature extraction methods, it was claimed in that DCNN had two advantages:

- Detection using DCNN is robust to distortions such as changes in shape due to camera lens, different lighting conditions, different poses, presence of partial occlusions, horizontal and vertical shifts, etc.;
- The computational cost of feature extraction by DCNN is relatively low because the same coefficients in the convolutional layer are used across the input image.

The images (discussed in more details below) used to train our specific DCNN model presented some problems:

- images are collected from different medical institutions so the texture scales varied across the data set, and
- artifacts such as fiducial markers added by radiologists degrade the learning process.

Therefore, some pre-processing methods to enhance the image qualities and suitable augmentation of image samples would improve the performance of fine-tuned DCNN in classifying thyroid ultrasound images [18].

Since ultrasound imaging is used for thyroid cancer diagnosis, CNN's can be used to make the diagnosis easier. Liang and his colleagues use a dataset consisting of 537 ultrasound images, which they preprocessed using the windows drawing software to center the sample images and manually outline the boundary of the region. However, in their study they create models for both breast and thyroid cancer. For thyroid cancer the number is 158 for training and 50 for validation. The preprocessing process is needed to have the same size for all the images and a 315 × 315 pixel size is selected. The performances analyzed are sensitivity, specificity, PPV and NPV. In the final discussion they have obtained models with 92% accuracy on the segmented images, but for the separate images the accuracy did become 42.9%. For breast cancer the results are better, going from 91% for segmented to 82.9% [16].

Song et al use a technique called feature cropping with their networks. Their method is based around CNN. The architecture of the CNN is built by having 4 sets of Convolutional and max looping layers followed by 2 fully connected layers. The feature cropping is used to divide the feature map into smaller pieces and input them into CNNs. To compensate for the high number of computations, the share computation technique is used. Two types of cropping are used: random feature cropping and boundary feature cropping. The authors compare their method with a number of different other methods to check for the better performances. The performance criteria evaluated are: accuracy, precision, recall and F1-measure. For every instance the proposed method presents superior values compared with the other techniques [14].

Chi et al use a dataset consisting of 428 ultrasound images with the size of 560 × 360 and a dataset which consists of 164 images with different sizes. For training 306 images are used, while 61 are used for testing and another 61 for validation. The preprocessing part consists of resizing the images and removing writing and annotations from the images. The images are resized with MATLAB's *imresize()* function, while the annotations are by using a certain algorithm, which removes the zone and then fills in the gaps. To create the model the GoogLeNet model is used. The only performance criteria to be analyzed is the Accuracy of the model which is compared with a number of other models created with different methods. The accuracy of the model is at 99.13% which has the best performance from the bunch [19].

A hybrid method is proposed by Jinlian *et al.* Their method consists of combining 2 pretrained CNN models. The images are taken from the ImageNet database. The validation process is done upon 15000 images. To train the network a number of 8148 images are used. The input images are 225 × 225 pixels in size. The first CNN uses 3 sets of convolutional layers with max pooling layers and use the PReLu activation function. After the convolutional layers 3 fully-connected layers are used. The second CNN uses the same architecture as the first, only difference appears at the input layer, size differs. The 2 CNN are connected at their output with a summation layer and end with a softmax layer. The performance of the method is analyzed using the accuracy criteria which is at 83%. When compared with other methods the AUC (Area Under Curve) is used and the proposed method has a performance of 89.3%, better than the other methods [20].

ANN methods can be used as well. For the input parameters 29 are considered in the study. A single hidden layer is used with 6 neurons with the sigmoid activation function. The Levenberg-Marquadt training function is used and the performance is evaluated using the mean square error. The authors specify an accuracy performance of 98.6% [10].

In another study the fine-needle aspiration biopsy is used, this method cannot rule out cancer reliably, but the authors proposed to improve the reliability of the method using ANNs. For training, a number of 464 nodules are used, while for validation 225. To avoid the overtraining problem, which may occur when a large number of data is used, the network is retrained using a smaller number of 332 and 132 values. The model is considered to have 6 input parameters and one output which tells whether the tumor is malignant or not. The model presents an accuracy of 83.1% with sensitivity of 83.8% and specificity of 81.8% [21].

Asma et al use ANN with a number of 3772 training data and 3428 for testing. In the study they emphasize the need to use datamining, because they need only certain data to train their network. The technique used is bi-directional RNN, which is described to save time due to its structure and knowing that it works with a forward and a backward pass mode to increase the performance of the model as well. This feature allows it to exhibit a temporal dynamic behavior. This type of network is mostly used for handwriting recognition and speech recognition. The published result is compared with an existing system with the values for that system being at 79.58% and reaching the value of 98.72% [22].

