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A Comprehensive Strategy for the Identification of Arachnoid Cysts in the Brain Utilizing Image Processing Segmentation Methods

Aziz Ilyas OZTURK, Osman YILDIRIM, Onur DERYAHANOGLU

***Abstract:** This study focuses on segmenting and characterising arachnoid cysts in brain MRI images, aiming to enhance diagnostic accuracy through advanced image processing techniques. Arachnoid cysts are cerebrospinal fluid-filled sacs located between the brain or spinal cord and the arachnoid membrane. These cysts can be asymptomatic but may also cause neurological symptoms such as headaches, seizures, or cognitive impairments when they increase in size or pressure. Accurate detection and characterisation are crucial for timely intervention and effective treatment. In this study, 269 brain MRI images were analysed using connected component analysis (CCA) and contrast-limited adaptive histogram equalisation (CLAHE). CLAHE was employed to enhance image contrast, particularly in regions with subtle intensity differences, while CCA facilitated the segmentation of connected regions corresponding to cysts. The smallest connected components were identified and analyzed to isolate arachnoid cysts with high precision. Following segmentation, quantitative analysis was performed to extract features such as size, shape, and density, thereby enabling comprehensive characterisation of the cyst. Additionally, calculations for area and approximate volume were conducted, providing critical information for clinical assessment. Visual validation of segmentation outcomes confirmed the effectiveness of the applied methods in accurately delineating cyst boundaries. This research addresses a significant gap in the existing literature. While most studies focus on brain tumour segmentation, there is limited work on arachnoid cyst detection and volume estimation. By integrating image processing techniques tailored explicitly for the diagnosis and monitoring of arachnoid cysts, this study presents a novel approach to their management. The findings demonstrate the potential for automated diagnostic tools to reduce subjectivity and improve efficiency in clinical workflows. The proposed methodology aligns with advancements in medical imaging. It contributes to the development of improved tools for neuroimaging diagnostics, paving the way for more precise and reliable assessments in the detection of brain pathologies.*

***Keywords:** Arachnoid Cyst, Segmentation, Cyst Analysis*

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*Correspondence Author(s)

Dr. Aziz Ilyas OZTURK*, General Electric Healthcare Istanbul, Turkey. Email ID: aziz.ozturk@gehealthcare.com, ORCID ID: 0000-0003-2350-5880

Prof. Dr. Osman YILDIRIM, Istanbul Aydin University, Faculty of Engineering, Department of Electrical and Electronics Engineering, Istanbul, Turkey. Email ID: osmanyildirim@aydin.edu.tr, ORCID ID: 0000-0002-8900-3050

Dr. Onur Deryahanoglu, General Electric Healthcare Istanbul, Turkey. Email ID: onur.deryahanoglu@gehealthcare.com

I. INTRODUCTION

Tissue is a structure composed of cells with similar Structures and functions make up the body of an organism. These specialized cells combine to form structures that perform specific functions.

The body contains various types of tissues, each providing the structure and function of specific organs or systems. For example, muscle tissue is formed by the aggregation of muscle cells, enabling the contraction and relaxation movements of muscles. Nerve tissue is composed of nerve cells and carries out functions such as nerve transmission and information processing.

Tissues fulfil various tasks in the body by constituting organs and organ systems. These tasks are crucial for the organism to sustain its vital functions.

An arachnoid cyst is a cyst that forms in the arachnoid layer between the membranes surrounding the brain and spinal cord. The brain is surrounded by three layers of membranes: the pia mater (innermost), the arachnoid (middle layer), and the dura mater (outermost). An arachnoid cyst is a fluid-filled sac that develops within the arachnoid layer. Although usually congenital and asymptomatic, they may grow and exert pressure on surrounding tissues, causing various symptoms such as headaches, dizziness, nausea, and visual problems.

Arachnoid cysts are typically discovered incidentally during imaging tests. The symptoms and the size of the cyst normally determine treatment. Small, asymptomatic cysts usually do not require treatment. Surgical intervention or other treatment methods may be considered for large cysts causing symptoms. A specialist's evaluation determines the treatment plan, and each case is individual.

