



# Neutrosophic Sets and its Applications in Biomedical Image Processing: A Review

Loveneet Kaur<sup>1</sup>, Madan Lal<sup>2</sup>

<sup>1,2</sup>Department of Computer Science & Engineering, Punjabi University, Patiala-147002  
Email id:<sup>1</sup>loveneet.mangat91@gmail.com,<sup>2</sup>mlpbiuni@gmail.com

## Abstract:

Medical images are being used on a large scale to detect the presence of abnormalities within the human body. Because of the expert's limited subjectivity and fuzziness in medical images, diagnosis and prediction are among the most challenging tasks in medical science. As a result, different professional's assessments of the severity of various diseases may result in incorrect conclusions. To deal with the uncertainties present in the medical data and for the help of medical experts in early and accurate diagnosis, different researchers have applied a logic known as neutrosophic logic in the field of medical science. This study presents a systematic review of research on the applications of neutrosophic logic in biomedical image processing. This work reviews 37 research papers published in prominent journals and conferences during the last ten years by exploring different digital libraries, including IEEE Xplore, Science Direct, Wiley, Springer, and ACM digital libraries. This research helps to understand how neutrosophic logic is superior to previous versions, its current uses in medical image processing, and its future potential in this field.

**DOI Number: 10.48047/nq.2020.18.12.NQ20242**

**NeuroQuantology 2020; 18(12):85-103**

## 1. Introduction

Many real-world applications provide deficient, imprecise, fuzzy, and conflicting information. One of them is medical image diagnosis systems. These systems are developed for the help of medical experts to take a second opinion. Still, the information generated by medical imaging systems may be vague due to some acquisition errors or lack of knowledge [1]. Different theories have been used to deal with vague information in medical images, including probability theory [2] and fuzzy set theory [3]. However, these theories can deal with a single imprecise problem aspect rather than the entire problem in a single framework. For example, the fuzzy set theory can only handle vague and fuzzy data without dealing with inconsistent and incomplete issues within the same data. To deal with such a

problem, a new concept known as Neutrosophic logic has been introduced. It is a branch of philosophy that investigates the origin, nature, and scope of neutralities and their interactions with various ideational spectra. Many researchers have applied Neutrosophic logic to deal with the uncertainties present in medical images for better diagnosis [30, 32, 41].

### 1.1 Motivation

Due to experts' restricted subjectivity and fuzziness in medical images, diagnosis of critical illness is challenging. Sometimes, in observing the severity of different diseases, professionals may make the wrong diagnosis due to the vagueness of the data to be monitored. To perform diagnosis intuitively in the medical images, additional image processing methods have been explored in terms of Neutrosophic



theory to interpret the inherent uncertainty, ambiguity and vagueness. This review paper examines the application of Neutrosophic theory during the last decade, especially in medical image denoising, segmentation and classification.

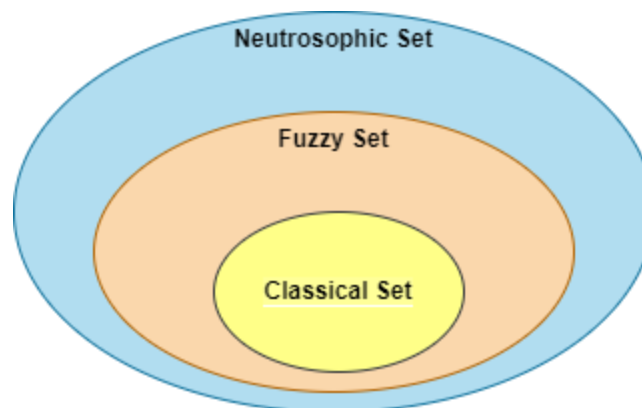
### 1.2 Neutrosophic Logic

To handle the neutralities, Smarandache introduced the concept of Neutrosophy [4]. This concept is used to manage indeterminacy in the given data. The term 'Neutrosophy' arose from the Latin term 'Neuter' meaning neutral, and the Greek term 'Sophia' meaning skill [5-6]. The real-world applications contain vague and ambiguous data. Fuzzy logic has been used to process this imprecise data, which permits a certain varying numerical degree of membership that ranges between 0 and 1 compared to classical binary logic. Fuzzy logic can manage hazy and incomplete data but

### 1.3 Neutrosophic Set

cannot interpret ambiguous and contradictory information frequently found in belief systems. Therefore, Neutrosophy provides a logic known as Neutrosophic logic, which deals with vagueness, ambiguity, imprecision, inconsistency and redundancy in the data [7].

Fuzzy logic only creates membership functions that describe a specific class's degree of membership value. On the other hand, Neutrosophic logic is unquestionably a better representation of the medical data as it provides a clear insight into the truthness, indeterminacy and falsity associated with the input captured, as opposed to fuzzy logic, which lacks the provision of capturing indeterminacy corresponding to non-availability of information, or falsity functions to record the imprecision or degradation of the equipment with which input is captured [1].



**Figure 1: Relationship among the classical set, fuzzy set and Neutrosophic set [39]**

Neutrosophic logic, in contrast to fuzzy logic, introduces the extra domain known as indeterminate membership (IM) that offers a more effective technique to manage higher degrees of indeterminacy in the data that are exceedingly challenging for fuzzy logic to handle. In the case of a classical set True Membership (TM) and False Membership (FM) can either have a value of 0 or 1 and a value of  $IM = \emptyset$ , and in the case of Fuzzy sets, values of TM and FM are real numbers  $\in [0, 1]$  with the condition that sum of TM and FM should be equal to 1 and value of  $IM = \emptyset$  but in Neutrosophic Sets the sum of TM, FM, and IM

could be  $] - 0, 1+[$ . Where TM, FM and IM are membership sets whose values depend on the known and unknown facets. So in the Neutrosophic Set, TM, FM and IM are used to estimate the degree of truth, degree of indeterminacy (neither true nor false), and the degree of falsity. Figure 1 illustrates the connection among the classical, fuzzy, and neutrosophic sets.

Let  $U$  be a universe of discourse, and a Neutrosophic set  $A$  is included in  $U$ . An element  $x$  in set  $A$  is noted as  $x(T, I, F)$  where the functions  $T, I, F: U \rightarrow ] - 0, 1+[$  are the degree of membership (or Truth), the degree of

indeterminacy and the degree of non-membership (or Falsehood): respectively of the element  $x \in U$  to the set A. From the philosophical point of view, the NS takes its value from real standard or non-standard subsets of ]-0, 1+ [. Thus, instead of ]-0, 1+[, the interval [0, 1] is considered for the technical applications because ]-0, 1+ [ will be challenging to apply in real applications, including scientific and engineering problems [5].

