Neutrosophic Sets and Systems, Vol. 96, 2026
University of New Mexico

Improving Classification in Support Vector Machine Using Neutrosophic Logic

Hiba Habbak [1], Mohammad Taher Anan [2] and Abdulkader Jokhadar [3,*]

[1] Department of Mathematical Statistic, Faculty of Science, University of Aleppo, Aleppo, Syria 1; hiba.habbak@alepuniv.edu.sy

[2] Department of Mathematical Statistic, Faculty of Science, University of Aleppo, Aleppo, Syria 2; mohamadtaher@alepuniv.edu.sy

[3] Department of Mechatronics Engineering, Faculty of Electrical and Electronic Engineering, University of Aleppo, Aleppo, Syria 2; ajoukhadar@alepuniv.edu.sy

* Correspondence: hiba.habbak@alepuniv.edu.sy; Tel.: +963 962557606

Abstract: Support Vector Machine (SVM) is considered one of the most effective methods for classification tasks. However, randomness in classifying observations on the optimal separating hyperplane decision — which are often indeterminate in their class membership — and misclassified observations remain among the main challenges that researchers face when using SVM. To address these challenges, a Neutrosophic logic – based approach was proposed, enabling better handling of class ambiguity and reducing misclassifications in the neighborhood of the optimal separating hyperplane. A novel algorithm was introduced, which consisted of two main steps. First, the observations located near the optimal separating hyperplane were converted into Neutrosophic data, characterized by three components: truth, indeterminacy, and falsity. In the second step, the SVM classifier was reapplied to the Neutrosophic data to improve the classification accuracy. As a case study, the proposed algorithm was tested on two types of oil samples (sunflower oil and corn oil), and its performance was compared with that of a standard SVM without Neutrosophic data. The results demonstrated that the SVM models utilizing Neutrosophic data achieved higher accuracy compared to those without Neutrosophic data. Therefore, integrating Neutrosophic logic with SVM can significantly enhance the performance and reliability of SVM-based models.

Keywords: Support Vector Machine; Kernel Trick; Neutrosophic; Indeterminacy; Classification.

1. Introduction

The support vector machine (SVM) algorithm was introduced by Vapnik in 1995 as a supervised learning method and has garnered significant attention owing to its high accuracy in classification problems [1]. The fundamental idea behind SVM is to divide the dataset two sets: a training set, known as support vectors (SV), which is used to train the algorithm and identify the optimal separating hyperplane, and a test set to rigorously evaluate the classification accuracy of the trained model. Observations are assigned to the first class if the decision function yields a positive value, and to the second class if the value is negative. If an observation lies exactly on the optimal department hyperplane, it is typically assigned randomly to one of the two sets.

However, owing to its sensitivity to outliers, SVM may misclassify some training data, treating them as noise or anomalies. To address this limitation, Neutrosophic logic has been proposed as a complementary framework to handle such uncertain or indeterminate data. Neutrosophic logic, introduced by Florentin Smarandache in 1999, extends classical logic by characterizing each statement through three independent degrees: truth (T), indeterminacy (I), and falsity (F). This richer representation of uncertainty makes it a promising approach for enhancing SVM performance, particularly in scenarios involving noisy or ambiguous data [2], [3], [4].