Ling-Rui et al in their study analyzed a number of studies in order to compare the techniques used to diagnose thyroid cancer. The network types ranged from ANN to CNN and genetic algorithms. The performances that described the models are accuracy, sensitivity, specificity and AUC. Out of these the first three are percentage based while the AUC is taken differently, but it is represented by a positive number smaller than 1. A number of studies stand out since their values come to a close value to the ideal value, namely a technique called Inception-v3 (a widely used image recognition model), ANN, CNN and methods involving SVM (support vector machines). The table they analyzed has the role of identifying malign and benign tumors, while the next part of the study involves pathological information. In this case the accuracy is the only performance parameter to be analyzed and ANN, SVM and LDA with k-NN (Linear discriminant analysis with neural networks) have 100% accuracy [23].

TABLE 1. **Thyroid cancer method and performance table.**

Reference	*Neural Network type*	*Performance*
[16]	CNN	92% on training, 42.9% on validation
[14]	CNN+feature cropping	From 84.21% to 97.18%
[19]	CNN(GoogLeNet)	99.13%
[20]	Hybrid CNN	83% accuracy, 89.3% AUC
[10]	ANN	98.6%
[21]	ANN on biopsy	83.1%
[22]	ANN RNN	98.72%
[23]	ANN, SVM, LDA	(Multiple values and some reach 100%)
[24]	ANN, SVM, RF, NB	90.94%
[25]	FNN, CNN, ANN, RNN	98.89%

Olatunji et al obtain models in their study using ANN, SVM, RF (Random Forrest), NB (Naïve Byes). In the training part they consider a number of 15 types of inputs most of which are biological parameters like Hematocrit level, hemoglobin level. In order to obtain the models, they need to use some parameters specific to the methods. For SVM gamma is considered 0.001, the kernel type is linear with a cost of 1 and 42 random states. For the RF method the max depth is 5 with 2 min sample leaf and split and 42 random states. The ANN has the tanh activation function with 0.01 alpha a hidden layer with 100 neurons and a constant learning rate. There are 42 random states in this case as well. In the research the best results came from using the RF technique with an accuracy of 90.94% [24].

In their study Santillan et al use the FTIR spectroscopy with the help of neural networks to obtain their model. The data consisted of 76 malignant and 88 benign tumors. The models had results between 91.25% for recall rate to 98.89% for positive predictive value. These are obtained for the RNN model which are compared with CNN, different types of FNN and LDA method. In some areas the other methods outperform the RNN, but on average the RNN has the best results [25].

Table 1 presents a review of the best performance methods presented in the literature on this topic.

B. AI DIAGNOSIS FOR COLORECTAL CANCER

Colorectal cancer (CRC) is a type of cancer that appears in the rectum or the large intestine. It is also known as bowel, colon or rectal cancer. According to the statistics of Rebecca Siegel et al, CRC is one of the deadliest cancer types in the United States [23]. In the charts it is on the second place. Their statistics show that in the year of 2020 approximately 150000 individuals are diagnosed with the disease and one third of the patients die from it. Out of those 7% are below the age of 50.

Due to the large number of causes, it is difficult to pinpoint accurately the cause for which the cancer may appear. Some of the causes are related to lifestyle and old age. Since the intestines are part of the digestive system there is a correlation between red and processed meat and CRC. Abusive alcohol consumption over a large period of time is known to also cause cancer, even in the colorectal region. In rare cases CRC can be transmitted in a hereditary way: familial adenomatous polyposis and hereditary non-polyposis colon cancer. In the first case it may manifest as benign tumors, but if left untreated may become malign tumors. However, the other hereditary way, which is also known as Lynch syndrome, is a dominant genetic condition. Fortunately, these cases are rare and appear in less than 5% of the cases. Also, important to mention that the individuals that are known to have inflammatory bowel disease, including Crohn's disease, are more susceptible to CRC.

The symptoms of CRC are usually changing in bowel movement or even blood in the stools, this may be caused by the bowel hurting the affected zone. Other symptoms may be vomiting blood, wight loss and fatigue, usually anything that has to do with the digestive system. Unfortunately, it is shown that for 50% of the cases the patient did not show any of the symptoms. Since in most cases early detection and treatment is the best way to survive CRC, not having any symptoms usually means that people are less likely to do a medical checkup [3].

The most known diagnostic methods are tissue biopsy [27], colonoscopy or fecal occult blood testing. Colonoscopy is believed to be a good standard for detecting the cancers, the process itself is trying to find the polyps, which basically are the tumors. They often are small in size are flat bumps or in some cases have a mushroom like shape [28].

In figure 4 an example of a colonoscopy with a polyp can be seen. In this case due to the difference in color it can be easier to detect by the human eye, but there are cases in which this decision is much harder. For comparison is added in Figure 5 a healthy bowel image.

In the case of CRC an AI tool can be used to help with the diagnosis. With the help of convolutional neural networks, for example, a number of colonoscopy imaging can be used, for which it is already known whether the individual has or does not have CRC. Since the properties of CNN include shape detection it mostly is necessary to find a large enough database of images which can be used to train the network. The images usually have to be preprocessed before using

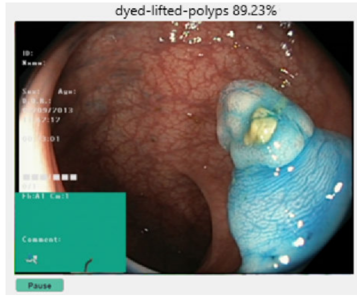

FIGURE 4. Colonoscopy picture with CRC polyp.