#### 1.4 Neutrosophic Image

An image in the Neutrosophic domain is represented by using three membership sets:  $T$ ,  $I$  and  $F$ . A pixel  $x(i, j)$  in the image  $I_{NS}$  in the Neutrosophic domain is represented as  $x(t\%, i\%,$

$f\%)$  where  $t\%$  represents the degree of truth,  $i\%$  represents degree if indeterminacy and  $f\%$  represent the degree of falsehood. For example, if the segmentation operation is applied to the input image  $I$  then for each pixel  $x(t, i, f)$  in the Neutrosophic domain,  $t$  represents that the pixel is  $t\%$  true means it represents the degree by which pixel  $x(i, j)$  belongs to foreground area i.e the area of the object to be segmented in the image,  $i$  represents that it is  $i\%$  indeterminate means pixel belongs to boundary region, and  $f$  represents the % age by which the pixel belongs to the background area. The following equations are used to transform the input image into Neutrosophic domains [5].

$$T(i, j) = \frac{\bar{g}(i, j) - \bar{g}_{min}}{\bar{g}_{max} - \bar{g}_{min}} \quad (1)$$

Where

$$\bar{g}(i, j) = \frac{1}{wxw} \sum_{m=i-\frac{w}{2}}^{i+\frac{w}{2}} \sum_{n=j-\frac{w}{2}}^{j+\frac{w}{2}} g(m, n) \quad (2)$$

$$I(i, j) = \frac{\delta(i, j) - \delta_{min}}{\delta_{max} - \delta_{min}} \quad (3)$$

$$\delta(i, j) = abs((g(i, j) - \bar{g}(i, j))) \quad (4)$$

$$F(i, j) = 1 - T(i, j) \quad (5)$$

Where  $\bar{g}(i, j)$  is the mean intensity value of pixels in the window of size  $(wxw)$  and  $\delta(i, j)$  is the absolute difference between the intensity value of a pixel  $g(i, j)$  and its local mean value  $\bar{g}(i, j)$ .

## 2. Research Methodology

A three-phase methodology has been used to carry out the review, including the following steps.

### 2.1 Planning the review

- During the planning phase, some research questions are designed.
- Related data is identified from the searched results based on these questions.

- After carefully analyzing the related data, the relevant information is framed in the form of tables and graphs.
- In the end, the findings of the review are reported.

#### 2.1.1. Research Questions and Motivation.

The main goal of the research questions is to explore the use of Neutrosophic logic in the field of medical image enhancement, segmentation, analysis and medical diagnosis. Table 1 describes the primary research questions and their motivation.

Research Question	Motivation
1. How Neutrosophic logic is helpful in biomedical image processing and diagnosis.	It helps to know how Neutrosophic logic better deals with inconsistent information present in medical images than fuzzy and binary logic.

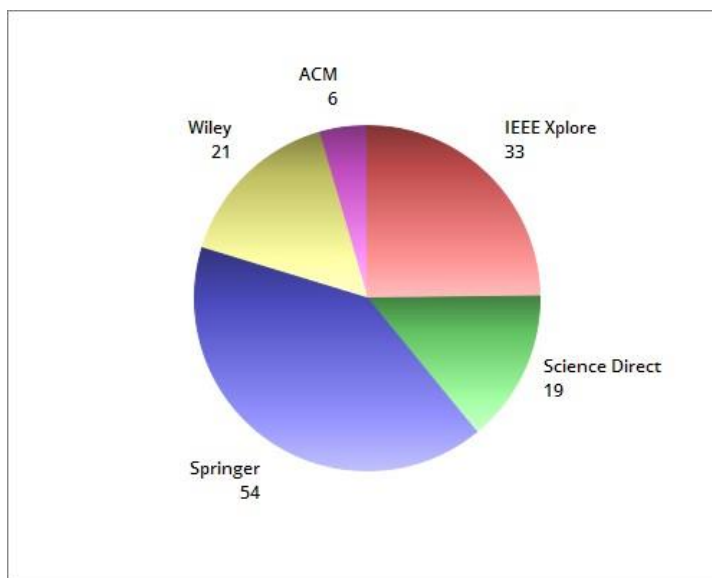
2. What is the current status of applications of Neutrosophic logic in medical image processing?	It helps in understanding the present status of Neutrosophic logic applications in medical image enhancement, segmentation, and diagnosis.
3. Neutrosophic logic is applied to which kind of biomedical images.	It helps understand different biomedical images on which Neutrosophic logic is applied.
4. How many methods are proposed in the literature with the combined application of Neutrosophic logic, artificial intelligence and machine learning/ deep learning algorithms in medical science?	It is used to understand the current status of the combined application of Neutrosophic logic,artificial intelligence and machine learning/ deep learning algorithms in medical science.

**2.2 Conducting Review**

**2.2.1 Dataset (Source of information)**

To standardize the review process and to answer the research questions, relevant, high-quality research papers published in the last ten years (Jan-2010 to Dec-2019) are searched from various digital journals and conference proceedings. The electronic sources that are

searched for relevant articles include IEEE Xplore (<https://ieeexplore.ieee.org>), Science Direct (<http://sciencedirect.com>), Springer (<http://springerlink.com>), Wiley (<https://onlinelibrary.wiley.com>) and ACM (<https://dl.acm.org>) digital library. The number of papers retrieved through various search engines is presented in Figure 2.



**Figure 2: Number of papers retrieved through various search engines**

**2.2.2 Search Criteria**

Research papers are searched from all five sources to fully cover all the publications in this field. To carry out a relative search, some keywords are used. The primary keywords used to search the papers from various digital sources are "Neutrosophic logic" and "medical images". Table 2 shows the search results.

**Table 2: Search results from digital sources**

Sr. No	Digital Source	Search within	Keywords used	Duration	Count	Count (following filtering)	Count (after title abstract filtering)	Final count (after full paper study)
.								

1.	IEEE Xplore	Full text & Metadata	Neutrosophic Logic or sets and medical image	2010 to 2019	33	19	17	16
2.	Science Direct	Title + Abstract + keywords	“Neutrosophic Logic” + “medical image”	do	19	15	14	11
3.	ACM	anywhere	Neutrosophic and Medical Image	Jan-2010 to Dec 2019.	06	5	2	0
4.	Wiley	anywhere	“Neutrosophic” “Medical Image”	01-01-2010 to 31-12-2019	21	10	8	7
5.	Springer	all	Neutrosophic and Medical Image	2010 to 2019	81	8	5	3

All five sources are searched for research papers with the goal of covering all documents in this field. Since each source has different search engines, a slightly different process is adopted to find relevant papers. To approach a relative search, various keywords are used, which include 'Neutrosophic', 'Neutrosophic Sets', 'Neutrosophic Logic' and 'Medical Image'.

In the case of IEEE Xplore, the 'Neutrosophic Logic' or 'Neutrosophic Sets' keywords are used for searching in the abstract and the 'Medical Image' keyword is used for the whole text. This operation searched 33 relevant papers, including 30 papers from conference proceedings and 03 articles from journals.

Neutrosophic Logic and Medical Images keywords are used to search relevant papers from the Science Direct database. Search is applied to the title, abstract and keywords sections. The total outcome of this search is 19

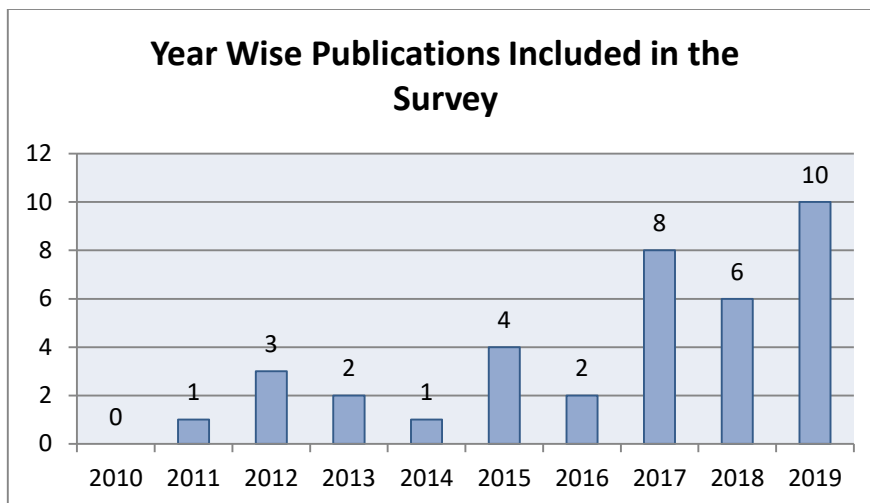
papers, which include 10 research articles and 9 book chapters.