Tissue segmentation, the process of identifying a specific tissue type or region in an image, is a commonly used technique in various fields, including medical imaging, computerized tomography (CT), magnetic resonance imaging (MRI), and histology. Tissue segmentation, the process of identifying a specific tissue type or region in an image, is a commonly used technique in various fields, including medical imaging, computerized tomography (CT), magnetic resonance imaging (MRI), and histology. This technique is essential for accurate analysis and diagnosis. It is vital to ensure that the segmentation is objective, comprehensible, logically structured, and employs clear, objective, and value-neutral language. Tissue segmentation, the process of identifying a specific tissue type or region in an image, is a commonly used technique in various fields, including medical imaging, computerized tomography (CT), magnetic resonance imaging (MRI), and histology. The language should be formal, avoiding contractions, colloquial words, informal expressions, and unnecessary jargon. The text should be grammatically correct, free from spelling mistakes, and punctuation errors. The content of the improved text must be as close as possible to the source text, and the addition of further aspects must be avoided at all costs.

In histology, tissue sections are examined under a microscope. Tissue segmentation can identify specific cell types or structures in images obtained from histological preparations examined under a microscope.

Ultrasound (USG) imaging can apply tissue segmentation to distinguish specific organs or regions, such as fetal organs in fetal ultrasound.

Endoscopic images can use tissue segmentation to identify tissues or lesions. Tissue segmentation can be applied in endoscopic examinations of the gastrointestinal system or other internal organs, as well as in X-ray imaging and nuclear medicine images to identify specific tissues and bones, and evaluate organs or tissues.

Additionally, it can be used in digital pathology. During digital imaging of pathological samples, tissue segmentation enables pathologists to identify specific cells or structures.

Tissue segmentation has a broad range of applications in the evaluation, diagnosis, and treatment planning processes of medical images. This technique plays a significant role in clinical applications by providing a more precise and efficient approach to automatic analysis and diagnosis.

When using an imaging method like magnetic resonance imaging, different tissues exhibit varying signal characteristics. For instance, in the brain, white matter and grey matter produce distinct signals in MRI images. By utilising these unique signal characteristics, the tissue segmentation method can effectively separate different tissues, such as white matter and grey matter. Tissue segmentation is utilised in medical imaging and biological research for detecting tumours, surgical planning, treatment monitoring, and identifying and analysing cell types, tissues, and organs.

II. MATERIAL AND METHODS

The dataset used to investigate Arachnoid Cysts was obtained from the Istanbul Betatom Imaging Centre. No personal patient information was included. The images were acquired using a GE Brand MR device, resulting in a total of 269 images.

PYTHON programming was used to detect cysts in the brain and calculate their respective areas.

III. SEGMENTATION

Segmentation is a commonly used term in the fields of image processing and computer vision. It refers to dividing or grouping an image into different parts or segments, often consisting of pixels or regions with specific or similar features.

The primary objective of segmentation is to isolate different objects or sections within an image. Segmentation is crucial in various applications, including object recognition, medical imaging, autonomous driving, and video analysis. Its primary purpose is to facilitate understanding of different objects or features within an image.

In medical imaging, image segmentation is a critical component and is carried out in the region of interest through automatic or semi-automatic procedures [1]. Numerous algorithms are employed in medical imaging for segmentation tasks. These tasks include tumour detection [2]. They also include brain function analysis [3]. Additionally, blood cell classification and mammography mass detection are other examples [4].

Segmentation methods vary based on different features. One standard method is thresholding, which assigns image pixels greater or smaller than a set threshold value to other segments.

Edge detection is the process of identifying sharp transitions or edges in an image to separate objects [5] Region-based methods are used to identify regions where similar pixels come together based on colour, brightness, or texture similarity [6].

Region growing involves selecting a specific starting pixel and creating an area of pixels that are similar to it. Watershed segmentation is performed by utilizing shadows and peaks in the image. Shadows are used to determine segmentation boundaries.

Clustering is a method of segmenting by grouping data points based on specific features. K-means clustering is a commonly used method.

Segmentation is a crucial stage in image analysis and understanding processes, widely employed by researchers and engineers in this field.

IV. THRESHOLDING PROCESS

In image processing, the thresholding process is an operation that separates pixels into two groups based on a specific grayscale value in an image, known as the 'threshold value.' It is a crucial step in image processing. In image processing, the thresholding process is an operation that separates pixels into two groups based on a specific grayscale value in an image, known as the 'threshold value.' This process is widely used in applications such as image segmentation, object detection, and image enhancement [7].