FIGURE 5. Colonoscopy picture with healthy bowel.

them to train the network. Some of the operations that can be done are noise removal, image resizing and segmentation. Sometimes the images contain writing or some other source that may cause inaccuracy and they have to be removed. If the number of images is small, they can be manually removed, or certain algorithms can be used to remove parts of an image. Oher applications that have been thought of are using different diagnosis methods such as the Fourier Transform spectroscopy or analysis of symptoms and biological parameters. Some applications which try to predict the survival chance or to predict the period in which the death of the individual may occur.

In their work Eun Hyo Jin et al made a CNN based diagnosis tool which aids novice doctors to identify diminutive polyps. These types of polyps are of two main categories, adenomatous and hyperplastic. The common properties of these polyps are that they rarely or never become malignant tumors. The main objective of their work is to obtain an AI tool with high accuracy in order to reduce diagnosis time and reduce the skill level required by the doctors to correctly identify the polyps. In their design of the CNN a number of over 2100 colonoscopy images are used just for the training. A collection of 300 images is used for the validation, note that using the same images for training and validating a network has an increased accuracy. As a measure of keeping enough information and not having big matrices as inputs the images are kept at a 128×128 size. They use ENAS (Efficient Neural Architecture Search) known to be part of the AutoML methods, which is a library for Python used to discover a machine learning pipeline for the application.

Their work provides an accuracy of about 85%, considered to be an accurate model [29].

In their work Sanidhya et al used the histopathological diagnosis to determine the cancer types. In their work the LC25000 dataset is used which has images of 3 types of lung carcinomas and 2 types of colon imaging. The images contain a microscopic representation of the cells. The CNN's are used to identify the visual characteristics of the cells. In their work the images are rescaled from 1024 × 768 to 768 × 768. The CNN uses multiple convolutional and pooling layers with additional filters being applied. In the end they obtained accuracies of 96%-97% [30].

Zaneta et al in their study of CNN in cancer detection compared several methods which are based around CNN: Patch classification, semantic segmentation, the You Only Look Once (YOLO) network and Locally Sensitive networks. The four methods work differently and therefor the results are different for each case. In the study the FI score is considered as the main comparing factor, since the highest values of these are highlighted. According to these values the semantic segmentation using U-nets appear to have the highest values around all situations [31].

Histopathology imaging can be used to predict the lymph node metastasis in colon cancer. In the study deep convolutional neural networks are used for the model development. For the training 100000 images of 224 × 224 images are used. The images are representative of stages 1 through 3 of cancer, which means that the cancer has not yet spread to other organs [32].

The polyps are the growths that can be become the tumors, some studies directly analyze them, since there is a chance, it does not become cancerous. Patel et al in their study trained a number of six CNN on their dataset. Their objective is to create a model able to classify the polyps and compare the performances of the different CNNs. The CNN models include VGG, ResNet, DenseNet SENet and MnasNet. They specify some of the training parameters used, including Learning rate epochs and Batch size. The best results came from the VGG19 method having an accuracy in the 75%-79% [33].

Ribeiro and Uhl in their work developed an application which similarly to the previous authors classifies colonic polyps with the help of CNN's. One of the steps that have been used is to extract subimages of smaller sizes from the original imaging. The original images have the size of 256 × 256 and 100 images are used to train the network. The CNN has as its input layer the images in the 128 × 128 × 3 format, which means they use colored images. After that 2 sets of convolutional and pooling layers are used, which is described as having 72 5 × 5 filters. After each set a ReLU rectifier function is used. Then a convolutional layer is used in order to map the features for the fully connected output layer, which has a hidden layer with 1024 neuron and choses the output from 2 classes. Later some parameters are slightly adjusted and after multiple trainings an accuracy of 90.96% is obtained. In order to verify if the results are sufficiently accurate, the method is compared with a number of different approaches. From their final table the authors method proves to be superior to the other methods it is compared with [34].

Using immunohistochemistry images certain biomarkers can be found which aid in colon cancer detection. This is possible since protein biomarkers can be present in high intensity which can lead to detecting certain cancer types. In their study Xue et al have created an application which uses 2 types of neural networks. A CNN is used with the IHC images to extract the feature maps. These maps are built by going through a number of steps in which the images are preprocessed and the CNN is trained. The second part of the work is represented by the use of fine-tuned deep neural networks. In the study seven pretrained networks are used, the main reason those networks are used is due to their robustness and popularity. The method used by these authors obtained models with accuracies of 84% [35].

Masud et al use the LC25000 dataset and CNN for CRC and lung cancer detection. The Wavelet Transform is used in their approach, a mathematical function can transform a continuous time signal into different scale components. In this case the WT is used to reveal spatial properties of the image. The CNN is fed 64 × 64 sized images and are trained over 500 epochs. Three convolutional layers with maxpooling layers are used with dropout layers. With their described parameters and with the dataset they used a model with 96.33% accuracy is obtained [36].

