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NEUTROSOPHIC MACHINE LEARNING APPLICATIONS IN MEDICAL DIAGNOSTICS: A REVIEW

Dr. Sangeeta Rani*

Department of Computer Science and Engineering Chaudhary Devi Lal University, Sirsa.

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***Corresponding Author**
Dr. Sangeeta Rani
Department of Computer Science and Engineering
Chaudhary Devi Lal University, Sirsa.

ABSTRACT

The field of medical diagnostics is always battling the intricacies that come with inaccurate and ambiguous data. A powerful mathematical paradigm for overcoming these difficulties is neutrophilic set theory, which provides a sophisticated framework for dealing with ambiguity, imprecision, and incompleteness in medical data. This study provides an extensive overview of the combination of machine learning techniques with neutrosophic set theory, outlining its significant influence on improving diagnostic performance in the medical field. Neutrosophic set theory's core ideas—truth-membership, indeterminacy, and falsity-membership—offer a flexible framework for expressing the complex nature of medical data. These features, which define neutrosophic sets, provide for a more complex depiction of data items than is possible with traditional binary set theories. Within medical diagnostics, the integration of neutrosophic set theory with machine learning techniques offers the door for transformative applications. Algorithms for neutrophilic clustering skillfully handle the uncertainties included in medical data, enabling meaningful grouping according to values for falsity-, indeterminacy-, and truth-membership. Simultaneously, neutrosophic classifiers provide a sophisticated method for classifying medical data, accounting for the related uncertainties and improving diagnostic accuracy. The work navigates through significant scientific contributions, investigating the usage of neutrosophic logic in medical imaging techniques. This investigation includes works that demonstrate the use of neutrosophic logic in medical picture categorization, segmentation, and diagnostic tool improvement. It also explores the alterations needed in machine learning methods to include neutrosophic sets,

highlighting the adjustments necessary to account for uncertainty and partial truth values that are common in medical datasets.

KEYWORDS: Neutrosophy, machine learning, medical diagnostics, N-kNN, N-SVM.

1. Neutrosophic Set Theory

Neutrosophic set theory, introduced by Smarandache, offers a comprehensive framework to manage uncertainty within medical data, defined by truth-membership (T), indeterminacy (I), and falsity-membership (F) components. A neutrosophic set, denoted as *(i)*

$A = \{(x, T(x), I(x), F(x)) \mid x \in U\}$ . . . *(i)*

Where

- U is the universal set and captures the spectrum of membership, and

- $T(x) + I(x) + F(x) = 1$ for each element x.

Unlike traditional set theories, these elements—which are frequently stated as functions or intervals—encapsulate underlying uncertainty and permit a more nuanced depiction (Smarandache, 2005). Within medical datasets, operations on these values—union, intersection, and complement—manipulate ambiguous information.

Using machine learning methods that make use of these sets, medical diagnostics can benefit from the application of neutrophilic set theory. While neutrosophic classifiers classify data while accounting for related uncertainties, neutrosophic clustering groups medical data based on truth, falsehood, and indeterminacy. In order to handle uncertainty and partial truth values in medical data, it is frequently necessary to modify objective functions, decision boundaries, or learning mechanisms when adapting conventional algorithms to accept neutrosophic sets (Zhang et al. 2010).

A promising new direction in medical research has been opened up by the combination of sophisticated mathematical frameworks and diagnostic imaging tools. While the inclusion of neutrosophic logic into algorithms enhances segmentation precision in medical imaging, Shang et al. (2010) addresses the complexity of medical image segmentation and has demonstrated its ability to enhance accuracy in ultrasound breast image segmentation.

Theoretical developments in logic and neutrosophic sets offer a basis for comprehending complex structures in medical imaging. The frameworks provided by geometric interpretations and unified logic as revealed by Smarandache (2005) have the potential to transform the field of medical imaging diagnostics. Ju (2011)'s pursuit of integrating neutrosophic logic into classifiers is an example of how it might be used to improve diagnostic instruments. The investigation of interval neutrosophic sets by Wang et al. provides a solid foundation for real-world uses in medical picture analysis and shows potential for improving diagnostic algorithms (Wang et al., 2005).

