A Study of a Support Vector Machine Algorithm with an Orthogonal Legendre Kernel According to Neutrosophic logic and Inverse Lagrangian Interpolation

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Abstract

The decision-making process is greatly affected by the data collection stage. If the data collection process is not well controlled, i.e. there is some data lost due to the poor quality of the devices used or the lack of accuracy in the data entry process...etc., this will affect the work of the SVM algorithm, which is considered one of the best. Most of the workbooks suffer from the problems of missing and anomalous data. In this paper, we propose a method to treat the missing and anomalous data by reshaping the data set defined by the classical method into the neutrosophical data set by calculating the amount of true T, false F, and neutrality I in the neutrosophical set using inverse Lagrangian interpolation. We noticed the superiority of our proposed method for processing missing data over the method of [21], then we trained a support vector machine algorithm with orthogonal legender kernel on a breast cancer dataset taken from the Statistics Department of Al-Bayrouni Hospital in Damascus, where the proposed algorithm achieved a classification accuracy of 97%. The reason we chose a support vector machine classifier with an orthogonal legender kernel has two goals: the first is to eliminate the repetition of support vectors in the feature space. The second is to solve the problem of non-linear data distribution.

Keywords: Neutrosophic logic; Support Vector Machine; Orthogonal legend Kernel; Neutrosophic Group; Inverse Lagrangian Interpolation.

1. Introduction

The wide spread of information technologies led to the increase of huge data storage warehouses. The random existence of data requires finding techniques, methods and means to extract information and knowledge from it and harness it in solving issues and making decisions. Modern applications depend on making the computer simulate human thinking in solving many problems without being explicitly programmed, this is what is known as machine learning [1,2]. Many machine learning algorithms have emerged, among the most important and common of these algorithms is the support vector machine algorithm [3]. The support vector machine algorithm is one of the statistical methods that have received great attention, presented by the scientist Vladimir Vabenek in 1995, and it is a learning algorithm by a supervisor The support vector machine algorithm has successful applications in solving many complex real-world problems, including: pattern recognition, neural and medical image analysis, computer vision, robotics, computer security, text and image classification, data retrieval, bioinformatics, self-driving cars, biodiversity analysis, and the stock market [4]. One of the most important applications that made the SVM algorithm popular is handwritten digit recognition as it gave greater accuracy compared to artificial neural networks.

Based on the wide applications of the support vector machine algorithm and since the kernel is the backbone on which the support vector machine algorithm is based, we find many research that presented studies to develop

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this algorithm and solve its problems. [5] presented a new kernel for the SVM algorithm by assembling the Chebchev kernel with the Gaussian kernel to classify regular data on the range [-1,1]. [6] improved the SVM algorithm by merging the Chebyshev kernel with the Hermite kernel, as it gave better results in terms of fewer support rays and faster classification speed. [7] presented a support vector machine with an orthogonal legender kernel and demonstrated its significant role in avoiding duplication of features in space Features, however, the presence of neutral elements affecting decision-making was considered an open issue until the scientist Florentin Samarandakeh presented the nitrosophic logic as a generalization of the fuzzy logic by adding a new component to the degrees of organic and inorganic, which is the degree of indeterminacy [8,9,10,11,12,13,14, 15,16,17,18,19,20] and accordingly [21] studied the support vector machine according to the nitrosophic logic. Although the support vector machine algorithm was studied according to the nitrosophic logic, the study was limited to linearly separable data. Missing values were also processed depending on the average in the formation of neutrosophic groups, but the obtained values were far from their neighbors in the same column.

2. Discussion

In [21] the support vector machine was studied according to the nitrosophic logic. However, this study of the support vector machine algorithm according to the nitrosophic logic was limited to linearly separable data. Missing values were also processed depending on the average in the formation of nitrosophic groups, and the obtained values were far from their neighbors in the same column.

