# A Review on Metaheuristic Algorithms with Neutrosophic Sets for Image Enhancement

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**Abstract**

Breast cancer has emerged as a major killer in recent years. With a yearly rate of about one million new cases, it is the most prevalent among women in the world's poorest countries. Grading of cellular images has emerged as a key prognostic factor during the past decade. Neutrosophic sets used to enhance medical images in the last decade. Neutrosophic sets can overcome the uncertainty and indeterminacy of information. In recent years, metaheuristics have integrated with neutrosophic sets. Because of their adaptability, simplicity, and task independence, metaheuristics have been extensively employed to tackle many difficult non-linear optimization problems. The purpose of this research is to investigate several approaches to image classification for breast cancer pictures. This includes the use of metaheuristics and neutrosophic sets for optimization and image enhancement. This research was undertaken to better understand the current state of the art in breast cancer identification from medical pictures and to provide insight into the difficulties that lie ahead. We hope that this will encourage academics to investigate hitherto understudied facets of breast cancer identification.

**Keywords:** Neutrosophic Sets; Metaheuristics; Uncertainty; Breast Cancer; Image Enhancement

## 1. Introduction

Breast cancer has emerged as a major killer in recent years. With a yearly rate of about one million new cases, it is the most prevalent among women in the world's poorest countries. Grading of histologic images has emerged as a key prognostic indicator over the past decade. Breast cancers are graded according to how closely their tiny cells resemble normal breasts. Low-, intermediate-, and rising cancers are distinguished by the degree to which they differ from "normal" cells under the microscope and, hence, by the severity of their outlook. Nottingham Grading System (NGS), also referred to as the Elton-Ellis method, is a widely used method for classifying the severity of breast cancer. Metastatic tumor grades are calculated by the number of mitoses, the number of tubules formed in the nucleus, and the nuclear pleomorphic score. The total points earned across all of these factors determine an overall result and letter grade[1]–[5].

An essential problem in clinical radiology is the early and correct staging of malignancy. A key sign for cancer diagnosis and evaluation is the presence of mitotic cells in histological sections. Mitosis



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counting is often done manually by histologists by observing the dividing cells in a dividing region. Under the microscope, pathologists evaluate breast tissue samples for abnormal cell formations and assign a grade. Histology slides may be rather numerous, and a psychologist may have to analyze and evaluate many of them. A lot of time and effort is required for this. The time and money needed for mitotic counting may be cut down significantly with the use of automated systems. In addition, it may reduce the number of mistakes made and boost the consistency of data from various laboratories[6]–[10]. The mitotic cell's atypical form, together with artifacts and other distractions, make this a difficult process. In reality, different picture regions are primarily characterized by various kinds of tissue, each of which has a notably distinct look. Furthermore, an observer without considerable training would be unable to discern between a mitotic cell and a quasi cell, between a meiosis cell as well as other dark-blue patches and regular cells, in most phases[11]–[14].

There are many methods suggested in the literature for locating nuclei in H & E pictures. Automatic mitotic identification in histopathology slide pictures was suggested by Khan et al. His method relies on estimating the likelihood density function (pdf) of mitotic and interphase cells using a gamma-Gaussian mixture model (GGMM). To identify mitosis, a Support Vector Machine (SVM) algorithm was developed using the collected data sets[15]–[17].

Another strategy was given by Sommer et al. His method for identifying mitosis involves two distinct categories. He employed a random forest classifier to weed out potential candidates in the first round. Second-level cells were distinguished from those not undergoing mitosis using SVM. Blue ratio mapping was utilized by H. Irshad in to convert the original histopathological picture from red-green-blue (RGB) to blue-ratio (BRB) color space, to distinguish the nucleus area from the environment. The pixels in the azure ratio color space have a greater blue intensity than the red or green channel. Using this projection, nuclei show as bluish-purple spots and may be removed with a straightforward threshold technique and certain structural manipulations. Gray level founder matrix (GLCM), run-length matrix (RLM), and scale-based feature transformation (SIFT) based features were retrieved from each contender for identification. Classifiers such as a decision tree (DT), a linear support vector machine (SVM), and a non-linear SVM were fed with these characteristics[18]–[20].