In diagnosis the classification of histological nuclei can be used for image analysis. The analyzed work has its objective the use of CNN to do this challenging task. A number of architectures are used to compare different performances for the created models. A set of 2 convolutional levels and a pooling layer is used, followed by another set with smaller size. After those 3 fully connected layers are added from which 4 possible classes of output can be obtained. In the results section the proposed RCCNet had the best results in the testing and overfitting part, while in the training section the GoogLeNet has the best result. Usually, the results obtained in the testing, or validation, part are the more important ones since it is done on a different set of data [37].

Another way of analyzing the histological nuclei is with the help of spatially constrained CNN. In their work the authors used rotated patches of the input images which were rotated at 90-degree angles and have a common size of 500 × 500. A series of convolutional and max-pooling layers are used with 2 fully-connected layers at the end for SC-CNN and 3 for the CNN. The performance of the models is analyzed using the F1 score, which is a weighted average between the precision and the recall values obtained. From the results the SC-CNN has the best F1 score, which is the method proposed by the authors for their study [38].

A method that uses Graph Neural Networks (GNN) can be used in CRC diagnosis. In her study Franziska uses histopathology images to identify cancer grades. Her idea is to use the cell graph representation which can allow a generalized inspection of the colon in the different layers the colon can be broken down to. The architecture of a GNN is made from a graph modification and a classification part. The first part usually is made from convolution blocks that are used to modify the values of the edges and vertices; these are the main parts of a graph. For the training a dataset of 300 images of 5000 $\times$ 7000 pixels is used. For validation 41 images of 1000 $\times$ 1000 is used. The results obtained have an accuracy above 90%. Analyzing the method and the resolution of the images, in this particular application high resolution images are used, which for convolutional neural networks can present some problems. Big images are usually avoided since the training process can take an extended amount of time and the results may not improve. Even for smaller images of 100 $\times$ 100 depending on the architecture and the specifications of the computer used it can take minutes to hours. The author does not present the training time, but it is known that this type of neural networks is efficient, probably why high-resolution images can be used when training these networks [39].

A method to find cancerous cells is the FTIR (Fourier Transform Infrared) study. The method uses FTIR microspectroscopy and ANN for analysis. It is believed that using IR spectroscopy on formalin-fixed tissue samples. A comparison is made between tissues of healthy, early and developed stages of the cancer. In the study a clear distinction can be made between the three results proving that via this method it is possible to detect CRC. With ANN the results for correct prediction are at around 80%, meaning that there are still inconsistencies with the method which need to be improved [40].

Proteomic analysis is another diagnosis method used to identify CRC. In their paper Ward et al use ANN to analyze the proteomic fingerprints with the aid of SELDI (surface enhanced laser desorption/ionization). In the study different cases are analyzed depending on the serum being whole, depleted or eluted protein. With their method an accuracy of 93% is obtained [41].

In their study Burke et al use ANN to determine the survival chance of colorectal and breast cancer. The TNM staging system is used, which stands for tumor, nodes and metastases [42]. For the computation the tumor size, the number of positive regional lymph nodes and the period till the metastasis is used. The ANN used has one hidden layer and uses the sigmoid function as the activation function. The number of neurons is not specified but in the data section they specify a high number of inputs, most of which are binary except the ones used in the TNM part. As their results, a higher accuracy model is obtained via neural networks some results for TNM are 47% accuracy against 63% or 74% if the collected variables are increased in number [43].

In their work Chen et al are pursuing a supervised model for detecting CRC. In their study they use ANN and the Monte Carlo Algorithm. In their approach the parameters form the neural network are updated by selecting a random variable from either the weights or biases and recomputed with the help of some other parameters set by the user. A high number of genes are used as input parameters, with the help of principal component analysis that number is reduced. Their results include a model with a high accuracy of 84% [44].

Dulf et al in their study created an application that detects colorectal polyps and use a number of architectures and training methods. GoogleNet is the first analyzed method with which the best accuracy was 99.38%, a sensibility of 97.53%, specificity of 99.65%, precision of 97.55% and an F1 score of 97.54%. After the augmentation process the results vary, but the values do not go under 90%. For the AlexNet the best results are: accuracy of 98.98%, a sensibility of 94.7%, specificity of 99.24%, precision of 94.78% and an F1 score of 94.74%. For the Inception method the results are: accuracy of 99.53%, a sensibility of 98.13%, specificity of 99.73%, precision of 98.15% and an F1 score of 98.14%. CNN are used with a learn rate of 10 and drop factor of 0.3, the initial lear rate is 10^{-3}, the momentum parameter is 0.9, the validation frequency is 50, maximum number of epochs is 40 and batch size is 2. The kvasir dataset is used to train the network [45].

A summary of existing methods, the corresponding reference and the best obtained performances is presented in Table 2.