In this paper, we study the support vector machine algorithm according to the neutrosophic logic in the case of non-linear separation of data using the orthogonal legender kernel. We presented a method to treat the missing values based on the inverse Lagrangian interpolation in the formation of neutrosophic groups, as we applied the proposed method to data used in [21]. The results we obtained were as shown in the following table:

Table 1: Finding the missing values based on the inverse interpolation of Lagrangian and neutrosophic groups

Africa	Beach	Bulildeing	Bus	Dinosaur	Elephant	Flower	Horese	Mountain	Food
0.029	0.008	0.036	0.016	0.008	0.056	0.004	0.016	0.024	0.020
0.028	0.024	0.024	0.016	0.008	0.020	0.008	0.012	0.012	0.008
0.036	0.040	0.012	0.008	0.004	0.016	0.012	0.008	0.016	0.024
0.004	0.008	0.000	0.004	0.000	0.000	0.000	0.000	0.004	0.004
0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.004
0.024	0.004	0.008	0.004	0.000	0.002	0.000	0.012	0.036	0.032
0.008	0.004	0.000	0.008	0.000	0.004	0.000	0.008	0.008	0.024
0.008	0.008	0.000	0.000	0.000	0.008	0.000	0.008	0.004	0.008
0.008	0.148	0.032	0.016	0.004	0.040	0.004	0.008	0.006	0.004
0.032	0.016	0.008	0.012	0.008	0.020	0.012	0.008	0.008	0.004

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We conclude that the missing values that we obtained are better than the results of the method used in [21], because each missing value that we obtained, shown in yellow above, was very close to its neighbors in the same column, unlike the missing values that were created by [21], as it was very far from the values of We formulated a support vector machine algorithm with an orthogonal Legender kernel according to neutrosophic logic and inverse Lagrange interpolation. We applied the developed algorithm to breast cancer data that we obtained from the Statistics Department of Al-Bayrouni Hospital in Damascus, which are shown as follows.:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	\
0	842302	M	17.99	10.38	122.80	1001.0	
1	842517	M	NaN	17.77	132.90	1326.0	
2	84300903	M	19.69	21.25	130.00	1203.0	
3	84348301	M	11.42	20.38	77.58	386.1	
4	84358402	M	20.29	14.34	135.10	1297.0	
..	...	...	...	...	...	...	
564	926424	M	21.56	22.39	142.00	1479.0	
565	926682	M	NaN	28.25	131.20	1261.0	
566	926954	M	16.60	28.08	108.30	858.1	
567	927241	M	20.60	29.33	140.10	1265.0	
568	92751	B	7.76	24.54	47.92	181.0	

	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	\
0	0.11840	0.27760	0.30010	0.14710	
1	0.08474	0.07864	0.08690	0.07017	
2	0.10960	0.15990	0.19740	0.12790	
3	NaN	0.28390	0.24140	0.10520	
4	0.10030	0.13280	0.19800	0.10430	
..	...	...	...	...	
564	0.11100	0.11590	0.24390	0.13890	
565	0.09780	0.10340	0.14400	0.09791	
566	0.08455	0.10230	0.09251	0.05302	
567	0.11780	0.27700	0.35140	0.15200	
568	0.05263	0.04362	0.00000	0.00000	

	...	texture_worst	perimeter_worst	area_worst	smoothness_worst	\
0	...	17.33	184.60	2019.0	0.16220	
1	...	23.41	158.80	1956.0	0.12380	
2	...	25.53	152.50	1709.0	0.14440	
3	...	26.50	98.87	567.7	0.20980	
4	...	16.67	152.20	1575.0	0.13740	
..	...	...	...	...	...	
564	...	26.40	166.10	2027.0	0.14100	
565	...	38.25	155.00	1731.0	0.11660	
566	...	34.12	126.70	1124.0	0.11390	
567	...	39.42	184.60	1821.0	0.16500	
568	...	30.37	59.16	268.6	0.08996	

	compactness_worst	concavity_worst	concave points_worst	symmetry_worst	\
0	0.66560	0.7119	0.2654	0.4601	
1	0.18660	0.2416	0.1860	0.2750	
2	0.42450	0.4504	0.2430	0.3613	
3	0.86630	0.6869	0.2575	0.6638	
4	0.20500	0.4000	0.1625	0.2364	
..	...	...	...	...	
564	0.21130	0.4107	0.2216	0.2060	
565	0.19220	0.3215	0.1628	0.2572	
566	0.30940	0.3403	0.1418	0.2218	
567	0.86810	0.9387	0.2650	0.4087	
568	0.06444	0.0000	0.0000	0.2871	

	fractal_dimension_worst	Unnamed: 32
0	0.11890	NaN

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1	0.08902	NaN
2	0.08758	NaN
3	0.17300	NaN
4	0.07678	NaN
..	...	...
567	0.12400	NaN
568	0.07039	NaN