To search the papers from Springer, keywords 'Neutrosophic Logic' and 'Medical Image' are used to search from 'all', with the condition “with all of the words”. The result of this search gives 81 papers, which consist of 54 research articles, 27 book chapters, 13 conference papers and 01 reference paper.

To find the papers from the Wiley database, keywords 'Neutrosophic' and 'Medical Image' are applied with the condition 'anywhere'. This query gives 21 documents, of which 20 papers are from journals, and 01 are book chapters.

For searching the ACM digital library, the keywords 'Neutrosophic' and 'Medical Image' are used with the condition 'anywhere'. This search resulted in 06 research articles.

89



**Figure 3: Year-wise publications included in the survey**

Figure 3 displays data pertaining to the distribution of publications by publication year. The bar chart reveals the inclusion of publications from the past decade, illustrating the growth in research output each year. Notably, the year 2019 stands out with the highest number of publications incorporated in this research study.

### 2.2.3 Selection criteria

The survey comprises research papers in which Neutrosophic logic has been utilized to enhance and/or segment medical images, diagnose and classify disease, and has been published in reputable journals and conferences.

### 2.2.4 Inclusion and exclusion criteria

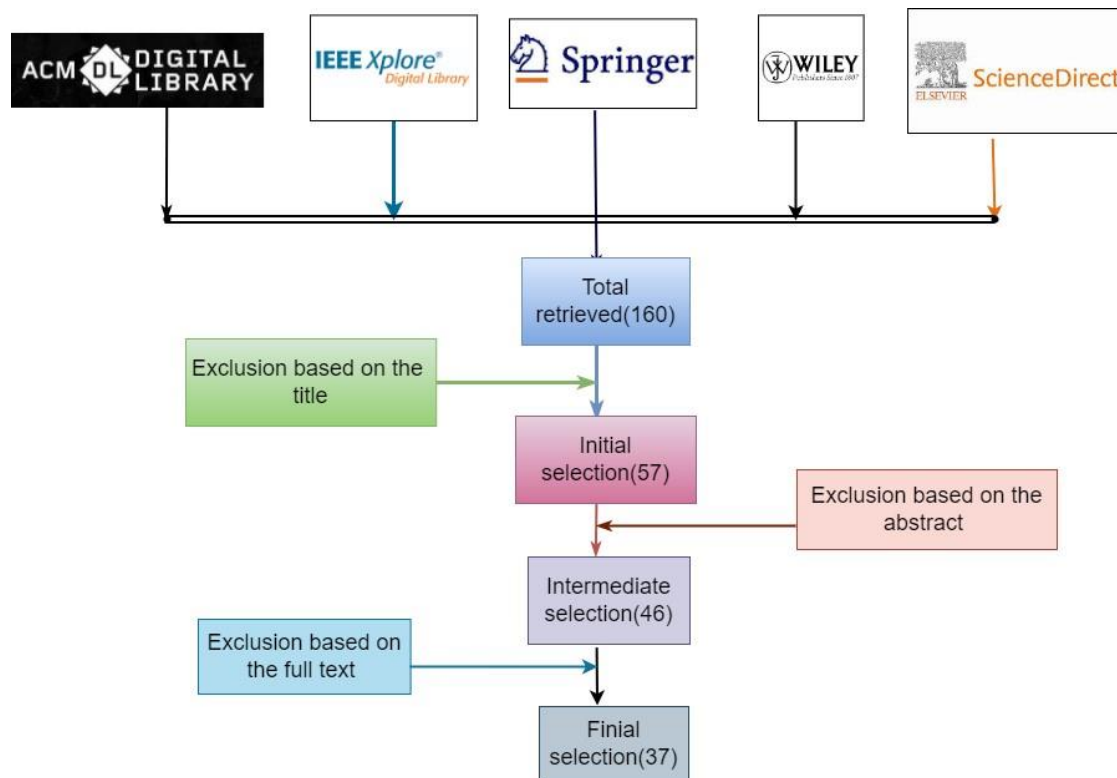
This is the most important part of the review process because this process decides the final papers to be included in the database

and acts as a foundation of the paper. The inclusion and exclusion process is completed in three steps [8]. Articles written in English containing the work done in the field of medical science using Neutrosophic sets and published in reputed journals and conferences are included in the final database. After carefully analyzing all the titles/abstracts and full text, most irrelevant papers have been excluded.

Step1: In this step, research papers are searched using the selected title keywords.

Step 2: In the second step, abstracts of the searched papers are analyzed for inclusion and exclusion.

Step 3: In the third step, the whole text of the papers is read out for the final inclusion of documents for the review process. The paper inclusion and exclusion process at different stages is presented in Figure 4.



**Figure 4: Study selection procedure**

### 3. Review Reporting

#### 3.1 Neutrosophic logic in biomedical image processing and diagnosis

Detecting and diagnosing diseases within the human body's interior is a formidable challenge in medical science. Unlike external ailments, internal diseases demand specialized detection methods. Therefore, visual representations of body organs and tissues, facilitated by medical images, are indispensable for this purpose. Various techniques, collectively known as medical imaging, are employed to capture these images. However, images obtained through medical imaging devices are often marred by noise, necessitating thorough preprocessing to extract meaningful information from them, aiding in diagnosing and treating medical conditions.

Much like in medical diagnosis, situations arise where not all the essential information required for patient decision-making is accessible, and the available data may be imprecise or exhibit inconsistencies. In such

scenarios, Neutrosophic logic proves to be a valuable tool for effectively handling imprecise and inconsistent data within the context of medical diagnosis.

Medical image analysis involves complex computational methods, encompassing tasks like preprocessing, classification, segmentation, compression, and security. Neutrosophic logic offers valuable contributions to biomedical image processing and diagnosis by providing a robust framework for handling the inherent uncertainties and complexities in medical data and images. In this context, neutrosophic logic excels at capturing biomedical information's imprecise, uncertain, and inconsistent nature. It allows for the representation of precise data and information with degrees of truth, indeterminacy, and falsity, which are common in medical imaging and diagnosis. Neutrosophic logic aids in refining image segmentation, enhancing feature extraction, and improving classification accuracy. Moreover, it assists in fusing multi-

modal medical data, thereby enabling more comprehensive and precise diagnosis. By accommodating ambiguity and uncertainty, neutrosophic logic plays a pivotal role in advancing the capabilities of biomedical image processing and facilitating more accurate and confident medical diagnoses.

Neutrosophic logic stands out as a superior approach for addressing the challenge of inconsistent information within medical images compared to traditional fuzzy and binary logic systems. Neutrosophic logic excels by accommodating precise values and degrees of indeterminacy, truth, and falsity, making it highly adaptable to the inherent complexities of medical data. This capability allows neutrosophic logic to effectively model and manage inconsistent information, ensuring that the inherent uncertainties in medical images are properly represented and processed. Consequently, neutrosophic logic contributes significantly to improving image analysis, diagnosis, and decision-making in the medical field, where inconsistent information is a common challenge.