C. AI DIAGNOSIS FOR LUNG CANCER

Lung cancer is known to be the deadliest type of cancer, having the highest number of casualties. The severity of the disease is caused by it affecting the most important respiratory organ in the human body. The lungs are made of different sections called lobes. The right side of the lung is made of 3 lobes, while the left side has only 2 lobes. The respiration process is made possible by the air sacs known as alveoli which are surrounded by blood vessels. The dangers of lung cancer are mostly caused by 2 problems. The first one being that respiration is one of the important necessities without which all the other organs would die if not oxygenated properly. The second problem is due to it being in close proximity of blood vessels the chances of the cancer moving to other parts of the body is high [42].

For most cases lung cancer is associated with smoking, it has been proven that smokers have a higher chance to get cancer in their lifetime. Over 80% of lung cancer patients are long-term smokers. For the other percentage it is a combination of genetic factors and exposure to different chemicals or polluted/ dirty air. There are different studies which prove that miners who are exposed to a harsh environment for their lungs are likely to develop lung tumors [42].

The symptoms for lung cancer can start with coughing, chest pains and shortness of breath to coughing blood and weight loss, usually the later ones appear in severe cases. Some of the symptoms, however, can be mistaken for a cold which may not convince people to go to a medical checkup. As any other cancer type early detection increases the survival chance of the individual, while other treatments like chemotherapy or radiotherapy are used and can prompt a full recovery.

TABLE 2. Colorectal cancer method and performance table.

Reference	*Method*	*Performance*
[29]	CNN & AutoML	85%
[30]	CNN	96%-97%
[31]	U-net CNN	49%-82.5%
[32]	Deep CNN	0.2917 (MSE)
[33]	CNN	75%-79%
[34]	CNN	90.96%
[35]	CNN	84%
[36]	CNN (Wavelet Transform)	96.33%
[37]	RCCNet	80.61%
[38]	CNN	0.692 (F1-score)
[39]	GNN	90%
[40]	ANN with FTIR	80%
[41]	ANN & SELDI	93%
[43]	ANN	63%-74%
[44]	ANN with Monte Carlo Algorithm	84%
[45]	CNN	99.53%

The diagnosis is done usually by computer tomography or magnetic resonance imaging, which are expensive and time-consuming methods, so alternative methods are in progress. For example, diagnosis by ultrasound images. In such images the lungs are usually a shade of gray. The tumors on the other hand are of a different gray. Human errors may occur when the tumor is small or some shadow is in the same spot [1].

In figure 6 an ultrasound image of a lung cancer patient can be observed, in it the most useful information is that the cancerous part of the lungs has different color. In contrast is presented in figure 7 a healthy lung.

A tool developed by Shakeel et al consists of using biomedical lung data which is used to model lung cancer prediction. The data is collected from the ELVIRA Biomedical Data Set Repository, which basically is a dataset in which a number of institutes have introduced their data. The Adaboost optimization method is used in concordance with neural networks to develop the tool. For missing data, the estimated median value is used. Since the dataset has a lot of values, some of them considered to be irrelevant and complexity in NN based applications is not desired, some elements have to be eliminated and such features like entropy, variance and mean are used to accomplish this task. In the next part the authors explain how the AdaBoost technique is used, basically the process is continuously trained and extracted features are analyzed in order to determine what information is relevant. For performance analysis a lot of values are used: starting from F measure, precision and mean square error to G mean, Sensitivity and specificity. Multiple types of NN structures are used and compared for each performance characteristic. In their final discussion they have obtained the best results for the NN enhanced with the AdaBoost technique. The smallest MSE is obtained with it and for the other features a value of over 99% [46].

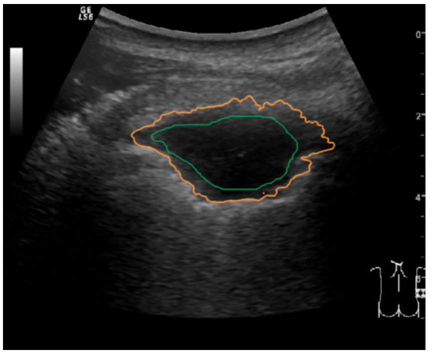

FIGURE 6. Lung cancer ultrasound image with contour detection.

FIGURE 7. Healthy lung ultrasound image.

A method that has been tried in multiple diagnosis tools is the Content Based Image Retrieval (CBMIR). The main disadvantage of the technique is that it requires a lot of computational power and have been shown to have low efficiency. For the study a dataset containing multiple CT images is used, consisting of 400 images for training and 100 images for testing. The images are preprocessed using several algorithms starting with the adaptive median filter, which is used to remove noise from the images. The basis of the algorithm is to extract pixels by brightness and rank and to compute the median value for each pixel. Then the corrupted pixels are replaced by the computed median values. Then the image is segmented to extract the affected regions using different algorithms like the watershed algorithm or the pattern based modal medical image segmentation. After these filters are applied a probabilistic neural network (PNN) is developed. In the results section the proposed method proved to have the smallest error margin which meant that it had the highest accuracy of the compared methods [47].