In histopathology slide pictures, automated identification of cells undergoing mitosis presents a number of obstacles. The first difficulty is that cells in mitosis have many characteristics with normal cells and lymphocytes, making diagnosis difficult. In addition, there are notable differences in the size, intensity pixel value, and shape of mitotic nuclei. Secondly, there is a large number of mitoses that must be removed[21]–[24].

Therefore, this study offers an automated mitotic detection method as a means of addressing these difficulties. They transferred each improved pixel to the neutrosophic domain. The images in the truth subset for each channel were then improved using morphological techniques. Multiple statistical, color, texture, form, and energy properties were retrieved from each coupled part (candidate mitosis). We used MFO principles to zero down on the most discriminatory traits possible. Each candidate was classified as being in mitosis or not using the information fed into the categorization and regression tree (CART)[25]–[27].

## 2. Neutrosophic Sets

The fuzzy sets, a variant of traditional fuzzy sets, were first proposed by Atanassov. Intuitive fuzzy sets take into account both reality T and willful misinterpretation F, wherein T and F are in the interval [0, 1]. Since intuitionistic linguistic variables can only deal with partial information and not the ambiguous and conflicting information that is so prevalent in fuzzification, the concept of neutrosophic sets has been brought into the field by Smarandache. Understanding of neutral thinking is what is meant by the word neutrosophic, and it is this neutrality that serves as the primary dividing line between intuitionistic fuzzy logic and collections and traditional fuzzy logic. A new parameter I am introduced in neutrosophic sets to formally quantify indeterminacy. There is no unique relationship seen between reality (T), fuzzification (I), and demonstrable falsehoods (F), therefore the total of these three might be anything from 0 to 3. Risk in intuitionistic fuzzy sets is proportional to the number of members and nonmembers. The fuzziness factor (I) in neutrosophic sets does not rely on the truth or



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falsehood of the values it contains. Degrees of truth, uncertainty, and falsehood are not limited to one another[28]–[34].

It is the single-valued neutrosophic set (SVNS) that has been utilized most frequently in the research. Classic collections, fuzzification, interval-valued subsets, and intuitionistic fuzzy rules are all subsets of neutrosophic groups, of which SVNS are an example. The degrees of truth, falsehood, and uncertainty of a claim are often best described by interval values rather than discrete ones. So, the field has seen the introduction of the interval-valued neutrosophic set (IVNS).

To address issues of indeterminacy, several researchers turned to the philosophical set (NS) theory. Intuitionistic sets, fuzzy sets, paraconsistent sets, dialetheist sets, paradoxist sets, and tautological sets are all subsets of this more broad collection. The key innovation of NS compared to fuzzy logic is the addition of a new membership labeled "indeterminate." There is more information stored in this current membership element than in fuzzy logic. NS and its attributes were briefly examined. In this study, we used NS for the problem of segmenting mitotic candidates.

Neutrosophy is bringing each pixel of a picture into the neutrosophic realm. Neutrosophic domain pixels are denoted by the letters T, I, and F, correspondingly, which indicate that the pixel is t percent true, I percent indeterminate, and f percent false, while t changes in T, I changes in I, and f changes in F NS: t=0, i=0, f=100. While in a crisp set, I = 0, t = 0, and f = 100, in a fuzzy set I = 0, t = 0, and f = 100.

Assume we have a linguistic universe denoted by U, and that W is a subset of U made of visually arresting pixels. Three distinct groups make up the neutrosophic domain P N S image: T, I, and F. Every pixel in the input image, P(i,j), is converted into the neutrosophic domain, P N S (i,j) = T(i,j), I(i,j), F(i,j), where T(i), I(i,j), and F(i,j) are the chances of membership to the white set, the ambiguous set, and the non-white set, correspondingly. Here are some definitions:

$$P_{NS}(i,j) = \{T(i,j), I(i,j), F(i,j)\} \tag{1}$$

$$q(i,j) = \frac{1}{w \times w} \sum_{m=i-\frac{w}{2}}^{i+\frac{w}{2}} \sum_{n=j-\frac{w}{2}}^{j+\frac{w}{2}} q(m,n) \tag{2}$$