We note that the previous data contains missing values shown above in red color NaN, we processed this data by inverse Lagrangian interpolation and then trained a support vector machine algorithm with orthogonal Legender kernels on this data and got better results than the traditional algorithm. The results are represented in the following criteria (precision , recall, f1-score, accuracy)

3. Performance Measures

i. precision

Precision represents the ratio of the relationship of well-expected positive cases to overall expected positive cases. [22]

ii. recall

This is the magnitude relation of the properly expected positive notes to any or all operations within the actual class i.e. true positive rate. The confusion matrix is employed to assess sensitivity and is mathematically assessed as [23]

iii. f1-score

The F1 score is a comprehensive calculation of model accuracy that blends recall and accuracy[22].

iv. Accuracy

It is a parameter that tests the method's capacity by accurately calculating the proportion of cases predicted from all cases. ACC is mathematically expressed as follows [24]

Accuracy	f1-score	Recall	Precision
$\frac{TP+TN}{ALL}$	$2*\frac{precision*Recall}{precision+Recall}$	$\frac{TP}{TP+FN}$	$\frac{TP}{TP+PF}$

Four major components are used to generate the confusion matrix

TP: It stands for values that are classified correctly and belong to positive values.

TN: It stands for values that are classified as true and belong to negative values.

FP: It stands for values that are incorrectly classified and belong to positive values.

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		Actual Value (as confirmed by experiment)	
		Positive	Negative
Predicted Value (predicted by the test)	Positive	True Positive (TP)	False Positive (FP)
	Negative	False Negative (FN)	True Negative (TN)

Figure 1:Confusion matrix

FN: It stands for values that are incorrectly classified and belong to negative values.

2-Legendre polynomials

2-1 Orthogonal boundaries [25]

The set of functions $g_0, g_1, \dots, g_n$ is orthogonal to the domain [a,b] ; a,b∈R with respect to the weight function w(x) if the following is true

$$\int_a^b h(x).\, g_i(x).\, g_j(x)\, dx = \{\ 0\ ; i \neq j\ \ Number\ ; i = j \quad ; i,j \in \{1, \dots, n\}$$

2-2 The weight function [25]

The function h(x) is a weight function on [a,b] if and only if it satisfies the followin**g:**

h(x) is continuous -1

$h(x) > 0$ -2

$\forall n \in N\ ; x \in]a,b[: \int_a^b h(x)\, |x^n| dx < +\infty$ -3

2-3 Basic properties of Legendre polynomials[25]

$P_n(1) = 1$

$P_n(-1) = (-1)^n$

$P_n(0) = \{0 \quad if \ \ n\ \ is\ odd\ \frac{(-1)^m (2m)!}{2^{2m}(m!)^2}\ \ if\ \ n\ \ is\ even$

2-4 The Kernel [26]

It is a function that measures the distance between the training sample, that is, between the input points, and this kernel can deal with nonlinearly issues.

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Table 2: The most important drugs used in data processing

Function	Kernel
$K(x,y) = exp^{\left(-\frac{\|x-y\|}{\delta}\right)}$	Laplacian
$K(x,y) = 1 - \frac{\|x-y\|^2}{\|x-y\|^2 + c}$	Rational Quadratic
$K(x,y) = \sqrt{\|x-y\|^2 - c}$	Multiduadratic
$K(x,y) = \frac{\theta}{\|x-y\|} sin\ sin\ \frac{\|x-y\|}{\theta}$	Wave
$K(x,y) = -\|x-y\|^d$	Power
$K(x,y) = \frac{J_{V+1}(\delta\|x-y\|)}{\|x-y\|^{-n(V+1)}}$	Bessel
$K(x,y) = \frac{1}{1 + \frac{\|x-y\|^d}{d}}$	Cauchy
$K(x,y) = \prod_{m=1}^{N} \quad h\left(\frac{x_i - c}{a}\right) h\left(\frac{y_i - c}{a}\right)$	Wavelet