In some cases, the disease may not be cancer and there have been some applications that have obtained a chest disease diagnosis tool. For the diseases the following are considered: tuberculosis, COPD (chronic obstructive pulmonary disease), pneumonia, asthma and lung cancer. The dataset is taken from the Diyarbakir Chest Disease Hospital and contains a number of 357 samples. The study uses the PNN structure having a single hidden layer and 6 possible outputs (one for each type of disease and one for healthy). At the end of the study the PNN is compared with a number of different types of NN with one or more hidden layers. From the comparison it has been proven that the PNN has the better average performance [48].

Kuruvilla and Gunavathi use neural networks for a classification tool. The images are processed by segmenting it and converting them to binary images. The Otsu method is used to choose the threshold level. They create models using 13 different training functions and compare their accuracy and mean square error. Out of these methods the best accuracy, of 91.11%, is obtained by using the gradient descent method with variable learning rate and momentum and a mean square error of 0.112 [49].

Arulmurugan and Anandakumar use the wavelet feature to develop their tool. The wavelet feature is used to compute the gray level cooccurrence matrix which is fed to the network. The data set is taken from the Lung Image Database Consortium (LIDC). The neural networks are trained using four different training functions. Their results show that the traingdx function has the best performance, of 92.61% [50].

In their work Perez and Arbelaez use CNN to develop their lung cancer diagnosis tool. To train their network the LIDC-IDRI dataset and the Kaggle DSB 2017 dataset are used and the images are enhanced by using the median filter which is used for noise reduction. The first part of the study is to create a nodule detector. For this a 3D CNN is used. The network structure is not entirely specified, after the convolutional layers max pooling layers are used to halve the dimensions of the images. The input images vary in size going from, $32 \times 32 \times 9$ to $16 \times 16 \times 16$ and $24 \times 24 \times 24$. After training the network the best result is and average precision of 41.9%. However, for cancer detection the results obtained have a performance of 97.3%, for this a number of convolutional and pooling layers are used until the size of 6×6 is reached then using the dense layer the probability is computed [51].

A technique which can be used to enhance the quality of an image is improved profuse clustering. In their tool Shakeel et al use the Cancer Imaging Archive (CIA) dataset. Due to the images containing noise these need to be preprocessed before they can be used to train the network. This is done by using pixel intensity examination and different image histogram techniques, mainly the weighted mean histogram equalization. After the noise removal the image is enhanced in order to detect the affected region. This works by analyzing similar pixels in different images and grouping them to similar super pixels. After training the network their method is compared with 6 other different methods. A number of different performance parameters are analyzed: accuracy, specificity, precision, recall and F1 score. The compared methods are: region growing, global threshold, fuzzy c-means, canny method, Sobel method, watershed approach and the IPCT method presented in the study. In every analyzed performance the presented method has the highest performance, in some by a large margin. Their final result is a 98.42% accuracy model for cancer detection, using the optimal neural network with the IPCT method [52].

In their study Chon et al use 3D CNN. Their first attempts have had bad results, due to this their decision is to use segmentation. The images which are used to train the network are from the Kaggle dataset and use 420 images for training and 420 images for testing. Watershed, clustering and thresholding are tried and after testing the methods the threshold method is used. The input images are $256 \times 256 \times 1$ and the Unet network uses 6 sets of 2 convolutional layers with ReLu activation function and a Max Pooling layer and a few Concat layers. A traditional CNN is used with 6 convolutional and Max Pooling layers with a Dense layer at the end. For this the images fed into the network are of $64 \times 64 \times 64 \times 1$ size. The same input size is used for the 3D Googlenet architecture. In this case the architecture is more complex by having convolutional layers with max pooling at the start and then 3 sets of 2 incerption layers and max pooling layers followed by and average pooling layer and a dense layer at the end. Generally, it is a 22-layer deep CNN used for image classification, quantization, and object detection, with the distinctive feature of using the inception layers. The study shows that the 3D Google net has the best performances in three of the 4 analyzed performances. However, the results have an average performance of 75%, which compared to some other techniques presented is low [53].

Shervan et al use the LIDC dataset which is represented by 1018 cancerous and healthy CT scans of lungs. The authors analyze several techniques used for accurate modeling while applying a number of image processing techniques to increase the accuracy of their model. The modified Sobel filter and the super pixel algorithm are both used to enhance the images in different ways. The Sobel filter is used on the edges of the images by using two vertical and horizontal masks. The super pixel algorithm is used to cluster the image into more meaningful segments. The algorithm is known as the simple linear interactive clustering. A center is chosen in the sample image from which the super pixels are generated. There are two important parameters in this algorithm: the compression rate, which needs to be determined via experimentation, and the number of super pixels, which is set by the user. Their final result has an accuracy of 84.88% measured with the Dice similarity measure [54].

TABLE 3. Lung cancer method and performance table.

Reference	Method	Performance
[46]	ANN+AdaBoost	99.725%
[47]	PNN with CBMIR	0.871-0.956 (Recall)
[48]	PNN	92%
[49]	ANN+ Otsu method	91.11%
[50]	ANN and Wavelet feature	92.61%
[51]	CNN	97.3%
[52]	DITNN	98.42%
[53]	GoogLeNet	75%
[54]	ANN	84.88%

As in previous cases, a summary of the best methods published in the specific literature with the corresponding performances helps the reader in their choice for method.