In address the problem at hand, it is essential to mention some of the previous research conducted in this area. In ref. [5] the authors proposed a novel classification model called Neutrosophic Logic SVM (N-SVM), which integrates Neutrosophic logic with support vector machine for the purpose of image categorization. This approach employs a self-organizing map (SOM) to segment images into regions based on features such as color and texture. Subsequently, the N-SVM model was used to classify the segmented regions. The experimental results demonstrated that incorporating Neutrosophic logic significantly improved the performance of SVM when dealing with uncertain or imprecise data. In ref. [6] a model known as the Neutrosophic support vector machine (NS-SVM) was developed by integrating Neutrosophic sets with traditional SVM. The approach utilizes the Neutrosophic C-Means algorithm to assign each data sample with three membership degree-truth, indeterminacy, and falsity. These values are then converted into weights that are used during the training phase of the SVM model. This integration enhances classification accuracy, particularly in scenarios involving uncertain or noisy data. In ref. [7] some points located in the neighborhood decision limit and misclassified in the support vector machine were addressed and the accuracy of the classification was improved after applying Neutrosophic logic in the neighborhood decision limit. In ref. [8] the author focused on enhancing the quality of medical images by processing them within the Neutrosophic domain. In this approach, the image is divided into three components, each processed independently to improve visual quality. The study incorporates algorithms such as K-means clustering for image segmentation and Support Vector Machine (SVM) for classification. These methods facilitate the extraction of features such as color and texture, contributing to a better analysis of medical images. In ref. [9] a novel method for predicting kidney disease was proposed by integrating enhanced Neutrosophic sets with machine learning algorithms. The approach tackles uncertainty in medical data by transforming it into a Neutrosophic form using membership functions for truth, indeterminacy, and falsity. Three classifiers-logistic regression, SVM, and K-NN – were applied, with results showing improved prediction accuracy. Notably, logistic regression achieved the best performance when using Neutrosophic-based data, outperforming traditional approaches under uncertain conditions. In ref. [10] recent efforts have been made to integrate Neutrosophic set theory with advanced machine learning models to improve breast cancer detection. This integration aims to manage uncertainty, imprecision, and ambiguity inherent in medical datasets. By combining Neutrosophic data processing with multiple classification models, the proposed approach enhances diagnostic accuracy while reducing computational complexity, ultimately supporting more reliable decision-making in clinical applications.

Despite extensive research on improving SVM classification, selecting an appropriate Neutrosophic membership remains a critical factor in addressing the issues of random classification and misclassification in SVM models. In this paper, a novel approach based on Neutrosophic logic is proposed, in which the traditional decision values are replaced by Neutrosophic membership components-truth (T), indeterminacy (I), and falsity (F). This approach enhances the performance of SVM by effectively handling observations that are either misclassified or are in the neighborhood of the optimal separating hyperplane, in both linear and nonlinear classification of the data, the proposed model shows significant improvement in classification accuracy, outperforming both traditional and fuzzy-based methods.

This paper is organized as follows: in the first section, we provide a brief overview of the support vector machine algorithm. The second section presents the concept of Neutrosophic logic. The third section describes the proposed Neutrosophic-SVM approach. The fourth section presents a case study of the proposed method to existing data, followed by a summary of these results in the final section.

The Contribution of the Study:

This paper introduces an innovative integration of Neutrosophic logic into SVM to address the random classification and misclassification of data located near the optimal separating hyperplane. The proposed method transforms the decision values into the Neutrosophic domain, where they are represented by three components: truth (T), indeterminacy (I), and falsity (F). The SVM is then reapplied to the Neutrosophic-transformed dataset. Experimental evaluation on sunflower and corn oil samples confirmed the method's efficacy, demonstrating consistent and significant accuracy improvements for both linear and nonlinear classification over conventional SVM models.

The Importance of Neutrosophic Approach:

The core contribution of the Neutrosophic approach lies in enhancing the performance of SVM by effectively addressing observations located near the optimal separating hyperplane, without altering the intrinsic operational machine of the algorithm. By transforming decision values into a triadic representation-truth (T), indeterminacy (I), and falsity (F)-the model gains a more refined capacity to discriminate between definitive and ambiguous observations. This capability to explicitly model uncertainty enables the SVM to deliver more accurate and stable classification outcomes, particularly in regions where class boundaries are indistinct or overlapping. Moreover, the Neutrosophic framework facilitates the explicit quantification of both confidence and uncertainty for each data point, thereby enhancing the reliability of predictions and improving the interpretability of the model. Consequently, this approach represents a strategic augmentation to SVM-based classification methodologies, offering a systematic and adaptable machine for handling challenging cases and uncertain dataset, ultimately strengthening the model's generalization capability and applicability in complex real-world scenarios