Taken as a whole, these research endeavours demonstrate the revolutionary potential of neutrosophic logic and contribute to improving diagnostic precision and accuracy in medical imaging, paving the way for a bright future in healthcare diagnostics.

2. Neutrosophic machine learning

Neutrosophic machine learning (NML) expands on existing paradigms to address the ambiguity, incompleteness, and uncertainty present in complex datasets. This section has discussed neutrosophic variants of two classifiers, namely, kNN and SVM, as well as the neutrosophic linear regression model.

2.1 Neutrosophic kNN

Neutrosophic k-nearest neighbours (kNN) is a classification algorithm that operates based on similarities in neutrosophic feature spaces. Here are the steps in neutrosophic kNN algorithm:

(a). Choose a value of $\boldsymbol{k}$ (a positive integer)

(b). Calculate neutrosophic distances

Calculate the neutrosophic distance (Euclidean distance or some other distance measure) between the test data instance and each instance in the training dataset.

$$NED_j = \sqrt{(D_{tj})^2 + (D_{ij})^2 + (D_{fj})^2} \qquad \ldots \qquad (i)$$

Where

- NED_j is the neutrosophic Euclidean distance between j^{th} training data instance and the test data (unknown) instance.
- D_{tj}, D_{ij} and D_{fj} are Euclidean distance between truth, indeterminate, and false components of j^{th} training data instance and the test data (unknown) instance.

(c). Sort the training dataset in ascending order of NED

(d). Select the top k instances of the training dataset

These instances are the 'nearest neighbours' to the test data instance.

(e). Perform majority voting.

Find out the majority crop label among the selected k instances. This will be the predicted crop label for the test instance based on the neutrosophic kNN algorithm.

2.2 Neutrosophic SVM

The neutrosophic SVM algorithm, a variation of the standard SVM, uses the neutrosophic components to improve accuracy and reduce the impact of unusual data points during learning. Assuming we have a set of neutrosophic training data (x_i, y_i) where each x_i represents neutrosophic input feature space data and y_i shows its class in neutrosophic terms.

(a). Calculate three Neutrosophic components (t_i, i_i, f_i) for each data point:

- t_i is the measure of data's distance from the positive class centre.
- i_i is the measure of data's distance from the average centre.
- f_i is the measure of data's distance from the negative class center.

(b). Define g_j as a combining function using these neutrosophic components:

$$g_j = t_i + i_i + f_i \qquad \ldots (ii)$$

(c). Optimise the hyperplane using the combining function g_j.

The goal is to minimise the weighted sum of these components. The optimisation seeks the best hyperplane that separates classes well.

(d). Ensure that the optimised hyperplane satisfies the conditions specified in eq. *(iii)* to correctly classify each data point:

$$(y_j.(\omega_j + b) > 1 - \zeta_j - g_j) \ldots (iii)$$

Where:

- y_j represents the neutrosophic class label or output associated with the data point j.
- ω_j denotes the neutrosophic weight vector assigned to the data point j.
- b represents the neutrosophic bias or intercept term in the model.
- ζ_j represents the neutrosophic slack variable associated with data point j, allowing for misclassification or outliers within the margin.

The equation *(vi)* states that the product of the class label y_j and the dot product of the weight vector ω_j and the data point plus the bias term b should be greater than $(1 - \zeta_j - g_j)$ for proper classification. This formulation ensures that correctly classified points lie beyond the margin and are not within the margin boundary (controlled by ζ_j).

2.2 Neutrosophic linear regression

Extending the notion of classical linear regression to neutrosophic datasets with only one input feature, the simple linear regression model may be represented as (*iv*) below

$$Y_i = \beta_0 + \beta_1 . X_i \qquad ...(iv)$$

Where

- Y_i denotes the neutrosophic predicted value of target variable for i^{th} training instance,
- X_i denotes the neutrosophic independent variable in i^{th} instance of training data,
- β_0 is the estimated (to be optimised) neutrosophic intercept, and
- β_1 is the estimated (to be optimised) neutrosophic slope or regression coefficient.