### **3.2 Current status of applications of Neutrosophic logic in the field of medical image processing**

Neutrosophic logic (NL) is a generalization of fuzzy logic and intuitionistic fuzzy logic that represents three distinct truth values: truth, falsehood, and indeterminacy. This makes NL well-suited for modeling the uncertainty and vagueness often present in medical images. NL has been applied to a variety of tasks in medical image processing, including:

#### **3.2.1 Neutrosophic sets in Medical Image denoising**

NL can enhance medical images by reducing noise and improving their contrast, brightness, and other properties. This can make it easier to detect and identify abnormalities.

Different forms of images are used in medical science for diagnosis. These include X-rays, Computerized Tomography (CT), Magnetic Resonance Imaging (MRI) and Ultrasound

Images. To capture these images, different kinds of waves (radio waves/ sound waves) are used [9]. When the medical images are performed using high-frequency waves, some vague, imprecise, inconsistent, incomplete, and indeterminate information is also captured in the images. Due to the presence of imprecise information and fuzziness in the medical images, it becomes challenging to segment the abnormal regions, feature extraction and classification regions into normal and abnormal [10]. To handle the fuzziness in medical images, fuzzy sets can be used [11], but their limitation is that fuzzy sets don't consider the spatial context of the pixels due to the presence of noise and other artifacts [12]. So, researchers have applied a generalized form of fuzzy sets known as Neutrosophic sets for medical image enhancement and segmentation.

Various techniques have been developed to reduce the noise in medical images [13, 15-17,27,37,46,51]. As per the reviewed literature, 22% of the papers on Neutrosophic logic in medical images are published containing new techniques that can be used to enhance the biomedical images for better diagnosis.

Mohan J. et al. [13, 16] integrated the Neutrosophic logic and median filter to reduce the Rician noise from MRI images. Authors in [17] used the Weiner filter and neutrosophic logic to minimize the noise in MRI images. Koundal D. et al. [27] proposed a technique to reduce the speckle noise inherent in ultrasound images. In [37], Koundal et al. proposed an efficient speckle reduction method by utilizing a Neutrosophic-based total variation approach employing Nakagami statistics. Ashour A.S. et al. [46] introduce a new medical image denoising method based on an NS indeterminacy filter with an optimized kernel. This optimized indeterminacy filter (OIF) filter is then applied to dermoscopy image denoising. In [51], Nilofaar R. et al. proposed a new neutrosophic logic-based weight function to improve the performance of the non-local



means (NLM) filter for speckle noise removal in ultrasound (US) images.

### 3.2.2 Neutrosophic sets in Medical Image Segmentation:

NL can be used to segment medical images into different regions of interest, such as tumors, organs, and tissues. This can be useful for diagnosis, treatment planning, and research.

Image segmentation is a critical step in biomedical image analysis, helping researchers better understand the type, location, and detection of diseases. It is commonly used to trace tumors and other pathologies, measure tissue volumes for computer-guided surgery and diagnosis, support treatment planning, and study anatomical structures. However, image segmentation in medical imaging is often challenging due to factors such as the variation in region of interest (ROI) shapes, confusion in ROI boundaries, image quality, lack of ground truth, and the need to carefully select the appropriate technique.

There are many different approaches to image segmentation [19, 21], depending on the specific application, imaging modality, anatomical structure, and size measurement. For example, the segmentation of a thyroid nodule is different from the segmentation of a liver nodule. No single segmentation method works well for all medical images [37]. General methods exist, but methods designed for specific applications can achieve better performance by leveraging prior knowledge of the tissue. However, selecting the right segmentation approach can be difficult.

Medical images like Ultrasound, CT, and MRI images contain some background area along with the desired organ area. The medical images are segmented to analyze the important organ area for effective diagnosis. The segmentation process separates the informative region called the region of interest (ROI) from the background. Segmentation may be performed manually or automatically using a computer-aided diagnosis (CAD) system[14]. Accurate segmentation leads to better diagnosis. In ultrasound images, the tumor

regions contain blurred boundaries [41], which create hurdles in precise segmentation. Researchers have proposed various techniques for automatic segmentation of medical images [14, 18, 24-25, 28-32, 35, 38-42, 44, 45, 47, 49, 50, 52].

To professionally isolate the ROI from the background, clustering algorithms can be used to extract the image's general features [22]. Many methods are used for clustering, including mean shift, divisive, hierarchical, and K-means clustering [21]. Furthermore, Neutrosophic set theories become crucial in the segmentation process to address uncertainty in medical images because most medical images have erratic and fuzzy borders. Following are the different NS-based methods given by other authors that are applied to segment the medical images.

Shan J. et al. [14] proposed a Neutrosophic logic-based l-means clustering (NLM) method for ultrasound image segmentation. Initially, the Breast ultrasound image (BUS) is taken as input, and the region of interest (ROI) is calculated, which contains the tumor region with vague boundaries. ROI is then enhanced by reducing the speckle noise using a new phase in the max energy orientation method. Finally, Fuzzy c-means clustering and neutrosophic logic are integrated to separate the tumor region from the background. Guo Y. et al. [18] proposed an iterative neutrosophic lung segmentation method in CT Images. This work generated an initial outline of the lungs using the EMM method. Then, the anatomic features of ribs and lungs were mapped into the neutrosophic domain, and neutrosophic operation was applied to refine the initial lung region. Mohan J. et al. [24] proposed a brain tumor segmentation approach to segment the tumor region in MR Images. First of all, a Non-local neutrosophic wiener filter is applied to enhance the quality of the image then the k-means clustering method is applied to segment the tumor region. In [25], Sayed G.I. et al. used neutrosophic logic and modified watershed

segmentation to segment the liver from the abdominal CT Images. Kaur G. & Kaur H. [28], applied NS and morphological operations to segment the MRI images. In the study conducted by Sangeeta K.S. et al. [29], a novel approach was introduced to segment the liver region within abdominal CT images. The process begins by enhancing the input liver image through a median filter. Subsequently, the enhanced image is transformed into the neutrosophic domain, which encompasses three key components: True, False, and Indeterminate, reflecting different attributes of the image. To isolate the liver contour from the abdominal CT image, the researchers employed a combination of the Chan-Vese model and morphological operations on the indeterminate component of the neutrosophic image. Koundal D. [30] integrated the neutrosophic clustering and texture features to segment the images. Nugroho H.A. et al. [31] applied neutrosophic sets and a watershed approach to segment the tumor region in the ultrasound image. In their study, Nugroho H.A. et al. [32] combined neutrosophy with fuzzy c-means clustering to segment tumor regions within ultrasound images effectively. The segmentation process initiates with the enhancement of the input ultrasound image using an anisotropic diffusion filter. Following this enhancement, the image is transformed into the neutrosophic domain. Ultimately, the researchers utilize fuzzy c-means clustering as the key technique to segment the tumor region within the ultrasound image. Lotfollahi M. et al. [35] introduced an innovative approach aimed at segmenting regions of skin cancer lesions within Dermoscopic images. Anter A.M. et al. [38] proposed an enhanced tumor segmentation method tailored for abdominal CT liver images. This approach combines Neutrosophic logic, Fast Fuzzy C-means clustering (FFCM), and Particle Swarm Optimization (PSO) to segment tumor regions precisely. Koundal D. et al. [39] have introduced a fully automated Computer-Aided Diagnosis (CAD) system designed to enhance and segment Thyroid Ultrasound images. This system