2. Materials and Methods

2.1. Support Vector Machine (SVM)

In this section, we summarize the basic SVMs theories, including the linear separation case, the nonlinear separation case, and the nonlinear case through a binary classification problem. Let's us assume that the training samples are $S = \{x_i, y_i\}_{i=1}^{n}$ where $x_i \in R^N$, $y_i \in \{-1, +1\}$, when the samples are linear separable, the SVM can separate them with the largest margin. This can be achieved by solving the following quadratic program [11], [12]:

$$f(w) = \min_{w} \frac{\|w\|^2}{2} \qquad (1)$$
$$Subject\ to \qquad y_i(w'x_i + b) \geq 1 \quad ; \quad i = 1,2, \dots, n$$

By solving this problem using Lagrange's method, we obtain the following decision function:

$$g(x) = sign\left(\sum_{i=1}^{n} \hat{\lambda}_i y_i x_i' x + \hat{b}\right) \qquad (2)$$

Where the weight $\hat{w} = \sum_{i=1}^{n} \hat{\lambda}_i y_i x_i$, and the bias $\hat{b} = -\frac{1}{2}(\hat{w}'x_+ + \hat{w}'x_-)$.

For a nonlinear separate case, the optimal separating hyperplane is obtained by using a soft margin that allows for small errors in the training data to enable the optimal separating hyperplane method to be generalized, thus a slack variable ($0 \leq \xi_i < 1$) is introduced, and the nonlinear programming problem is as follows [11], [13]:

$$f(x) = \min_{w,\xi} \left\{\frac{\|w\|^2}{2} + \alpha \sum_{i=1}^{n} \xi_i\right\} \qquad (3)$$
$$Subject\ to \qquad y_i(w'x_i + b) \geq 1 - \xi_i \quad ; \xi_i \geq 0 \, , i = 1,2, \dots, n$$

Where $\alpha > 0$ controls the Trade-off between the width of the margin and the constraints, and it's calculated from the partial derivative of the Lagrange function when it equals zero. By solving the programming problem (3) we obtain a decision function of the from:

$$g(x) = sign\left(\sum_{i=1}^{n} \hat{\lambda}_i y_i x_i' x + \hat{b}\right) \tag{4}$$

However, if the dataset has a nonlinear optimal separating hyperplane decision, it is transformed such that a linear optimal separating hyperplane decision can be used to separate the training dataset in the transformed space. The attributes X in the original space are replaced by the transformed attributes $\Phi(X)$ by using the Kernel Trick. The Lagrange function of the constrained optimization problem is as follows [14], [15]:

$$\begin{gathered} Max\ L_D(\lambda_1, \dots, \lambda_n) = \max\left\{\sum_{i=1}^{n} \lambda_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \lambda_i\lambda_j y_i y_j K(x_i, x_j)\right\} \\ Subject\ to\ \sum_{i=1}^{n} \lambda_i y_i = 0 \quad ; \lambda_i \geq 0 \quad , i = 1,2, \dots, n \end{gathered} \tag{5}$$

Where the $K(x_i, x_j)$ function can take one of the following forms [15], [16], [17]:

$k(x_i, x_j) = e^{-\|x_i - x_j\|^2/(2\sigma^2)}$ Gaussian Radial Basis Kernel

$k(x_i, x_j) = tanh(bx_i'.x_j + c)$ Sigmoid Kernel

$k(x_i, x_j) = (x_i'.x_j + c)^\gamma$ Polynomial Kernel

By solving the quadratic programming problem (5), the following decision function with maximal margins is obtained:

$$g(x) = sign\left(\sum_{i=1}^{n} \hat{\lambda}_i y_i K(x_i, x) + \hat{b}\right) \tag{6}$$

2.2. Neutrosophic Logic [18], [19]

This logic was introduced by Florentin Smarandache in 1995 as a generalization of fuzzy logic, where he added a new component to the degrees of membership and non-membership, namely, the degree of indeterminacy.