The thresholding process involves determining the threshold value and dividing the pixels into two groups. The threshold value is typically determined through trial and error or based on the desired image features.

To separate pixels into two groups, each pixel is divided based on the specified threshold value. Pixels with values greater than the threshold are assigned to one group, while those with values less than the threshold are assigned to the other.

For example, let's consider a simple black-and-white image. If the threshold value is set to 128, pixels with grayscale levels of 128 and above will be assigned to one group, and pixels with grayscale levels below 128 will be assigned to the other group. This allows for the emphasis or isolation of regions in the image with a specific feature.

The thresholding process is often used as a preprocessing

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step to enhance the meaning of an image or to isolate specific objects. Pixel segmentation is a process that involves dividing pixels into two groups using a particular value of threshold in a grayscale image. This process is used to identify, highlight, or distinguish different objects or regions within an image.

The first step in this process is to determine the threshold value, which is often chosen based on application or analysis requirements. This value represents a specific brightness level in a grayscale image.

After determining the threshold value, each pixel is compared to it. Pixels greater than the threshold are assigned to one group, while those smaller than the threshold are assigned to the other group.

This process results in the emergence of regions or objects with two different brightness levels. A new image is created based on the pixel groups obtained from the thresholding process. In this image, pixels above or below the threshold value are represented in white and black, respectively. This improves the visibility of specific objects or regions in the image.

Thresholding is commonly used in applications such as object recognition, edge detection, image enhancement, and image segmentation. For instance, it can be applied to determine the boundaries of a specific organ in a medical image or to differentiate cells under a microscope.

V. CONNECTED COMPONENT ANALYSIS

Connected component analysis is a technique used in image processing for tasks such as object recognition and segmentation. This involves grouping adjacent pixels in an image based on a specific criterion, with each group typically representing an object or region.

The fundamental steps of connected component analysis include thresholding or edge detection. The first step typically involves applying thresholding or edge detection processes to identify areas of interest in the image. These processes are used to detect and analyze the boundaries of objects or regions.

Connected Pixels Labelling: Using the determined threshold value or edge information, connected pixels that belong to the same object or region are grouped and labelled. A label usually represents each group.

Analysis of Connected Components: After the labelling process, each labelled group is considered a connected component. Analysis of these components can be performed by calculating features such as area, centroid, and orientation.

Based on the identified features, connected components meeting specific criteria can be filtered or classified. This step can be used, for example, to eliminate components below or above a particular area.

It can be used to distinguish different objects in an image and analyze specific properties of cells or anatomical structures. Connected component analysis has various applications, including object recognition and segmentation, cell counting and analysis in biomedical images, and tissue analysis in medical images.

Face recognition and biometric applications can utilize connected component analysis.

This technique offers a powerful tool for understanding, classifying, and analysing structures within an image.

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, SC, DC, and RMS do not require definition. Do not use abbreviations in the title or heads unless they are unavoidable.

VI. SMALLEST CONNECTED COMPONENT

In image processing, the term 'smallest connected component' generally refers to one of the objects or region groups identified during connected component analysis. Connected components are structures formed by grouping connected pixels based on a specific criterion.

Each group represents an object or a region. The term 'smallest connected component' typically denotes the group with the smallest size or area compared to others.

For example, in image analysis using connected component analysis, multiple objects or regions may be identified. The object with the smallest area is referred to as the 'smallest connected component.' This component may represent minor details in the image and is crucial to focus on in applications that require detailed analysis and isolation of objects of specific sizes.

VII. CLAHE (CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION)

CLAHE is an acronym for Contrast-Limited Adaptive Histogram Equalisation. It is a widely used image processing technique that enhances contrast and emphasizes details in an image. The fundamental principle of CLAHE is to make the histogram equalization process adaptive within an image. Traditional histogram equalisation employs a single threshold value for all pixels in an image, which limits its ability to enhance contrast uniformly. CLAHE, on the other hand, divides the image into small blocks and performs histogram equalization within each block. This aims to achieve better results by independently adjusting contrast in different regions [8].

Key features of CLAHE include adaptive processing, which enables independent contrast adjustment in different image regions by applying histogram equalisation within small blocks.