operates through a three-phase approach. It effectively diminishes speckle noise within ultrasound images in the initial phase while preserving essential diagnostic information. The second phase involves the calculation of the Region of Interest (ROI), which encompasses the primary tumor region while excluding unwanted background elements. Finally, in the third phase, the system employs the Neutrosophic-based Distance Regularized Level Set (NDRLS) Method to precisely segment the thyroid nodule within the ROI. Ali M. et al. [40] authors proposed a new technique to segment dental X-ray images. In this algorithm, image data is transformed into a neutrosophic set, which subsequently computes the inner products of the input cutting matrix. The segmentation process employs the orthogonal principle to group pixels into distinct clusters. Lal M. et al. [41] have proposed a modified spatial neutrosophic clustering technique for tumor segmentation in breast ultrasound images. This method has two-fold contributions for better image segmentation, and spatial information is incorporated in neutrosophic l-means clustering and membership functions are updated using the type-2 membership function, which aids in the convergence of cluster centres to more desirable locations than conventional fuzzy membership functions. Rashno A. et al. [42] proposed a segmentation strategy for identifying fluid/cyst regions in optical coherence tomography (OCT) images associated with diabetic macular edema using neutrosophic sets and graph-based methods. Sert E. et al. [44] introduced a novel edge detection technique that combines the attributes of neutrosophic sets and expert maximum fuzzy-sure entropy (EMFSE) methodologies. This innovative approach precisely segments brain tumor boundaries in MRI images. Guo Y. et al. [45] developed a method for segmenting dermoscopic skin lesions using a neutrosophic set-based kernel graph cut approach. This technique consists of several critical steps: Initially, clusters and their centroids are determined using a histogram-

94

based clustering estimation (HBCE) method. The neutrosophic c-means (NCM) technique is then used to translate dermoscopic images into the neutrosophic domain. Finally, the segmentation is completed in the final stage using a kernel graph cut (KGC) process. Amma Palanisamy T.S.C. et al. [47] presented the work based on a neutrosophic set (NS) combined with fuzzy c-means clustering (FCM) and modified particle swarm optimization (PSO) for MR image segmentation. Initially, a non-local means filter was applied to enhance the image; then, for optimized clustering, FCM guided by a modified PSO was used. This proposed method outperformed FCM alone and FCM with NS on 100 MR images regarding sensitivity, specificity, Jaccard, and dice, achieving 95%, 98%, 87%, and 94%, respectively. Wen J. et al. [49] introduced a novel approach incorporating neutrosophic fuzzy clustering with non-local information. This method leverages the concept of neutrosophic sets within NCM clustering to enhance the precision of clustering centres for fuzzy terms, thereby improving segmentation accuracy. Additionally, non-local spatial information is integrated to mitigate NCM's sensitivity to noise. Jiang X. et al. [50] introduced a segmentation method based on neutrosophic logic for breast ultrasound images (BUS). This approach begins by transforming the BUS image into the neutrosophic domain, where each pixel is characterized by calculating similarity set scores and homogeneity set values. Subsequently, adaptive Otsu-based thresholding and morphological operations are employed to compute seed regions. The direction of region growth is determined by evaluating differences in similarity set scores, texture homogeneity values, and distance values between the seed region and candidate growth points. A deep convolutional neural network based on VGG-16 architecture is applied to enhance accuracy and reduce false positives to attain the final segmented results. Ashour A.S. et al. [52] introduced a method for delineating skin lesion boundaries within dermoscopic images. The approach

begins by transforming the input dermoscopic image into the neutrosophic domain, characterized by True, Indeterminate, and False components. A unique method for generating neutrosophic images is devised by employing various high-pass filters to define the indeterminate components and different low-pass filters to define the True components.

### 3.2.3 Neutrosophic Sets in Disease Classification and Diagnosis:

A large amount of patient data is available with medical experts to classify and diagnose a disease [54]. This data typically contains a large number of unclear, inconsistent, incomplete, and indeterminate data, making retrieval, handling, and processing extremely challenging. Neutrosophy has the advantage of handling this indeterminate data. Different researchers have applied NS for diagnosis [20, 26, 33, 34, 36] and classification [23, 48, 53] of disease to provide medical experts with a second opinion.

In [20] Arockiarani I, introduced a new idea of fuzzy neutrosophic set relations to design an expert system for diagnosing patients using a newly developed score function. A fresh approach to Hamming distances and similarity measures, along with the derivation of several of their properties, is ultimately employed in constructing a decision-making methodology. Gabet T. et al. in [26] proposed a computer-aided diagnosis system to classify breast cancer thermograms. It works in two parts; in the first part, neutrosophic logic and Fast-Fuzzy C – Means algorithms are employed to segment the ROI. The second part uses different Support Vector Machine kernel functions to classify the breast parenchyma into normal or abnormal cases. Dang Thanh N. et al. [33] proposed a neutrosophic recommender system based on the concepts of neutrosophic sets, recommender system and neutrosophic clustering. A neutrosophic recommender system with a neutrosophic similarity measure is proposed to predict diseases. Neutrosophic clustering is used to identify neighbours of a patient with common characteristics. A

95

prediction formula is established using the neutrosophic similarity measure and the neighbours to compute the patient's membership values. The deneutrosophication process is used to determine the final disease. A new medical diagnosis system based on neutrosophic sets is proposed by De S. and Mishra J. [34] to identify patients' diseases using different pathological reports. Pathological reports contain uncertain data that neutrosophic logic can handle. The authors propose a new decision-making approach using neutrosophic logic to handle this uncertainty. Sayed, G.I. and Hassanien, A.E. [36] present an automatic mitosis detection technique from histopathology slide images using neutrosophic sets and moth flame optimization. A Gaussian filter and morphological operations were applied to a histopathological image in the neutrosophic domain to enhance the appearance and extract features. A meta-heuristic algorithm was used to select the best discriminating features of mitosis cells. A classification and regression tree classifier was then used to classify the candidates as mitosis or non-mitosis. Chang RF. et al. [23] proposed a Computer Aided Classification (CAC) system to classify the echotexture patterns as heterogeneous or homogeneous using automated breast ultrasound (ABUS) images. Neutrosophic image

transformation and fuzzy c-mean clustering were used to define the lower and upper boundaries of fibroglandular tissues in breast ultrasound images. The number of hypoechoic regions and histogram features extracted from the fibroglandular tissues were then used to train a support vector machine model with leave-one-out cross-validation for breast cancer diagnosis. A hybrid method using neutrosophic sets and convolutional neural networks (NS-EMFSE-CNN) is proposed by Ozyurt F. et al. [48] for brain tumor classification. In the first stage, the NS-EMFSE approach segments tumor region areas from brain MRI images. In the second stage, features are extracted from the segmented images using CNN and classified using SVM and KNN classifiers. Muthuswamy J.[53] presented an automatic method to segment the liver from abdominal CT images and classify them as normal or abnormal liver. The median filter and neutrosophic sets with FCM clustering were used to segment the liver from abdominal CT images. GLCM features were extracted from the segmented liver images and used to train an SVM classifier to classify the liver as normal or abnormal. Figure 5 illustrates the number of papers considered in the review process across various aspects of medical image processing, including image enhancement, segmentation, disease classification, diagnosis and disease prediction.