If a Neutrosophic set is defined as <T, I, F>, then an element $x(t, i, f)$ belongs to aforementioned Neutrosophic set such that:

t represents the degree of truth (membership).

i represents the degree of indeterminacy (neutrality).

f represents the degree of falsehood (non-membership).

2.3. New Neutrosophic SVM

The following steps illustrate the new proposed method for enhancing SVM classification using Neutrosophic logic:

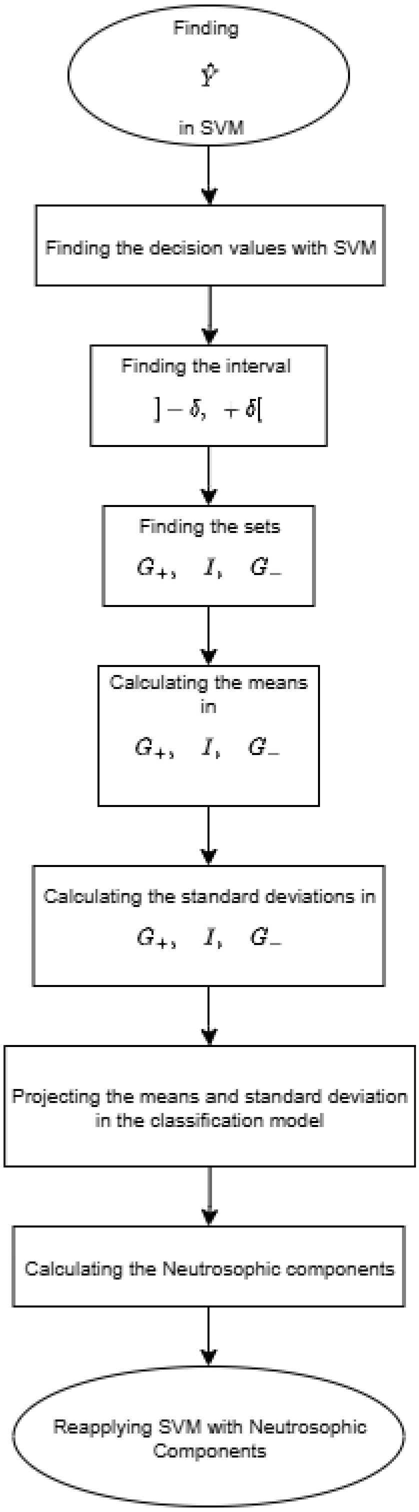

Figure 1. Flowchart of the proposed method

1- Finding the classification model in SVM:

$$\hat{Y} = \sum_{j=1}^{n} \hat{\lambda}_j y_j x_j' x + \hat{b} \tag{7}$$

2- Classify the data and find the decision values $\hat{Y}_i \quad ; \quad i = 1,2,\dots,N$ using SVM.

3- Finding the interval $]-\delta, +\delta[$ defined by the following:

$$\delta = \frac{|K_-| + |K_+|}{2} \tag{8}$$

$$K_- = cost * center_- \qquad K_+ = cost * center_+ \tag{9}$$

$$center_- = \bar{\bar{Y}}_i \;\; ; \;\; i = 1,2, \dots, n_- \qquad center_+ = \bar{\bar{Y}}_i \;\; ; \;\; i = 1,2, \dots, n_+ \tag{10}$$

Where: n_+ is the number of elements in the set where $y_i = +1$.

n_- is the number of elements in the set where $y_i = -1$.

4- Isolating the observations whose $\hat{Y} \in]-\delta, \delta[$ that are misclassified into a separate set, referred to as the neutrality set I.

The set of observations for which $y_i = +1$, excluding those belonging to I, is denoted by G_+.

The set of observations for which $y_i = -1$, excluding those belonging to I, is denoted by G_-.