Further, for a multi-criteria decision situation, the regression model (multi-linear regression) takes the form of *(v)* below:

$$Y_i = \beta_0 + \sum_1^m \beta_j . X_{ji} \; ...(v)$$

Where

- Y_i is the neutrosophic predicted value of the target feature for i^{th} instance of data,
- X_{ji} denotes the j^{th} neutrosophic input variable in i^{th} instance of training data,
- β_0 is the estimated (to be optimised) neutrosophic intercept,
- β_j represents the neutrosophic regression coefficient for j^{th} input feature, and
- m is the number of input features.

In neutrosophic linear regression, adjusting the intercept β_0 and regression coefficients $\beta_j \; \forall \; j = 1 \; to \; m$ involves employing gradient descent to minimise the error between predicted and actual neutrosophic values. The formulas for updating these parameters iteratively using the gradient descent method are derived from the partial derivatives of the error function for each parameter. The update rules are based on the direction and magnitude indicated by the gradients to move toward the minimum error.

The update rule for the intercept β_0 and $\beta_j's$ in each iteration is

$$\beta_0^{\;t+1} = \beta_0^{\;t} + \gamma \frac{2}{N} \sum_1^N (Y_{A_i} - Y_{P_i}) \qquad ...(vi)$$

$$\beta_j^{\;t+1} = \beta_j^{\;t} + \gamma \frac{2}{N} \sum_1^N X_i . (Y_{A_i} - Y_{P_i}) \; ...(vii)$$

Where:

- $\beta_0{}^{t+1}$ is the updated value of the intercept for the $(t+1^{st})$ iteration,
- $\beta_j{}^{t+1}$ is the updated value of the intercept for the $(t+1^{st})$ iteration,
- $\beta_0{}^{t}$ is the current value of the intercept in the t^{th} iteration,
- $\beta_j{}^{t}$ is the current value of the intercept in the t^{th} iteration,
- γ is the learning rate (step size) controlling the rate of gradient descent,
- N is the total number of instances in the dataset,
- Y_{A_i} is the actual value of target feature for i^{th} data instance.
- Y_{P_i} is the predicted value of target feature for i^{th} data instance.
- X_i is the i^{th} input feature vector

Here j varies from 1 to m: m is the count of input features and i varies from 1 to N: N is the count of training data instances.

3. Review of Medical Applications of NML

Neutrosophy is a unique method of interpretation and reasoning that embraces the idea of indeterminacy, which is present in a wide range of phenomena and fields of knowledge (Smarandache, 1995). Based on the fusion of truth, falsity, and ambiguity, neutrosophy subverts the conventional binary logic by admitting the presence of things or ideas that might have contradicting qualities at the same time, resulting in a triadic logic system. Fundamentally, neutrosophy acknowledges that opposing, complementary, or even contradictory components can coexist inside the same thing, concept, or creature. It presents the idea of a "neutrosophic set," which concurrently captures the idea of membership degrees in falsity, indeterminacy, and truth (Smarandache, 2003). A more nuanced portrayal of difficult and ambiguous notions that traditional set theories are unable to adequately convey is made possible by this novel set theory.

Neutrosophy is used in a wide range of disciplines, including computer science, linguistics, philosophy, epistemology, and even decision-making. Its applications go beyond logic and mathematics (Smarandache, 2004). Its usefulness comes from giving a framework for analysing, interpreting, and modelling concepts or occurrences when ambiguity, complexity, or contradictions predominate. This allows for a more thorough comprehension of complicated systems and paradoxical circumstances. Since Neutrosophy introduced the neutrosophic method, research in a number of disciplines has been conducted with the goal of utilising its potential to address issues related to unclear or ambiguous information. Because of this, it presents a unique and fascinating philosophical paradigm that encourages a new way of thinking about reasoning, making decisions, and interpreting the world—especially in fields where complexity and ambiguity are prominent (Smarandache, 2005).

Medical diagnostics are essential to the healthcare industry because they impact patient outcomes, treatment choices, and overall healthcare expenditures. The complex structure of medical data means that, even with great advancements in traditional machine learning techniques, their use in medical diagnosis continues to present difficulties. Due to the domain's intrinsic uncertainty, imprecision, and incompleteness, accurate and reliable diagnostic predictions are difficult to achieve. Conventional machine learning techniques have drawbacks, particularly where interpretability, flexibility in the face of uncertainty, and noise resistance are crucial (Zhang, 2010). As such, there is a growing need for more advanced and flexible methods that can better navigate the complex medical data landscape with more agility and precision.