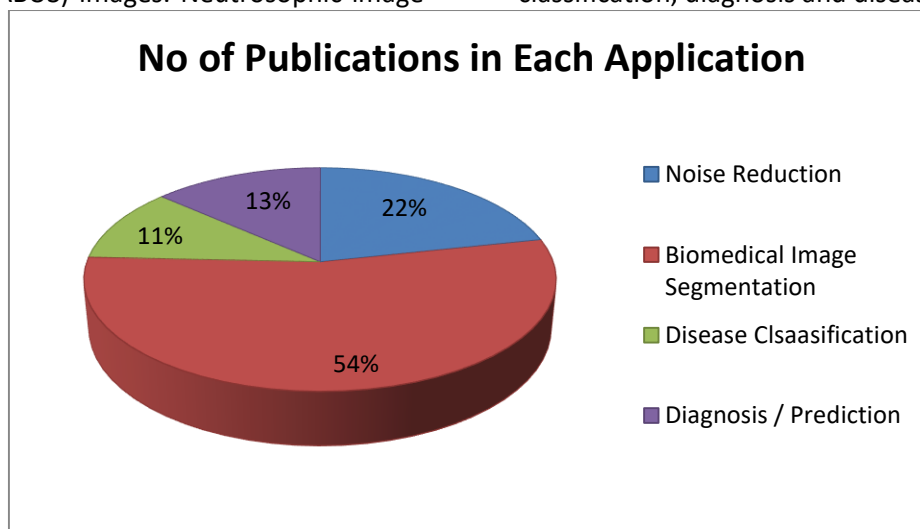


Figure 5: Different applications of NS in medical image processing.

### 3.3 Applications of Neutrosophic Sets on Different Kinds of Biomedical Images.

Different biomedical images have different features depending upon various factors, including the modality used to capture the image and type of organ or tissue to be captured. Various modalities include X-ray, computed tomography (CT), magnetic resonance imaging (MRI) and ultrasound. When different abnormalities are captured using different modalities, the generated biomedical images contain different features and thus require different processing methods for analysis and diagnosis.

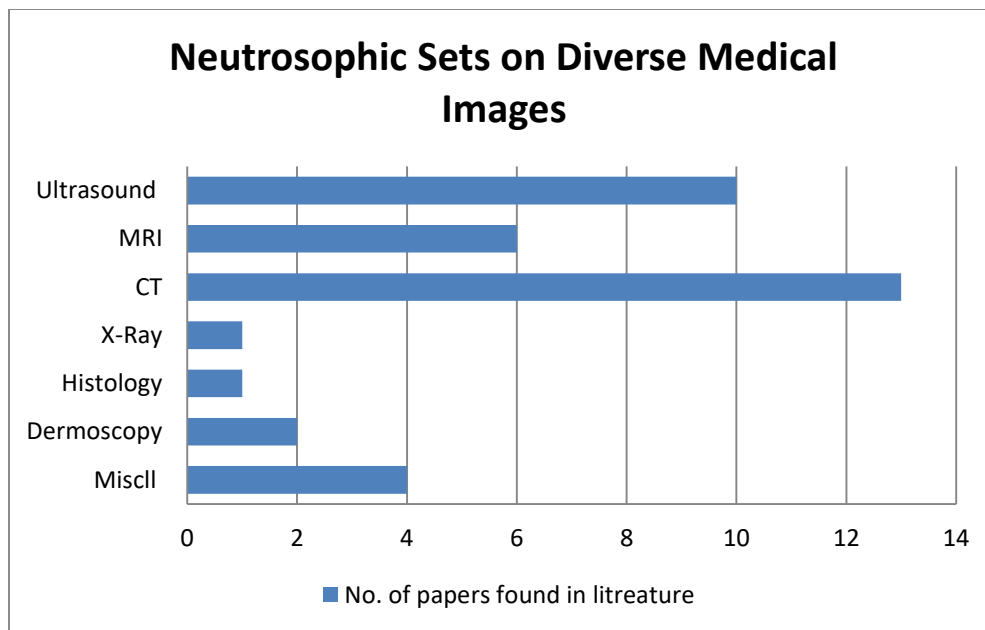
The revised literature shows that most of the work is proposed to process the Ultrasound images. Ultrasounds use sound waves to capture abnormalities present within the human body as it is non-invasive in nature and, therefore frequently used for diagnosis. In ultrasound, the operator's expertise can significantly impact the image quality because image clarity and accuracy can be affected by variables such as the probe's angle, the amount of pressure used, and the patient's participation. This can lead to an image containing more uncertain information. Moreover, ultrasound images contain speckle noise, which is a multiplicative noise that reduces the image resolution and contrast, thereby reducing the diagnostic value of this imaging technique. As the neutrosophic logic

can deal with uncertainties more efficiently, it is an effective tool for ultrasound image processing. Of 37 revised papers, 13 suggested different ultrasound enhancement or segmentation techniques.

Neutrosophic logic has also been used to enhance or segment the MRI images. In MRI, noise like Gaussian, Thermal, Rician, and Impulse noise can degrade image quality and make it challenging to interpret the underlying anatomical or pathological information. This noise leads to uncertain and indeterminate information. Neutrosophic logic helps in dealing with this uncertainty. Among the reviewed literature, 10 papers have applied NS on MRI images.

Images like Computed Tomography (CT) and X-rays are affected by quantum noise. It arises due to the discrete nature of X-ray photons. Quantum noise can produce pixel-to-pixel changes in image intensity in places with little X-ray exposure, resulting in a grainy look. 06 papers have used neutrosophic logic for processing CT images. In these papers, neutrosophic logic is applied with other techniques for better results. One paper has used neutrosophic logic for X-ray image processing, one in histology, two in dermoscopy, and 04 papers have applied this logic on miscellaneous biomedical images, as shown in Fig. 6.

97



**Figure 6: Applications of Neutrosophic Sets on different types of biomedical images.**

98

### 3.4 Methods that harness the integrated potential of neutrosophic logic, artificial intelligence and machine learning/ deep learning algorithms in medical science?

Upon reviewing the literature, it becomes evident that only a few instances exist where artificial intelligence, machine learning, and deep learning techniques are coupled with neutrosophic logic in biomedical image processing. The following five methods have been identified that merge the attributes of artificial intelligence, machine learning, and deep learning techniques with neutrosophic logic within the domain of biomedical image processing.

Sayed, G.I. and Hassanien, A.E. [36] used a combination of neutrosophic sets (NS) and moth-flame optimization (MFO) for automatic mitosis detection using histopathology slide imaging. This method works in two phases. The histopathological slide image is enhanced and mapped into the NS domain in the first phase. In the second phase, the best discriminating features of mitosis cells are extracted using MFO algorithm. Finally, these features are supplied to the classification and regression tree. In [48], a hybrid method using Neutrosophy and convolutional neural

networks (NS-CNN) is proposed. Brain MRI images are initially segmented using the set-expert maximum fuzzy-entropy (NS-EMFSE) approach. Then features are extracted from segmented images using CNN, and finally, images are classified as benign or malignant using support vector machines (SVMs) and k-nearest neighbours (KNN) classifiers. In [43], neutrosophic sets are employed to differentiate between homogeneous and speckled shapes in Indirect Immunofluorescence (IIF) images. To effectively handle edge boundary information for cell segmentation, NS is used. Geometric features are extracted from cell edges, and a Multilayer Perceptron (MLP) network is employed to classify the two patterns. Palanisamy TSCA et al. in [47] have applied the combination of NS, fuzzy c-means clustering (FCM) and modified particle swarm optimization (PSO) for segmenting the brain tumors in MRI images in reduced time consumption. In [53], Muthuswamy J. used NS and support vector machine (SVM) to recommend an automatic method for segmenting the liver from an abdominal CT image and classifying it as normal or abnormal.