5- Calculating the mean of the independent variables in the set where $y_i = +1$, the set where $y_i = -1$, and the set I:

$$\bar{X}_j^+ = \frac{1}{n_+} \sum_{i \in \{i | y_i = +1\} \backslash I}^{n_+} x_{ij} \qquad \bar{X}_j^- = \frac{1}{n_-} \sum_{i \in \{i | y_i = -1\} \backslash I}^{n_-} x_{ij}$$
$$\bar{X}_j^I = \frac{1}{n_I} \sum_{i=1}^{n_I} x_{ij} \qquad j = 1,2, \dots, p \tag{11}$$

Where: n_+ is the number of elements in the set G_+.

n_- is the number of elements in the set G_-.

n_I is the number of elements in the set I.

$\bar{X}_j^+$ is the mean of the independent variable j in the set G_+.

$\bar{X}_j^-$ is the mean of the independent variable j in the set G_-.

$\bar{X}_j^I$ is the mean of the independent variable j in the set I.

p denotes the number of independent variables.

6- Calculating the standard deviations of the independent variables in the sets G_+, G_-, and I:

$$S_j^+ = \frac{1}{n_+ - 1} \sum_{ii \in \{i | y_i = +1\} \backslash I}^{n_+} \left(x_{ij} - \bar{X}_j^+\right)^2 \qquad S_j^- = \frac{1}{n_- - 1} \sum_{i \in \{i | y_i = -1\} \backslash I}^{n_-} \left(x_{ij} - \bar{X}_j^-\right)^2$$
$$S_j^I = \frac{1}{n_I - 1} \sum_{i=1}^{n_I} \left(x_{ij} - \bar{X}_j^I\right)^2 \tag{12}$$

Where: S_j^+ is the standard deviation of the independent variable j in the set G_+.

S_j^- is the standard deviation of the independent variable j in the set G_-.

S_j^I is the standard deviation of the independent variable j in the set I.

7- Projecting the values of the previous means and standard deviations of the classification model to obtain the following values:

$$\bar{Y}_+ = \hat{\mathrm{w}}^T \bar{X}_j^+ + \hat{b} \qquad \bar{Y}_- = \hat{\mathrm{w}}^T \bar{X}_j^- + \hat{b} \qquad \bar{Y}_I = \hat{\mathrm{w}}^T \bar{X}_j^I + \hat{b} \tag{13}$$

$$SY_+ = \hat{\mathrm{w}}^T S_j^+ + \hat{b} \qquad SY_- = \hat{\mathrm{w}}^T S_j^- + \hat{b} \qquad SY_I = \hat{\mathrm{w}}^T S_j^I + \hat{b} \tag{14}$$

8- Calculating of Neutrosophic Components where $y_i = +1$ as follows:

$$T = \emptyset\left(\left|\frac{\hat{Y}_i - \bar{Y}_+}{SY_+}\right|\right) \qquad I = \emptyset\left(\left|\frac{\hat{Y}_i - \bar{Y}_I}{SY_I}\right|\right) \qquad F = \emptyset\left(\left|\frac{\hat{Y}_i - \bar{Y}_-}{SY_-}\right|\right) \tag{15}$$

Calculating of Neutrosophic Components where $y_i = -1$ as follows:

$$T = \emptyset\left(\left|\frac{\hat{Y}_i - \bar{Y}_-}{SY_-}\right|\right) \qquad I = \emptyset\left(\left|\frac{\hat{Y}_i - \bar{Y}_I}{SY_I}\right|\right) \qquad F = \emptyset\left(\left|\frac{\hat{Y}_i - \bar{Y}_+}{SY_+}\right|\right) \tag{16}$$

9- Considering the components $T, I,$ and F as independent variables and applying SVM to them to order to obtain the decision model and classification accuracy:

$$\hat{Y}_i = \hat{w}_1\, T + \hat{w}_2\, I + \hat{w}_3\, F + \hat{b} \tag{17}$$

However, if the observation i falls on the optimal separating hyperplane decision value, it is classified as follows:

$$\text{if} \quad \min\left(\left|\hat{Y}_j\right|\right) \in Y_+ \Rightarrow i \in Y_+ \; else \; i \in Y_- \; ; i \neq j \tag{18}$$

3. Case study and Result

The research sample consisted of 35 observations of vapors from two types of pure oils (15 observations from sunflower oil and 20 observations from corn oil). These observations were collected using an electronic nose system equipped with seven gas sensors (TGS813, TGS822, TGS800, MQ7, TGS2611, TGS2610, TGS2600).