The neutrosophic theory opens up new avenues for modelling the uncertainties present in medical data by accepting uncertainty and partial truth values, which has the potential to completely transform the field of diagnostic accuracy and dependability. The purpose of this review is to investigate the application of machine learning and neutrosophic set theory to medical diagnosis. It outlines the fundamentals of neutrosophic set theory, clarifies possible uses, and explores how it can revolutionise the field of diagnostics. This review aims to shed light on the promising trajectory of neutrosophic machine learning in healthcare, aspiring to contribute to the evolution of more accurate and reliable diagnostic tools for improved patient outcomes. Applications, implementation challenges, and future trajectories in adopting this technology in medical diagnostics are also studied (Zhang, 2010).

For, the neuromorphic machine learning is so good at detecting malignant tumours or anomalies in medical imaging data, it is essential to the diagnosis and treatment of cancer. When accurately segmenting tumours from MRI or CT scans, neuromorphic neural networks and clustering algorithms help to account for uncertainty and unpredictability in tumour borders. Additionally, by analysing features in imaging data, neutrosophic classifiers help to differentiate between benign and malignant tumours, giving oncologists strong diagnostic support (Ju 2011). NML shows promise in detecting various illness stages or forecasting the likelihood of developing particular disorders in disease categorization tasks (Zhang & Zhang 2011). These models' inclusion of indeterminacy and uncertainty allows for more nuanced classifications, enhancing the ability to distinguish between distinct illness phases and estimating the likelihood that a disease would manifest based on intricate medical data (Zhang et al. 2010).

In radiology, pathology, and other imaging modalities, neutrophilic algorithms are effective at properly identifying anatomical features or defects through image analysis and segmentation. These techniques considerably assist in the segmentation and classification of tissues or organs in the presence of picture noise or variations in patient anatomy, and they also improve the accuracy of region-of-interest identification. Uncertainty in patient data is incorporated by NML to produce reliable prognosis prediction and therapeutic planning. With the ability to estimate disease development, forecast patient outcomes, and personalise treatment techniques, neuromorphic classification and regression models empower physicians to make well-informed decisions based on distinct patient attributes and uncertainties (Zhang et al. 2010).

By taking into account uncertainties in patient data, the integration of neutrosophic machine learning in decision support systems improves the precision and dependability of medical choices. These systems make use of neutrosophic models to offer thorough insights that support medical decision-making by improving diagnosis, suggesting treatments, and increasing accuracy. When dealing with sparse medical data and uncertainty, NML shows resilience in data-poor environments. This makes it useful in situations where obtaining large amounts of labelled data is difficult. These methods greatly improve medical settings with sparse or diverse datasets by enabling robust and reliable diagnosis even with minimal data (Zhang & Zhang 2011).

Furthermore, NML efficiently combines and analyses heterogeneous data types from many sources in multimodal medical data scenarios. By accounting for the uncertainties that arise from merging several data modalities, these models produce thorough and precise diagnostic results. The wide range of NML applications in medical diagnostics promises to revolutionise healthcare by providing better tools for diagnosis, prognosis, and treatment planning. These applications offer increased robustness, accuracy, and adaptability in handling uncertainty (Ju 2011).

Deep learning has a considerable deal of success in handling nonlinear issues, which allows it to extract data characteristics. In terms of diagnosing and analysing medical images, deep learning performs well. Additionally, incompleteness or fuzziness in medical imaging data affects the performance of deep learning. The neutrosophic approach's excellent handling of ambiguity and inconsistency in medical data can improve deep learning performance. The survey by Mostafa et al. (2021) explores the different ways that neutrosophic systems can improve deep learning and gives an overview and definition of each. Based on several medical picture modalities in various medical image processing stages, including pre-processing, segmentation, classification, and clustering, the hybrid techniques are categorised. Lastly, consideration is given to future efforts. In this investigation, hybridization between LASTM and neutrosophic views produced the best classification accuracy for the cardiac views. While the merger of neural networks, support vector machines, and neutrosophics achieves the maximum capability to precisely recognise those with the disease (sensitivity). Neutrosophic and LSTM yielded the best specificity.