$$T(i,j) = \frac{q(i,j) - q_{min}}{q_{max} - q_{min}} \; q(m,n) \tag{3}$$

$$I(i,j) = 1 - \frac{R(i,j) - R_{min}}{R_{max} - R_{min}} \tag{4}$$

$$F(i,j) = 1 - T(i,j) \tag{5}$$

$$R(i,j) = abs\big(q(i,j)\big) - q(i,j) \tag{6}$$

where q(i,j) The final peak of the histogram that is bigger than the local maxima is denoted by the symbol "q min" (i,j) The absolute magnitude of the difference among the brightness q(i,j) and its regional mean value q(i,j) describes the homogeneity values of T at (i,j), denoted by R(i,j).

## 3. Metaheuristic Algorithms

### Moth Flame Optimization (MFO)

Moth flame optimization (MFO) was created by S. Mirjalili in 2015. Moths, like butterflies, are beautiful insects that belong to the same family. Over 160 thousand placental mammals of this beetle exist in the wild. The stages of larva and adulthood are the two most significant in their life cycle. Cocoons are used to transform the caterpillar into a moth. The fact that moths have evolved unique ways to navigate at night is the most fascinating aspect of their biology. Circumferential orientation was how they found their way. Using the moon as a reference point, moths maintain a constant angle of flight, which is an efficient method for covering great distances in a single direction[35], [36].



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Consider the potential answers to the issue to be moths, and their locations to be the independent variables. Moths primarily use the P function to explore the search space and locate food sources.

A moth's location concerning a flame is updated by using the given formula:

$$M_i = P(M_i, F_j) \tag{7}$$

$$P(M_i, F_j) = D_i . e^{bt} . \cos(2\pi t) + F_j \tag{8}$$

$$D_i = |F_j - M_i| \tag{9}$$

**Salp Swarm Algorithm (SSA)**

Several researchers have compared different metaheuristic approaches to see which one is more successful. SSA, a metaheuristic optimization that takes inspiration from nature and was developed by Mirjalili et al., is one of the most intriguing such algorithms. The success of SSA depends on the creation of an inhabitants optimizer that takes cues from the natural swarm behavior of salps. The SSA technique is popular in very many image processing jobs because of its ability to successfully show favorable intensification and diversification tendencies. Standard optimizers like GWO, PSO, and WOA cannot provide the same results as SSA. The SSA, on the other hand, is often praised for its seeming simplicity, power, adaptability, and convenience of use in either serial or parallel configurations. One adaptively declining parameter helps strike a nice balance between the system's tendencies toward intensification and diversity. To prevent premature local optimum converging, salps' position matrices are updated progressively while taking into account the positions of many other salps in a dynamic group of agents. Salps' kinetic motions improve SSA's search capabilities, allowing it to avoid immature convergence issues and break out of local optima. As a bonus, it remembers the best-found slap to help steer the rest of the swarm to other promising areas of the higher dimensional space. Nevertheless, SSA has an issue with exploitation, which might slow down the pace at which the algorithm converges. Although current studies show no indication of convergence for this optimizer, the concluding characteristics demonstrate SSA's effectiveness over other optimization techniques concerning accelerated fast convergence[37], [38].

Following is the modified form for the leading position.

$$D_j^1 = \begin{cases} F - a_1\big((L1 - L2)a_2 + L2\big) & a_3 \geq 0.5 \\ F + a_1\big((L1 - L2)a_2 + L2\big) & a_3 < 0.5 \end{cases} \tag{10}$$

$$a_1 = 2e^{-\left(\frac{4t}{I_{max}}\right)^2} \tag{11}$$

$$D_j^i = \frac{1}{2}(D_j^i + D_j^{i-1}) \tag{12}$$

**Firefly Algorithm**

The method known as the "firefly algorithm" is inspired by the blinking patterns of the insects of the same name. Specifically, suggests that it may help fix problems with the dependent variable. The degree to which a randomly generated configuration shines depends on the accuracy of the classifier's predictions. For the suggested FA algorithm, three criteria stand out as very important[39], [40].