These sensors are fabricated from semiconductor materials, with surface resistances that vary in response to interactions with the target gas. The stabilization onset time (Ts) for each of the seven sensors was used as the primary variables. Binary classification was performed using the SVM algorithm, and data analysis was conducted using R 4.3.1

The variables were defined as follows:

$Ts - S_i \;\; ; \;\; i = 1,2, \dots ,7$, represents the stabilization onset time for sensor i.

Y a categorical variable indicating the type of oil, with sunflower oil coded as 1 and corn oil coded as -1.

1- Classification based on SVM:

Table 1 displays the training and testing sets for the research sample:

Table 1. Number of training and testing sets data points for sunflower and corn oils

Classifier	Testing Set		Training Set	
	Sunflower	Corn	Sunflower	Corn
Linear Function	5	9	10	11
GRB Function	0	4	15	16
Sigmoid Function	2	6	13	14
Polynomial Function	0	3	15	17

From the table 1, we note that:

- Based on the linear function, the training set data ratio was 60.0 % of the total data, and the test set data ratio was 40.0% of the total data.
- Based on the GRB function, the training set data ratio was 88.57% of the total data, and the test set data ratio was 11.43% of the total data.
- Based on the sigmoid function, the training set data ratio was 77.14% of the total data, and the test set data ratio was 22.86% of the total data.
- Based on the polynomial function, the training set data ratio was 91.43% of the total data, and the test set data ratio was 8.57% of the total data.

The table 2 demonstrates the correct classification efficiency and its percentage over all data:

Table 2. Efficiency of the correct classification and its percentage

Classifier	Y	Classification		Total
		Sunflower	Corn	
Linear Function	Sunflower	10	5	15
	Corn	2	18	20
	Percentage of sunflower oil	66.67%	33.33%	100.0%
	Percentage of corn oil	10.0%	90.0%	100.0%
GRB Function	Sunflower	12	3	15
	Corn	0	20	20
	Percentage of sunflower oil	80.0%	20.0%	100.0%
	Percentage of corn oil	0.0%	100.0%	100.0%
Sigmoid Function	Sunflower	11	4	15
	Corn	2	18	20
	Percentage of sunflower oil	73.33%	26.67%	100.0%
	Percentage of corn oil	10.0%	90.0%	100.0%
Polynomial Function	Sunflower	8	7	15
	Corn	0	20	20
	Percentage of sunflower oil	53.33%	46.67%	100.0%
	Percentage of corn oil	0.0%	100.0%	100.0%

It is clear from the table 2 that:

- Based on the linear function, 28 observations were classifier correctly (80.0%), and seven observations were classified incorrectly (20.0%).
- Based on the GRB function, 32 observations were classifier correctly (91.43%), and three observations were classified incorrectly (8.57%).
- Based on the sigmoid function, 29 observations were classifier correctly (82.86%), and six observations were classified incorrectly (17.14%).
- Based on the polynomial function, 28 observations were classifier correctly (80.0%), and three observations were classified incorrectly (20.0%).

2- Finding the interval $]-\delta,+\delta[$ for indeterminacy set in table 3:

Table 3. The interval

Function	Mean		Cost	K		Rang
	$\mathbf{mean}_+$	$\mathbf{mean}_-$		$\|K_+\|$	$\|K_-\|$	$]-\boldsymbol{\delta},+\boldsymbol{\delta}[$
Linear	0.648859	-1.8877	1	0.64886	1.88771	]-1.268285,1.268285[
GRB	0.452415	-0.9274	1	0.452415	0.9274	]-0.689909,0.689909[
Sigmoid	0.358932	-0.9255	1	0.358932	0.9255	]-0.642209,0.642209[
Polynomial	0.113088	-0.8390	1	0.113088	0.8390	]-0.476065,0.476065[

3- Isolating the observation whose $\hat{Y}\in]-\delta,\delta[$ that are misclassified into a separate set, referred to as neutrality set I.