Ali et al. (2016) discusses the complex problems with medical diagnosis brought on by the profusion of erroneous and inconsistent data in contemporary medical technology. Previous work, employing strategies such as fuzzy logic and probability-based methodologies, has run into issues with missing data, past patient diagnoses, and dependence on de-neutrosophication procedures, which has weakened accuracy. In response, the paper suggests a revolutionary hybrid structure called the neutrosophic recommender system, which effectively combines recommender systems with neutrosophic sets. This unique framework, covering single-criterion neutrosophic recommender systems and multi-criterion neutrosophic recommender systems, sets the groundwork for the neutrosophic collaborative filtering approach. This study investigates algebraic structures including lattices and Kleen algebra as well as the algebraic operations of neutrosophic recommender systems, such as union, complement, intersection, probabilistic sum, and many others. The suggested approach improves prediction skills by including several kinds of similarity measures and is experimentally validated on several medical datasets. The superior accuracy and computational efficiency of NRS are demonstrated by comparative evaluations with well-established algorithms, which validate its effectiveness. The importance of this work is in its strong theoretical underpinning, which overcomes the shortcomings of current techniques and makes promising contributions to the field of medical diagnostics and related applications.

Videos and pictures are important parts of our life. Furthermore, computer data gathering methods have advanced significantly, making it possible for anyone to obtain a large number of photographs or videos—something that cannot be done manually. Since it became possible to show and handle certain types of data digitally, images and movies have become more appealing. Imprecision is required to understand this world because it is surrounded by indeterminacy, including the photos and films of it. This imprecision can be illustrated using probabilistic logic, set theory, and statistics. Therefore, translating image processing into the neutrosophic realm defines advanced image processing. Applications of the neutrosophic domain in image and video processing, including segmentation, noise reduction, and image retrieval, are introduced by Talouki et al. (2021). Despite this, grayscale natural or medical photos are typically employed as input images for neutrophilic image restoration and segmentation. The striking thing is the paucity of studies that take colour images into account and concentrate on image restoration or segmentation utilising neutrosophic. Consequently, colour image segmentation and restoration in a neutrosophic setting are innovative. When using neuromorphic algorithms for image retrieval, average recall and precision measures improve over previous approaches. Applications for image retrieval can make greater use of neutrosophic space by taking into account varying textures and shapes.

A crucial stage in computer vision, pattern recognition, and image processing is picture segmentation. Over the past 20 years, Guo et al. (2008) have proposed a number of algorithms on this topic. As a subset of neutrosophic theory, it examines the nature, origin, and extent of neutralities as well as how they interact with various ideational spectra. A recently proposed formal framework is the neutrosophic set. For a particular application or subject, the neutrosophic set must be described from a technological standpoint. The authors have defined certain notions and operations for picture segmentation and implemented the neutrosophic set in the image domain. The picture assumes a neutrosophic realm. Next, the definition and assessment of the indeterminacy are done using the entropy in the neutrosophic set. To lessen the set indeterminacy, a new operation called the mean operation is suggested. Finally, a new fuzzy c-means technique, α-fuzzy-c-means is developed to segment the image on neutrosophic domain. The outcomes of the experiment show that the suggested method is capable of efficiently and automatically segmenting the photos. In particular, it can handle "clean" photos and noise-filled images without identifying the kind of noise, which is the hardest thing to split an image into.

The study of neutralities' genesis, characteristics, range, and interactions with various ideational spectra is known as neutrosophy. Neutronosophic logic, probability, set theory, and statistics are all based on this new philosophy, which is an extension of fuzzy logic. Because the world is full of indeterminacy, the imperfection of knowledge that a human receives/observes from the external world also causes imprecision. Neutrosophy introduces a new concept, which is the representation of indeterminacy. However, this theory is mostly discussed in physiology and mathematics. Thus, applications to prove this theory can solve real problems are needed. Image segmentation is the first and key step in image processing. Neutrosophy is the study of neutralities' nature, genesis, and interactions with various ideational spectra. Fuzzy logic is expanded upon by this new philosophy, which also serves as the foundation for neutrosophic statistics, set theory, probability, and logic. The imprecision that results from human knowledge being imperfectly seen or received from the outside world is a result of the world's inherent indeterminacy. A novel idea, the representation of indeterminacy, is presented by neutrosophy. But the fields of physiology and mathematics are where this hypothesis is primarily explored. Uses are therefore required to demonstrate the practical applications of this theory. The initial and crucial stage of image processing is called image segmentation.