Additionally, CLAHE employs contrast limiting. CLAHE utilizes a mechanism that limits contrast to control excessive contrast increase while enhancing it. This method increases contrast without introducing excessive noise in the image [9].

CLAHE finds applications in various fields, including medical imaging, face recognition, and video processing. It is particularly effective in applications where images have uneven illumination and details require emphasis.

CLAHE is a valuable tool for enhancing visual analysis and diagnostic processes by improving overall contrast in an image and highlighting important details. However, it may be necessary to adjust the parameters to achieve optimal results in each application.

VIII. HELPFUL HINTS

Adaptive processing involves dynamically adjusting process parameters based on the characteristics of the input data. CLAHE (Contrast Limited Adaptive Histogram Equalization) is an adaptive histogram equalization technique that relies on these principles. The adaptive processing stages of CLAHE can be explained as follows:

Image Block Division - The image to be processed is initially divided into small blocks. These blocks are usually 8x8 pixels in size and represent subregions that undergo adaptive histogram equalization.

This process equalises the histogram of pixel values within each block, thereby enhancing contrast by ensuring a more even distribution of pixel values throughout the image. This process equalises the histogram of pixel values within each block, thereby enhancing contrast by ensuring a more even distribution of pixel values throughout the image. This process equalises the histogram of pixel values within each block, thereby enhancing contrast by ensuring a more even spread of pixel values throughout the image. The technique is known as histogram equalization and it improves the distribution of pixel values across the image.

Additionally, contrast limiting is employed. When performing adaptive histogram equalisation for each block, CLAHE employs a mechanism to restrict contrast. This is crucial for controlling excessive contrast increase and achieving a more homogeneous image without introducing noise. Limitation is typically applied based on the cumulative histogram of pixels within the block.

The processed blocks are combined to obtain the final image [10]. This step involves merging individually processed blocks [11]. These blocks are obtained through the adaptive processing of each block [12]. Adaptive methods play a critical role in achieving effective block processing [13].

CLAHE is particularly effective in images with non-uniform illumination and applications where local contrast needs to be emphasized. It allows for independent contrast adjustment in different regions and control of excessive contrast through limitation. This technique helps enhance contrast in visual analysis and medical imaging applications.

IX. CONTRAST LIMITING

Contrast-Limited Adaptive Histogram Equalisation (CLAHE) employs a mechanism called contrast limiting to prevent excessive contrast increase during the adaptive histogram equalisation process.

This technique regulates the effects of histogram equalization applied to each block during the process. Histogram equalisation enhances contrast by distributing pixel values in an image, but it can also increase noise and lead to excessive contrast enhancement, resulting in unwanted artefacts. Contrast limiting provides a mechanism to control and restrict this excessive contrast increase. During the adaptive equalisation process, a limiting value is determined from the cumulative histogram of pixels within a block. Contrast limiting helps maintain contrast at a specific level within a block [9].

This section discusses the reasons for employing contrast limiting in image processing.

It helps control the increase in noise that may result from the histogram equalisation process, resulting in a cleaner and more homogeneous image.

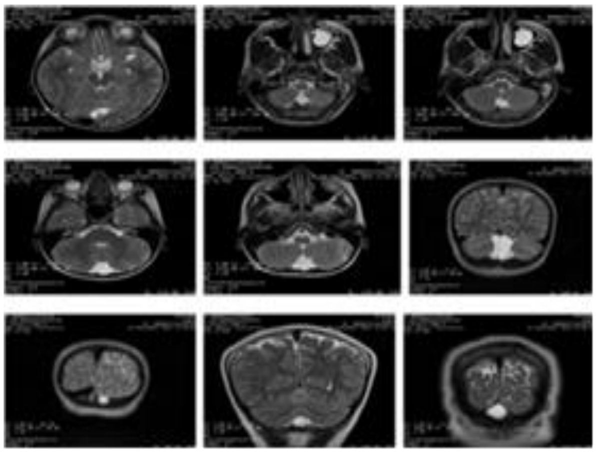
Additionally, it prevents excessive contrast. The use of comparison limiting is therefore recommended to improve image quality. In addition to controlling noise, contrast limiting also prevents excessive contrast increase during the adaptive histogram equalization process. This helps to avoid unwanted outcomes in visual analysis applications.

The user can adjust contrast limiting to adapt to different application scenarios [14]. This adjustment allows for the selection of the most suitable level of contrast limiting for a particular image [15].