4- Finding the means and standard deviations for the independent variables for the set where $y_i=+1$, the set where $y_i=-1$ and the set I in table 4:

Table 4. Means and deviations of the independent variables

Function	$\mathbf{mean}_+$	$\mathbf{mean}_I$	$\mathbf{mean}_-$	S_j^+	S_j^I	S_j^-
Linear	0.84702	-0.0105	-2.1185	1.522486	0.206633	1.742375
GRB	0.606464	-0.5489	-0.9274	0.522173	0.097889	0.210046
Sigmoid	0.459636	-0.08545	-1.04218	0.686848	0.32456	0.953486
Polynomial	0.327924	-0.13244	-0.83904	0.294858	0.098335	0.91613

5- Projecting the values of the means and standard deviations into the linear and nonlinear classification models in table 5:

Table 5. Means and standard deviations of the linear and nonlinear classification models

Function	$\overline{Y}_+$	$\overline{Y}_I$	$\overline{Y}_-$	SY_+	SY_I	SY_-
Linear	0.84702	-0.0105	-2.1185	1.117952	0.154001	2.508051
GRB	6.689573	1.240679	-2.92904	8.071087	12.75059	14.64154
Sigmoid	6.634627	4.383617	-6.72081	10.07528	13.078	20.19223
Polynomial	14.00938	2.977693	-6.88325	6.728825	9.395978	19.11234

6- Calculating the Neutrosophic components for all observations, considering $T, I,$ and F as independent variables and training SVM to derive the decision model and its classification accuracy, the effectiveness is summarized in table 6, which reports the number and percentage of correctly classified observations across the entire data set:

Table 6. Efficiency of the correct classification and its percentage for Neutrosophic data

Classifier	Y	Classification		Total
		Sunflower	Corn	
Linear Function	Sunflower	10	5	15
	Corn	2	18	20
	Percentage of sunflower oil	66.67%	33.33%	100.0%
	Percentage of corn oil	10.0%	90.0%	100.0%
GRB Function	Sunflower	15	0	15
	Corn	0	20	20
	Percentage of sunflower oil	100.0%	0.0%	100.0%
	Percentage of corn oil	0.0%	100.0%	100.0%
Sigmoid Function	Sunflower	15	0	15
	Corn	0	20	20
	Percentage of sunflower oil	100.0%	0.0%	100.0%
	Percentage of corn oil	0.0%	100.0%	100.0%
Polynomial Function	Sunflower	15	0	15
	Corn	0	20	20
	Percentage of sunflower oil	100.0%	0.0%	100.0%
	Percentage of corn oil	0.0%	100.0%	100.0%

It is clear from the table 6 that:

- Based on the linear function, 28 observations were classified correctly (80.0%), and seven observations were classified incorrectly (20.0%).
- By contrast, with the GRB, Sigmoid, and Polynomial functions, all the misclassified observations were correctly processed, resulting in a 100.0% correct classification rate.

The proposed method was tested in several real-world case studies, and it was proven to effectively handle misclassified observations.

4. Conclusions

The selection of an appropriate Neutrosophic membership function, which incorporates the components of Neutrosophic logic – truth, indeterminacy, and falsity – is crucial for resolving classification challenges in SVM. This research introduces a novel Neutrosophic – based membership function for both linear and nonlinear classification within the SVM algorithm to address misclassification issues. The proposed Neutrosophic -SVM approach has shown promising outcomes compared to the conventional methods in tackling misclassified observations and the method can be flexibly applied to a wide range of classification problems, thereby expanding the scope of applications for SVM.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

[1] V. V Vapnik, *The Nature of Statistical Learning Theory*, 2nd Edition. Verlag New York Berlin Heidelberg: Springer-Verlag, 1995.

[2] Florentin. Smarandache, *A Unifying Field in Logics : Neutrosophic Logic*. Rehoboth, New Mexico, USA: American Research Press, 2002.