#### 4. Discussion and future directions for Neutrosophic set-based medical image processing

Due to its nature of handling uncertainties, The NS can be applied to segment boundaries of tumors or other abnormalities contained in biomedical images having vague boundaries. NS can also be applied to extract the more robust and informative features from medical data because neutrosophic logic can extract both certain and uncertain data. As the neutrosophic classifiers can take into account the uncertain data, so these classifiers can be used to classify medical images more accurately, especially in the presence of noise or uncertainty. Additionally, it has been demonstrated that the fuzzy c-means (FCM) clustering technique is beneficial when used with NS to lessen uncertainty [32]. It is also advised to investigate combining NS with other clustering strategies.

From the previous studies, numerous medical image processing tasks, such as image denoising, thresholding, clustering, segmentation, and classification, have been demonstrated to benefit from the use of neutrosophic sets. However, NS hasn't been thoroughly investigated for image registration, compression, or restoration. Therefore, looking at NS's potential for these operations and evaluating its performance in relation to other options is advised.

NS can also be used in clinical decision support systems because Neutrosophic logic can provide a more nuanced representation of image-derived information, assisting healthcare professionals in making more informed decisions. Neutrosophic logic can be used to generate synthetic data points in data augmentation techniques that reflect the uncertainty and variability present in real-world biomedical images. This augmentation can help improve the training of machine learning models. Deep learning models have shown promising performance in biomedical image processing tasks such as segmentation and classification. However, these models are

sensitive to noise and uncertainty in data. Integrating neutrosophic logic with deep learning methods can lead to more robust models for biomedical image processing.

The future of machine learning (ML) and deep learning (DL) methods with neutrosophic logic (NL) in biomedical image processing is very promising. These techniques can potentially improve the performance of a wide range of biomedical image processing tasks, including image segmentation, object detection in medical images, and classification of images such as images containing normal, benign and malignant tumors. In addition, NS, ML and DL can be integrated to develop more accurate Computer Aided Diagnosis systems.

#### 5. Conclusion

This survey looks into medical image processing techniques based on the Neutrosophy theory. Neutrosophy, derived from the word "neutrality," expresses the qualities associated with memberships in truth, falsity, and indeterminacy. It is inferred as the fuzzy sets extension and it is used to deal with uncertainty.

Neutrosophic Sets and logic are gaining significant attention in solving many real-life decision-making problems that involve impreciseness, uncertainty, vagueness, incompleteness, and indeterminacy. The Neutrosophic Sets quantify indeterminacy, whereas indeterminacy membership, truth membership, and falsity membership are independent. Thus, the NS notion is regarded as a novel mathematical technique for dealing with uncertainties, and it has been used to develop a decision scheme for medical diagnosis.

The study's prime focus is exploring the applications of Neutrosophic sets in biomedical image processing. To achieve this objective, research papers focusing on Neutrosophic logic in the context of biomedical image processing and published during the last decade have been compiled. For this purpose, five digital sources, IEEE Xplore, Science Direct, Wiley, Springer, and ACM digital libraries, are explored. Initially, 160

papers were collected, however, after reviewing titles, abstracts, and full paper details, the final count narrowed down to 37. These papers are then reviewed and the results are presented using tables, bar charts, and pie charts.

As per the reviewed literature, it is observed that NS-based methods have been extensively proposed for medical image segmentation, denoising, accurate diagnosis, and classification of disease. However, the application of Neutrosophic Sets in medical image restoration and registration has not been reported, and it can be applied in future work. Neutrosophic logic can also be effectively integrated with machine learning and deep learning techniques within the realm of biomedical image processing.

### References

1. Ansari AQ, Biswas R, Aggarwal S, Proposal for applicability of neutrosophic set theory in medical AI. *International Journal of Computer Applications*. 27(5):5–11, 2011.
2. Feller W, *An introduction to probability theory and its applications*. Wiley, London.1968; 3.
3. Zimmermann H-J, *Fuzzy set theory Wiley interdisciplinary reviews. Computational Statics*. 2(3):317–332, 2010.
4. Smarandache F, Indeterminate masses, elements and models in information fusion, *Int. J. Adv. Mechatronic Syst*. 5 (6):365–372, 2013.
5. Guo Y, Cheng HD, Zhang Y, A new neutrosophic approach to image denoising. *New Mathematics and Natural Computation*. 5(3):653–662, 2009.
6. Shan J, Cheng HD, Wang Y, A novel segmentation method for breast ultrasound images based on neutrosophic I-means clustering. *Med. Phys*. 39 (9): 5669–5682, 2012.
7. Smarandache F, *A Unifying Field in Logics. Neutrosophy: Neutrosophic Probability, Set and Logic*. Rehoboth: American Research Press.1999.
8. KitchenhamB, *Procedures for performing systematic reviews*. Keele UK Keele Univ. 2004; 33: 1–26.
9. Umar AA, Atabo SM, A review of imaging techniques in scientific research /clinical diagnosis. *MOJ Anatomy & Physiology*.6(5):175-183, 2019.
10. Mondal K, Dutta P, Bhattacharyya S. Fuzzy logic based gray image extraction and segmentation. *International Journal of Scientific & Engineering Research*. 3 (4):1-14, 2012.
11. Yang Y, Huang S, Image segmentation by fuzzy C-means clustering algorithm with a novel penalty term. *Computing and Informatics*. 26(1):17-31, 2007.
12. Koundal D, Gupta S, Singh S, Applications of neutrosophic and intuitionistic fuzzy set on Image processing. *National Conference on Green Technologies: Smart and Efficient Management*. 2012.
13. Mohan J, Krishnaveni V, and Guo Y, A Neutrosophic approach of MRI denoising *International Conference on Image Information Processing*. 1-6, 2011.
14. Shan J, Cheng HD, Wang Y, A novel segmentation method for breast ultrasound images based on neutrosophic I-means clustering. *Med Phys*. 39(9):5669-82, 2012.
15. Mohan J, Guo Y, Krishnaveni Vand Jeganathan K, MRI denoising based on neutrosophic wiener filtering. *IEEE International Conference on Imaging Systems and Techniques Proceedings*.327-331, 2012.
16. Mohan J, Krishnaveni V and Guo Y, Validating The Neutrosophic Approach of MRI Denoising Based On Structural Similarity *IET Conference on Image Processing*, pp. 1-6, 2012.
17. Mohan J, Krishnaveni V, Guo Y, MRI denoising using nonlocal neutrosophic set approach of Wiener filtering. *Biomedical Signal Processing and Control*. 2013; 8:779-791.