CLAHE's contrast-limiting mechanism makes it an effective tool for enhancing contrast, particularly in medical imaging, face recognition, and other applications.

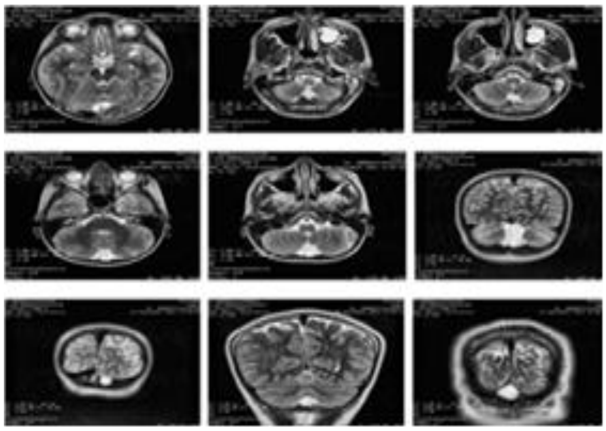
X. RESULT AND DISCUSSION

The study utilized brain images obtained from the GE Brand Signa Explorer Model with software version 29.1 MR device. The photos focused on Arachnoid Cysts and included Axial T2 FSE, Sagittal T2 FSE, and Coronal T2 FSE images. Figure 1 provides an example of Arachnoid Cysts with a section thickness of 5 mm.



[Fig.1: Images with Sample Brain Cyst]

The results of applying CLAHE to the analyzed images are presented in Figure 2 in the same order as in Figure 1.



[Fig.2: Images of Brain Cysts with Applied CLAHE]

Figure 2 shows that thresholding and connected component analysis were

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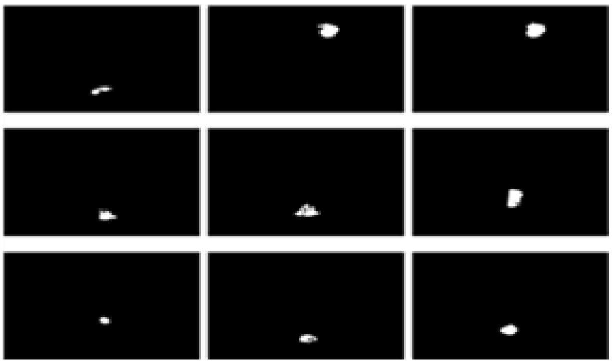
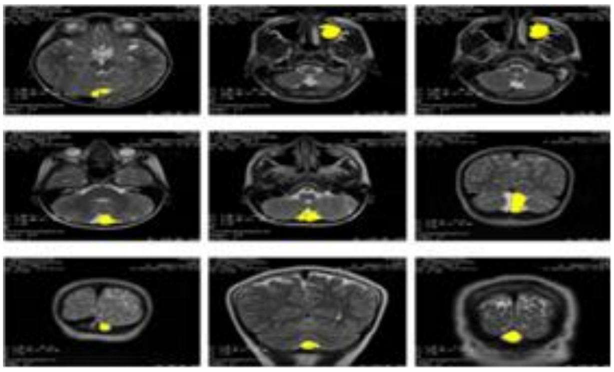
sequentially applied to the images enhanced by CLAHE. The cysts were then segmented after identifying the most significant connected component. Figure 3 displays the segmented images.



[Fig.3: Segmented Brain Cysts]

The Arachnoid Cysts segmented in Figure 3 have been colored in yellow using Python. The colored images are shown in Figure 4.

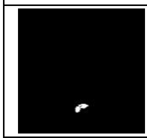
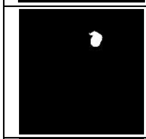
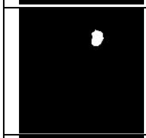
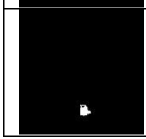
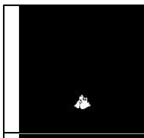
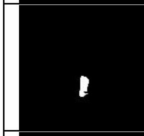
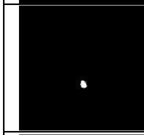
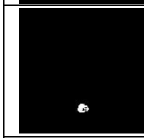
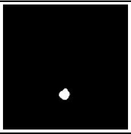


[Fig.4: Detected and Colored Cysts]

Table 1 presents the calculated areas and approximate volumes of the segmented sections with a slice thickness of 5 mm.