[3] W. Ju and H. D. Cheng, "Discrimination of Outer Membrane Pro-Teins Using Reformulated Support Vector Machine Based on Neutrosophic Set," *Proceedings of the 11th Joint on Information Sciences*, 2008.

[4] S. Broumi and F. Smarandache, "Possibility Single Valued Neutrosophic Soft Expert Sets and Its Application in Decision Making," *Journal of New Theory*, vol. 4, 2015.

[5] W. Ju and H. Cheng, "A Novel Neutrosophic Logic SVM (N-SVM) and Its Application to Image Categorization," *New Mathematics and Natural Computation, World Scientific Publishing Company*, vol. 9, 2013.

[6] M. Turhan, D. Sengür, S. Karabatak, Y. Guo, and F. Smarandache, "Neutrosophic Weighted Support Vector Machines for the Determination of School Administrators Who Attended an Action Learning Course Based on Their Conflict-Handling Styles," *Symmetry (Basel)*, vol. 10, no. 5, May 2018, doi: 10.3390/sym10050176.

[7] H. Habbak, M. T. Anan, and A. Joukhadar, "Processing of Points in the Vicinity of the Decision Boundary in the Classification of the Support Vector Machine Based on the Neutrosophic logic," *Research Journal of Aleppo University*, vol. 157, 2022.

[8] A. A. Salama, M. Y. Shams, H. E. Khalid, and D. E. Mousa, "Enhancing Medical Image Quality Using Neutrosophic Fuzzy Domain and Multi-Level Enhancement Transforms," *Neutrosophic Sets and Systems*, vol. 65, 2024.

[9] H. M. Al-Doori, T. S. Alkellezli, A. Abdelhafeez, M. Eassaa, M. S. Sawah, and A. A. El-Douh, "Enhanced Neutrosophic Set and Machine Learning Approach for Kidney Disease Prediction," *Neutrosophic Sets and Systems*, vol. 80, 2025.

[10] H. Elbehiery, H. Fathi, A. Abdelhafeez, M. Refaat, and H. Mahmoud, "Advanced Machine Learning Approaches for Breast Cancer Detection with Neutrosophic Sets," *Neutrosophic Sets and Systems*, vol. 81, 2025.

[11] S. Konishi, *Introduction to Multivariate Analysis Linear and Nonlinear Modeling*. Boca Raton, FL, U.S.A: Chapman & Hall/CRC (CRC Press – Taylor & Francis Group), 2014.

[12] Y. Liang, Q.-S. Xu, H.-D. Li, and D.-S. Cao, *Support Vector Machines and Their Application in Chemistry and Biotechnology*. United State of America: CRC Press (Taylor & Francis Group), 2011.

[13] X. Huang, L. Shi, and J. A. K. Suykens, "Sequential Minimal Optimization for SVM with Pinball Loss," *Preprint Submitted to ELSEVIER*, 2014.

[14] A. Abuzlam, "Studying Some ANNs, SVM, and Statistical Methods in Classification Problems to Support of Medical Decision," Master Thesis, University of Aleppo, Aleppo, Syria, 2013.

[15] G. James, D. Witten, T. Hastie, and R. Tibshirani, *An Introduction to Statistical Learning with Applications in R*. New York Heidelberg Dordrecht London: Springer, 2014.

[16] T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of statistical learning data mining, Inference, and Prediction* , Second Edition. Springer, 2001.

[17] S. Y. Kung, *Kernel Methods and Machine Learning*. Princeton: Cambridge University Press, 2014.

[18] M. Al-Tahan and F. Smarandache, *Theory and Applications of NeutroAlgebras as Generalizations of Classical Algebras*. in Advances in Computer and Electrical Engineering. IGI Global, 2022. doi: 10.4018/978-1-6684-3495-6.

[19] C. Ashbacher, *Introduction to Neutrosophic Logic*. Rehoboth, USA: American Research Press, 2002.

Received: April 9, 2025. Accepted: Sep 11, 2025