18. Guo Y, Zhou C, Chan HP, Chughtai A, Wei J, Hadjiiski LM, Kazerooni EA, Automated iterative neutrosophic lung segmentation for image analysis in thoracic computed tomography. *Med Phys.*40(8):081912, 2013.
19. Guo Y, Sengur A, A novel image edge detection algorithm based on neutrosophic set *Computers & Electrical Engineering.*40(8):3-25, 2014.
20. Arockiarani I, A fuzzy neutrosophic soft set model in medical diagnosis. *IEEE Conference on Norbert Wiener in the 21st Century.*1-8, 2014.
21. Akhtar N, Agarwal N, Burjwal A, K-mean algorithm for Image Segmentation using Neutrosophy. *International Conference on Advances in Computing. Communications and Informatics (ICACCI).* 2417-242, 2014.
22. Guo Y, Sengur A, NCM: Neutrosophic c-means clustering algorithm. *Pattern Recognition.* 48(8):2710-2724, 2015.
23. Chang RF, Hou YL, Lo CM, Huang CS, Chen JH, Kim WH, Chang JM, Bae MS, Moon WK. Quantitative analysis of breast echotexture patterns in automated breast ultrasound images. *Med Phys.* 42(8):4566-78 ,2015.
24. Mohan J, Krishnaveni V, Huo Y, Automated brain tumor segmentation on MR images based on neutrosophic set approach. *2nd International Conference on Electronics and Communication Systems (ICECS).* 1078-1083, 2015.
25. Sayed GI, Ali MA, Gaber T, Hassanien AE, Snasel V, A hybrid segmentation approach based on Neutrosophic sets and modified watershed: A case of abdominal CT Liver parenchyma. *11th International Computer Engineering Conference (ICENCO).* 144-149, 2016.
26. Gaber T et al., Thermogram breast cancer prediction approach based on Neutrosophic sets and fuzzy c-means algorithm, *37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).* 4254-4257, 2015.
27. Koundal D, Gupta S, Singh S. Speckle reduction method for thyroid ultrasound images in neutrosophic domain. *IET Image Processing.* 10(2): 167-175, 2016.
28. Kaur G and Kaur H, An automated method of segmentation for tumor detection by neutrosophic sets and morphological operations using MR images, *Conference on Emerging Devices and Smart Systems (ICEDSS).* 163-168, 2016.
29. Sangeeta KS, Mrityunjaya VL, Combined Endeavor of Neutrosophic Set and Chan-Vese Model to Extract Accurate Liver Image from CT Scan. *Computer Methods and Programs in Biomedicine.* 151:101-109, 2017.
30. Koundal D, Texture-based image segmentation using neutrosophic clustering. *IET Image Processing.* 11(8): 640-645, 2017.
31. Nugroho HA, Triyani Y, Rahmawaty M, Ardiyanto I, Breast ultrasound image segmentation based on neutrosophic set and watershed method for classifying margin characteristics, *7th IEEE International Conference on System Engineering and Technology (ICSET).* 43-47, 2017.
32. Nugroho HA, Rahmawaty M, Triyani Y, Ardiyanto I, Neutrosophic and fuzzy C-means clustering for breast ultrasound image segmentation. *9<sup>th</sup> International Conference on Information Technology and Electrical Engineering (ICITEE).* 1-5, 2017.
33. Dang TN, Son LH, Ali M, Neutrosophic recommender system for medical diagnosis based on algebraic similarity measure and clustering. *IEEE International Conference on Fuzzy Systems (FUZZ-IEEE).* 1-6, 2017.
34. De S, Mishra J, To Handle Uncertain Data for Medical Diagnosis Purpose Using Neutrosophic Set. *7th International Advance Computing Conference (IACC).* 901-903, 2017.
35. Lotfollahi M, Gity M, Ye JY, Mahlooji Far A, Segmentation of breast ultrasound images based on active contours using

101

- neutrosophic theory. *J Med Ultrasound*. 45(2): 205-212, 2017.
36. Sayed, GI, Hassanien AE, Moth-flame swarm optimization with neutrosophic sets for automatic mitosis detection in breast cancer histology images. *Applied Intelligence*. 47:397–408, 2017.
  37. Koundal D, Gupta S, Singh S, Neutrosophic Based Nakagami Total Variation Method for Speckle Suppression in Thyroid Ultrasound Images *Innovation and Research in BioMedical engineering*. 39(10):43-53, 2018.
  38. AnterAM, Hassenian AE, Computational intelligence optimization approach based on particle swarm optimizer and neutrosophic set for abdominal CT liver tumor segmentation *Journal of Computational Science*. 25:376-387, 2018.
  39. Koundal D, Gupta S, Singh S, Computer aided thyroid nodule detection system using medical ultrasound images *Biomedical Signal Processing and Control*.40:117-130, 2018.
  40. Ali M, Son LS, Khan M, Tung NT, Segmentation of dental X-ray images in medical imaging using neutrosophic orthogonal matrices *Expert Systems with Applications*. 91:434-441, 2018.
  41. Lal M , Kaur L, Gupta S, Modified spatial neutrosophic clustering technique for boundary extraction of tumours in B-mode BUS images *IET Image Processing*. 12(8): 1338-1344, 2018.
  42. Rashno A et al., Fully Automated Segmentation of Fluid/Cyst Regions in Optical Coherence Tomography Images With Diabetic Macular Edema Using Neutrosophic Sets and Graph Algorithms, *IEEE Transactions on Biomedical Engineering*.65(5): 989-1001, 2018.
  43. Govindarajan S, Parmaar NK, Swaminathan R, A Proposals to Differentiate Homogenous and Speckled Shapes in Indirect Immunofluorescence Images Using Neutrosophic Sets *Proceedings of the 2019 4th International Conference on Biomedical Imaging, Signal Processing*. 65-71, 2019.
  44. Sert E, Avci D, Brain tumor segmentation using neutrosophic expert maximum fuzzy-sure entropy and other approaches *Biomedical Signal Processing and Control*.47:276-287, 2019.
  45. Guo Y, Ashour AS, Neutrosophic sets in dermoscopic medical image segmentation *Neutrosophic Set in Medical Image Analysis*, Academic Press.229-243, 2019.
  46. Ashour AS, Guo Y, Advanced optimization-based neutrosophic sets for medical image denoising *Neutrosophic Set in Medical Image Analysis*, Academic Press.101-121, 2019.
  47. AmmaPalanisamy TSC, Jayaraman M., Vellingiri K, Guo Y, Optimization-based neutrosophic set for medical image processing *Neutrosophic Set in Medical Image Analysis*, Academic Press.189-206, 2019.
  48. Ozyurt F, Sert E,Avci E, Dogantekin E, Brain tumor detection based on Convolutional Neural Network with neutrosophic expert maximum fuzzy sure entropy *Measurement*, 147,106830, 2019.
  49. Wen J, Xuan S, Li Y, Peng Q, Gao Q, Image segmentation algorithm based on neutrosophic fuzzy clustering with non-local information *IET Image Processing*.14(3): 576-584, 2019.
  50. Jiang X, Guo Y, Chen H, Zhang Y. and Lu Y, An Adaptive Region Growing Based on Neutrosophic Set in Ultrasound Domain for Image Segmentation. *IEEE Access*.7:60584-60593, 2019.
  51. Rahimizadeh N, Hasanzadeh RP, Ghahramani M, Janabi-Sharifi F, A Neutrosophic based Non-Local Means Filter for Despeckling of Medical Ultrasound Images, 9th International Conference on Computer and Knowledge Engineering (ICCKE). 249-254, 2019.
  52. Ashour AS, Du C, Guo Y, Hawas AR, Lai Y, Smarandache F, A Novel Neutrosophic Subsets Definition for Dermoscopic Image

- Segmentation IEEE Access. 7:151047-151053, 2019.
53. Muthuswamy J, Extraction and Classification of Liver Abnormality Based on Neutrosophic and SVM Classifier. Advances in Intelligent Systems and Computing. 713:269-279, Springer, Singapore, 2019.
54. Muthukumar P& Krishnan GSS, A similarity measure of intuitionistic fuzzy soft sets and its application in medical diagnosis. Applied Soft Computing. 41, 148-156, 2016.