The formula used to determine the approximate volume is Volume = Area * Height (Slice Thickness), where Area is calculated as Pixel * 0.1 in an image with a pixel size of 0.1 mm.

Table 1: Areas and Volumes of Detected Cysts

Image	Area	Volume
	10.99 mm^2	54.95 mm^3
	25.78 mm^2	128.9 mm^3
	27.34 mm^2	136.71 mm^3
	14.99 mm^2	74.95 mm^3
	20.98 mm^2	104.91 mm^3
	101.14 mm^2	505.71 mm^3
	27.27 mm^2	136.35 mm^3
	45.11 mm^2	225.55 mm^3
	61.57 mm^2	307.85 mm^3

XI. RESULTS AND CONCLUSION

The impact of image processing in medicine is significant, with image segmentation playing a crucial role [16]. In medical imaging, the importance of the diagnostic field continues to grow daily [17]. Doctors are increasingly eager to explore anatomy further. Applications of images obtained from devices such as PET/MR, CT, and MRI have been significantly enhanced [18]. Image segmentation involves the automatic or semi-automatic separation of the region of interest in a given image. Various algorithms are used for image segmentation in fields such as tumour detection, brain functional studies, and mass studies in mammography devices [21].

Segmentation of images into different colored regions helps distinguish fluid, white, and grey matter in brain images [22]. It is also beneficial for analyzing the structure of breast tumours [18]. Deep learning applications are used for detecting cysts or tumours. In today's rapidly advancing computer technology, deep learning is becoming a crucial tool in medical imaging. It is now being used for image restoration in many MRI devices.

Valuable contributions to the literature would include the segmentation of brain arachnoid cysts and the calculation of the area and approximate volume of the segmented part. The

Detection of Brain Colloid Cysts using image-processing methods has also been reported [20].

This study demonstrates the effectiveness of image processing techniques, specifically CLAHE and connected component analysis, in the segmentation and characterization of arachnoid cysts. The segmentation process successfully identified cyst boundaries, and quantitative analyses provided critical data, including area and approximate volume. The results underscore the potential of these methodologies to enhance diagnostic accuracy and efficiency in neuroimaging workflows.

By addressing a notable gap in the literature, this research contributes to the field of medical imaging through its novel focus on arachnoid cysts rather than traditional tumour

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segmentation. The proposed methodology is a step toward developing automated diagnostic tools, thereby reducing subjectivity and enhancing the consistency of clinical assessments. Future integration of this approach into imaging devices or workstations could further streamline the diagnostic process, paving the way for advanced neuroimaging diagnostics and patient care.

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DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

- **Conflicts of Interest/Competing Interests:** Based on my understanding, this article does not have any conflicts of interest.
- **Funding Support:** This article has not been sponsored or funded by any organization or agency. The independence of this research is a crucial factor in affirming its impartiality, as it was conducted without any external influence.
- **Ethical Approval and Consent to Participate:** The data provided in this article is exempt from the requirement for ethical approval or participant consent.
- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Author's Contributions:** The authorship of this article is contributed equally to all participating individuals.

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AUTHOR'S PROFILE

Dr. Aziz Ilyas OZTURK has been working as a Field Engineer at General Electric Healthcare in Istanbul, Turkey, since 2012. He graduated from the Department of Electrical and Electronics Engineering at Fırat University in 2001. He completed his Master's and Doctoral degrees Studies at Istanbul Arel University. Currently, he continues his role at General Electric Healthcare, specializing as a field engineer in modalities including MRI, CT, PET/MR, PET/CT, and Mammography.

Prof. Dr. Osman YILDIRIM serves as the Head of the Department of Electrical and Electronics Engineering at Istanbul Aydın University. In 2003, he earned a second doctoral degree in Human Resource Management from the Faculty of Business Administration at Istanbul University.

Dr. Onur Deryahanoglu received his education in different fields. Biomedical Engineering, Hospital and Healthcare Management (MSc), and Logistics and Supply Chain Management in Healthcare (PhD). He has 20 years of professional experience working in Medical Systems, Project Management, Hospital Planning, SCM, and Operation Management in the healthcare industry. He is currently working as a Project

Manager at General Electric Healthcare.