The major definitions of neutrosophic sets and many medical applications based on neutrosophic sets were described in Nguyen et al. (2019) study. Furthermore, a thorough examination of the potential for extending the capabilities of fuzzy systems through the use of neutrosophic systems was provided. Previous research has demonstrated the importance of neutrosophic sets in the de-noising, grouping, and segmentation of medical pictures. It was proposed that the continuous truth/indeterminate/falsity versions of traditional scoring schemes, known as neutrosophic scores, may be obtained by utilising the medical systems that are neutrosophic in the future. In the medical area, the integrated approaches of the neutrosophic sets would result in a mapping from input to output variables that is tabular or rule basis. The qualitative simulation of the published research proved that the diagnosis based on the neutrosophic model is a potential avenue for further investigation. In addition, the current work emphasised the primary medical imaging processes—de-noising, thresholding, segmentation, grouping, and classification—that can be constructed with the neutrosophic sets. The general algorithms that can be utilised to include neutrosophic sets in each task were proposed.

\\engur et al. (2019) presents a survey on medical picture segmentation using neutrosophic theory. Examining the literature reveals that neutrosophy-based image segmentation techniques have been used on a variety of medical imaging, including dental X-rays, liver computed tomography, brain CT scans, dermoscopy, retinal, and eye angiography. Furthermore, neutrosophic has been applied in several optical image segmentation applications. Neutrosophic logic is very useful for texture image segmentation. Neutron surface physics has typically been applied for picture augmentation or denoising in these investigations. Furthermore, neutrosophy has been utilised for image segmentation in the majority of research. In addition to the literature review, some well-known neutrosophy-based medical picture segmentation methods are presented. Neutrosophy was applied in these methods to either segment the image into regions of interest and background, or to improve the image quality by contrast enhancement and noise removal. A detailed account of the techniques and findings of the methods under investigation is provided. Additionally provided are the general limits of the medical picture segmentation techniques based on neutrosophy. With some conclusions and ideas for the future, the chapter comes to a close.

4. CONCLUSION

A novel strategy that offers promising ways to deal with the inherent ambiguities, imprecisions, and complexity of medical data is the incorporation of neutrosophic set theory into machine learning techniques for medical diagnostics. In this review, we have clarified the fundamental ideas of neutrosophic set theory and examined its applications in a number of different areas related to medical diagnosis. It has been demonstrated that the use of neutrosophic machine learning algorithms, such as clustering methods, classification models, and neural networks, can significantly improve the precision, robustness, and adaptability of diagnosis. In healthcare contexts, these techniques facilitate more nuanced representations and informed decision-making by accommodating inherent ambiguities in medical data.

Neuroscientific machine learning is being applied in a variety of medical diagnostic fields, such as prognosis prediction, medical imaging analysis, disease classification, cancer detection, and decision support systems. These approaches have proven to be effective in managing uncertainty, data shortages, and heterogeneous data sources, which highlights their importance in improving diagnostic precision and supporting physicians in making well-informed decisions. Despite the significant promise of neutrosophic machine learning in medical diagnostics, there are still obstacles to overcome. There is further work to be done in the areas of interpretability, computational complexity, integration into clinical practise, and the requirement for larger annotated datasets.

Going future, it will be crucial to continue investigating and improving neutrosophic machine learning models. Improving interpretability, scalability, and seamless integration into clinical workflows ought to be the main goals of future research endeavours. Furthermore, in order to ensure that these developments are translated into actual clinical settings, cooperation between researchers, clinicians, and stakeholders is essential to bridging the theory-practice divide. In conclusion, a revolutionary paradigm for the future of medical diagnostics is presented by the combination of machine learning techniques with neutrosophic set theory. These approaches have the potential to transform healthcare by addressing the ambiguities present in medical data, which will ultimately result in better patient care, more precise diagnoses, and well-informed treatment plans.

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