D. AI DIAGNOSIS FOR PANCREATIC CANCER

The pancreas is another organ which is part of the digestive system. Its role is to produce different enzymes used in the digestive process. The cancer is known to start in the part of the pancreas that produce these enzymes [55].

Some of the causes of pancreatic cancer come from the lifestyle of the individual, like smoking and heavy drinking, but it can be genetic as well. Individuals suffering from diabetes or obesity also have a higher chance to get pancreatic cancer.

The symptoms can range from abdominal or back pain, light colored stool or dark urine to yellow skin. The diagnosing method used is medical imaging, blood tests or tissue biopsy. For the diagnosis usually ultrasound imaging is used [56].

In figure 8 a pancreas CT imaging is shown, in which the tumor is shown as a round shape that can blend into the imaging. In this case it is much harder to detect, but still possible even by the human eye. As comparison, in figure 9 is presented a normal pancreas ultrasound.

A number of casualties occurs due to the non-optimal treatment of individuals, mistakes which can occur to even an experienced doctor. In their work Walczak and Velanovich use ANN to improve the prognosis. They evaluate the performance of the ANN via sensitivity, used in accurately predicting survivability in the following 7-month period, and specificity. The main goal of the authors is to obtain over 90% sensitivity and a high overall performance. A single hidden layer with 21 neurons is used to train the network. As input parameters age, sex, resection, stage, duration are all necessary biological parameters which have a direct influence on the survivability of the patient. The Sf-36 domain variables which have high correlation values are used as well. In total there are 14 input parameters. The model concluded to be the best one has 91.3% sensitivity accuracy and 37.04% specificity, with an overall of 71.23% which they slightly increased to 71.69% by adjusting a certain parameter. In the study a certain behavior of the 2 analyzed performances can be observed. It is possible to obtain 100% accuracy for the sensitivity, but then the specificity is at 0% and if the accuracy for specificity is increased the accuracy for sensitivity is decreased [57].

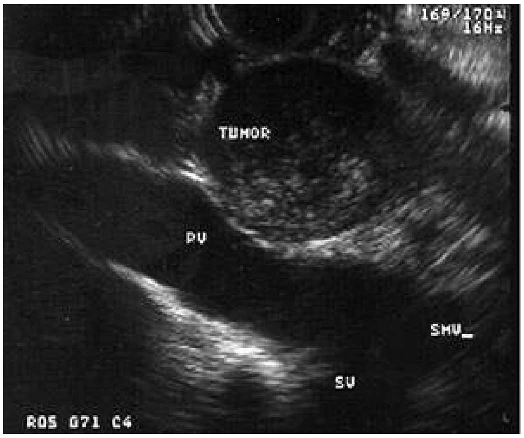

FIGURE 8. Pancreatic cancer ultrasound image.

FIGURE 9. Normal pancreas ultrasound image.

In their study Harlid et al analyze a number of ANN tools created by others and compare their results. Pancreatic cancer and acute pancreatitis are the 2 analyzed diseases. For pancreatitis there have been models obtained with 85% accuracy with a large number of input variables. Another study reduces the number of inputs to only 6: fluid aspiration, serum creatinine level, presence of another illness, blood pressure and calcium level. They analyzed other studies which use linear regression and compare it to ANNs. The advantages discovered are about the training data amount being necessary to be over a certain value and unnecessary input variables should not be used. In the case of pancreatic cancer, the first analyzed paper uses ANN's with EUS. The results are of around 80% accuracy overall. The studies analyzed later in the paper compare ANNs with Bayesian and linear discriminant method. In their final discussion they describe ANNs as having a large potential in diagnosis and due to both pancreatic cancer and pancreatitis being diseases with high complexity causing difficulties in both diagnosis and treatment, neural networks have the capability to obtain accurate predictions and can become a much-needed tool in medical applications [58].

Ansari et al use ANNs to predict survivability after the surgical procedure has been done on the patient. The premise is that after the surgery for 5 years the survival chance of the patient, from adenocarcinoma derived from ductal cells of the pancreas, is low. A number of 33 input variables are used, which are considered significant for the diagnosis. Several experiments are done to determine the number of neurons. The authors start with 1 and go on until the highest performance is achieved. They consider overfitting for the model and use a weight decay term. The study is performed on 84 patients and for the performance the C-index is used. Their performance was at the value of 0.79 which is compared with several studies in which the performance of the C-index ranged from 0.66 to 0.81 [55].

Pancreatic cancer and chronic pancreatitis are hard to differentiate when endoscopic ultrasounds are the method of evaluation. In their research Cazacu et al use CNN and ANNs are used to create a tool to help with the decision making. They specify a number of around 400 images used to train the network. The results are over 94% sensitivity and specificity. By using multilayer perceptron neural networks (MNN) the performance increased to an average of 95% on validation data and 97% performance in the training process [59].

Table 4 presents the best obtainable performances published in the literature, with the corresponding method.