The first criterion is that fireflies don't have sex differences, thus any firefly gene may be transferred to another.

The second principle is that a firefly's luminosity is heavily dependent on how well its predictions match the result.



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Third, a firefly's allure is proportional to its brightness and decreases with increasing distance. Given that we are interested in resolving a mistake minimization problem, it follows that a solution that provides an error estimate of the gene characteristic with a lower absolute value is more promising.

The neutrosophic classification has been suggested along the lines of fuzzy logic, but instead of providing a defuzzified value, it rewards the neutrosophic organization of the kind. The rest of the article is organized around the concept that using neutrosophic logic in programming is essential for situations where a degree of indeterminacy prevails in the created output. The criteria of the fluffy learning algorithm will determine the outline of the neutrosophic categorization inference architecture.

## 4. Results and analysis

### Evaluation metrics

Precision can be computed as:

$$Precision = \frac{x}{x+z} \tag{13}$$

Where x is a True positive,
y is a true negative
z is a false positive
u is a false negative

The recall can be computed as:

$$Recall = \frac{x}{x+u} \tag{14}$$

$$F1\ score = \frac{2*precision*recall}{precision+recall} \tag{15}$$

$$Accuracy\ = \frac{x+y}{x+y+z+u} \tag{16}$$

There are many datasets on the breast cancer problem. To put the suggested method through its paces, 640 x 480-pixel infrared images captured by the DMR-IR are used. Frontal infrared pictures of both healthy and unwell individuals. Instructions to the subject, examination room settings, and recording locations are only a few of the challenges that arise when using thermal imaging for cancer detection. To begin, the photograph has to be shot in a stable setting, where there is little chance of the subject's physiological state changing. The patient should be told to refrain from using any external factors that can cause a change in their condition, including but not limited to: cosmetics, personal care products, lotions, physical activity, smoking, drinking, caffeine, jewelry, and sun damage. The ideal range for taking a thermal picture is between 18 and 22 degrees Celsius. Sunlight and draughts of any kind are both strictly prohibited in this space. To capture a more detailed thermal picture of her breasts and armpits (called an ROI), a lady stands directly in front of an infrared sensor, hands on her head, at a range of [0.8 m - 1.2 m] based on her height and build.

The other dataset used in this problem Sayed and Hassanien [41] used a publicly available data set from ICPR'12, the 12th International Conference on Pattern Recognition. In all, there are five separate breast pathologic slides included. H&E staining was used for these slides. Fifty photos from histopathology slides were utilized in this study; each was scanned at 40x using an Aperio XT scanner. Histopathology images have a resolution of 2084x2084 pixels. An experienced pathologist counted 300 mitoses across 50 photos in the collection. By using the holdout technique, we randomly split the data in half, with half of the histopathological slide images being used for trained and feature engineering and the other half being utilized. This paper makes a comparison between metaheuristic algorithms only like (Genetic Algorithm (GA), Grey Wolf Optimizer (GWO), Ant Bee Colony (ABC),



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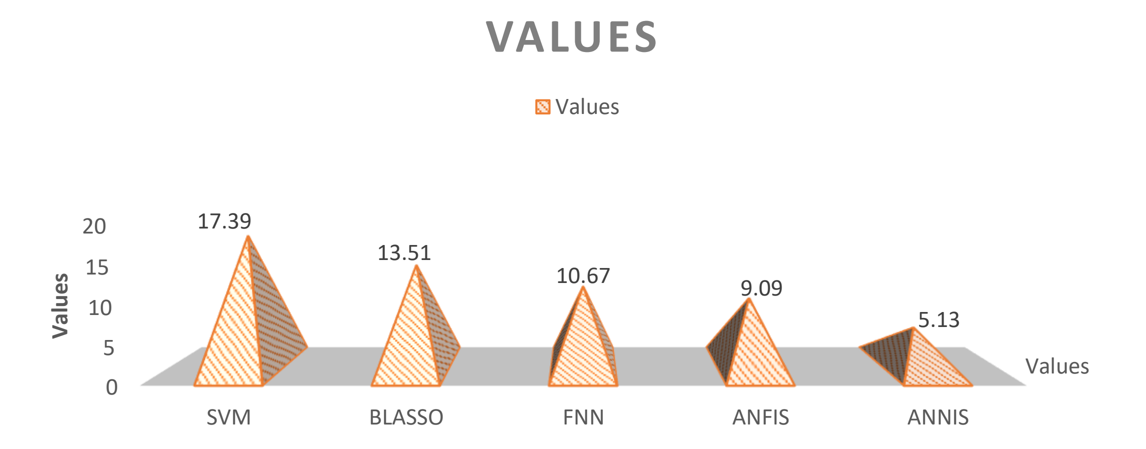
and Chicken Swarm Optimization (CSO)) and the hybrid metaheuristic with the neutrosophic sets. Table 1 shows this comparison.

Table 1: The comparison between metaheuristic algorithms only and neutrosophic integrated with metaheuristic

| Algorithms | Precision | Recall | F1 score | Accuracy |
|---|---|---|---|---|
| GA | 60% | 58% | 59% | 85% |
| GWO | 62% | 61% | 60% | 87% |
| CSO | 55% | 55% | 55% | 82% |
| ABC | 60% | 61% | 61% | 87% |
| MOF and neutrosophic sets | 63% | 63% | 63% | 88% |

From table 1, the accuracy of GA is the height value over the precision, recall, and f1 score. The GA had an 85% accuracy, 58% recall, 59% f1 score, and 60% precision. The GWO had 62% precision, 61% recall, 60% f1 score, and 87% accuracy. The CSO had a 55% precision, 55% recall, 55% f1 score, and 82% accuracy. The ABC had a 60% precision, 61% recall, 61% f1 score, and 87% accuracy. The MOF and neutrosophic sets had a 63% precision, 63% recall, 63% f1 score, and 88% accuracy. The MOF and neutrosophic had the highest value of precision, recall, f1score, and accuracy. So, the best algorithm is the MOF and neutrosophic sets. So, the integrated neutrosophic with the metaheuristic algorithm is the best solution to compute higher accuracy.

Umamaheswari and Sumathi [42]made a comparison between Adaptive Neuro-Fuzzy Inference System (ANFIS), Fuzzy Neural Network (FNN), Bayesian Least Absolute Shrinkage and Selection Operator (BLASSO) classifier, and Support Vector Machine (SVM).




| | SVM | BLASSO | FNN | ANFIS | ANNIS |
|---|---|---|---|---|---|
| Values | 17.39 | 13.51 | 10.67 | 9.09 | 5.13 |

Figure 1: The comparison of neutrosophic and metaheuristic algorithms

### 6. Conclusion

Developments in fuzzy sets and probabilistic reasoning had focused mostly on improving the specification of attribute values. Normal fuzzy set membership functions are either discrete numbers or functional and quality signifying membership. Type-2 linguistic variables emerged later in response



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to concerns about the membership degrees' sharpness. Atanassov modified the notion that the total of membership and quasi is precisely 1, renaming these sets as intuitionistic (IFS). By adding the parameter "indeterminacy" to the IFS specification, Smarandache was able to extend IFS to neutrosophic sets. Atanassov further expanded this concept to hesitant fuzzy type 2 fuzzification, showing that the total of the squares of the membership degrees and non-membership may never exceed 1. This gave decision-makers a wider space to work with when defining fuzzy sets. Yager has rechristened intuitionistic type 2 fuzzification as Pythagorean fuzzification (PFS). In this study, we offer methods for automatically identifying mitosis in histopathology slide pictures. The foundation of the method is NS and the metaheuristic. Specifically, a benchmark dataset from histopathology slides. To find the most discriminative collection of features, the paper employed the suggested metaheuristic methods. Experiments indicate that the metaheuristic algorithm integrated with neutrosophic sets outperforms other popular meta-heuristics—the CSO, the GWO, and the ABC algorithms in terms of efficiency and resilience.

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