TABLE 4. Pancreatic cancer method and performance table.

Reference	*Method*	*Performance*
[57]	ANN	71.69%
[58]	ANN with Bayesian and lkinear discriminant	85%
[55]	ANN	0.79 (C-index)
[59]	MNN	95% validation 97% training

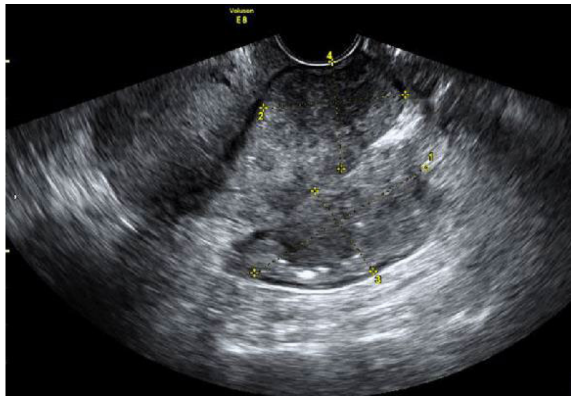

FIGURE 10. Cervical cancer ultrasound image.

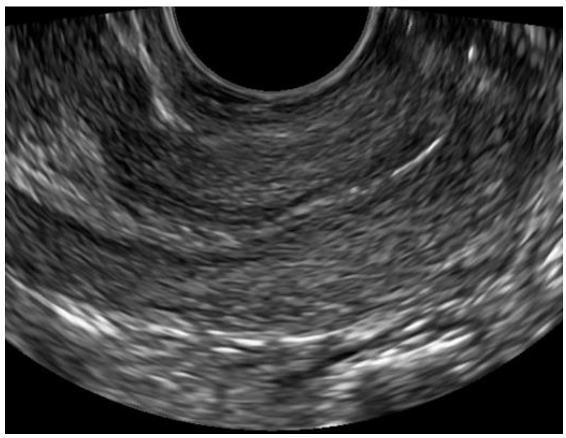

FIGURE 11. Normal cervix ultrasound image.

E. AI DIAGNOSIS FOR CERVICAL CANCER

Cervical cancer is one of the most common diseases diagnosed for women. Generally, it is treated with radiation therapy. Image processing techniques are also used for this disease. In figure 10 is presented such an image with cervical cancer, in contrast with figure 11, healthy cervix.

In their study Liu et al used CNNs to detect what organs are at risk when a patient is irradiated. The dataset used is from 105 patients with the average age of 52. The images are 512×512 pixels. The architecture they use is the U-Net which has been proven to be very effective when dealing with image segmentation. The structure of the network is broken into an encoder and decoder which contain the convolution pooling and interpolation layers. For the training the learning rate is set to 0.001 and after 50 epochs the best model was selected. From the evaluation the best obtained loss score is of 0.012 [60].

Shervan used the pap smear classification method, which already is known to have saved millions of lives. In the study the author compares several models obtained with neural networks with Bayesian networks for the classification accuracy.

TABLE 5. Cervical cancer method and performance table.

Reference	*Method*	*Performance*
[60]	CNN	0.012 (score loss)
[61]	NN and Bayesian Network	
[62]	GoogleNet	95%
[63]	CNN	

The hevlev dataset is used which is a set of 917 pap smear images broken into normal and cancer classes [61].

Hussain et al in their study use the pap smear classification method with 3 datasets, totalizing 3907 images. They use pretrained CNNs for the models. The authors test the performance of Alexnet, Vgg, Resnet and GoogleNet, out of which the GoogleNet gave the better results. The accuracy values are above 95% for each dataset [62].

Chen et al use a CNN based model to optimize the intensity-modulated radiation therapy for cervical cancer. The dataset consists of 140 images from which 100 are used to train with 20 for validation and 20 for testing. The structure of the CNN is made of a series of 2 convolution, ReLU and max pooling layers followed by two fully connected layers. There are a number of organs at risk from which different parameters of importance are extracted. In each case 3 plans are suggested, and they are organized in a hierarchy. In most cases the AP gave the best results with MP2 being the second best. MP1 gave the worst results in every case [63].

The summary of possible methods with the corresponding performances is presented in Table 5.

IV. CONCLUSION

Medical applications with neural network tools have increased in number due to the variety of uses and due to their properties. Only a number of cancer types and diagnosis methods is analyzed in this review. The results of the studies which are analyzed have a high accuracy and, in the future, might even start to be used in hospitals over the world. The biggest benefit is that mistakes made during diagnosis is going to be reduced, and the survival chance of cancer patients in going to increase. Although a powerful tool, the main disadvantage that which occurs is that each of these applications is working on certain scenarios and on certain types of cancers. The reliability of such tools is considered to be small; a large number of tools is required in order to have a proper diagnosis. Technology has come far, but there is still room for progress and some technological advances have to be made before diagnosis can be safely automated.

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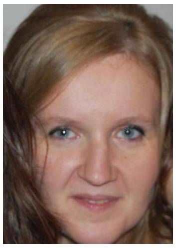

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