2-5 orthogonal legendar kernel [25]

The Legendar kernel is a series of Legendar bounds orthogonal to the domain [-1,+1] with weight function $h(x) = 1$, each of which can be obtained in the form:

The following iterative relation connecting the Legendar bounds is obtained:

$$P_{n+1}(x) = \frac{2n+1}{n+1} xP_n(x) - \frac{n}{n+1} P_{n-1}(x)\ ; n \geq 1 \qquad \ldots (1)$$

$$P_0(x) = 1$$

$$P_1(x) = x$$

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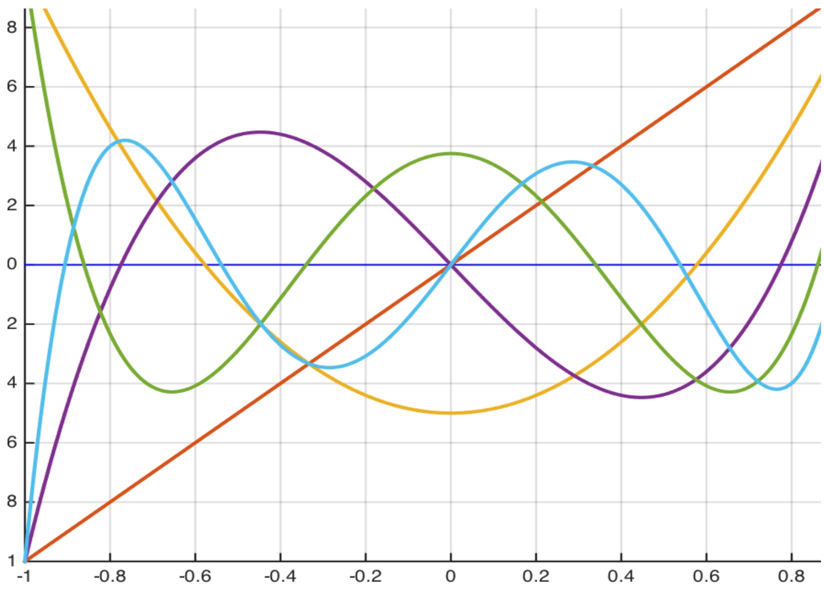

Figure 2: Legendar polynomials.

4. Inverse Lagrangian interpolation [31,32]

Inverse interpolation is to find the value of s corresponding to a given value of y of a given function in tabular form as well.

We know that the interpolation limits in Newton's direct method are given in terms of progressive differences in the form

$$y = y_0 + q\Delta y_0 + \frac{q(q-1)}{2!}\Delta^2 y_0 + \frac{q(q-1)(q-2)}{3!}\Delta^3 y_0 + \cdots + \frac{q(q-1)(q-2)\ldots(q-n+1)}{n!}\Delta^n y_0$$

Where

$$q = \frac{x - x_0}{h}$$

We calculate q from this relationship, so we will adopt the method of successive approximations by writing the relationship in the form:

$$q = \varphi(q)$$

Then write the successive approximations of the relationship

$$q_m = \varphi(q_{m-1})$$

So we solve the equation with respect to q we find

$$q = \varphi(q) = \frac{1}{\Delta y_0}\left[y - y_0 - \frac{q_{m-1}(q_{m-1} - 1)}{2!}\Delta^2 y_0 - \frac{q(q-1)\ldots(q-n+1)}{n!}\Delta^n y_0\right]$$

We take q_0 as an initial approximation to the figure

$$q_0 = \frac{y - y_0}{\Delta y_0}$$

And after finding the q_s that achieve the required accuracy, which makes $|q_s - q_s - 1| < \varepsilon$

Where ε is the required accuracy, we adopt $q = q_s$, then we find s from the relationship

$$s = x_0 + qh\,; h = x_{i+1} - x_i$$

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5. Formation of the neutrosophic data set

Let $X = (x_1, x_2, x_3, \dots, x_n)^T$ be the set of features for binary classification data, since when the data falls on the decision limit it is difficult for us to classify them, and in order to solve the problem of the data located on the decision limit we form the nitrosophic data set g that It is a generalization of the classical and fuzzy groups. The degree of neutrality was introduced and added to the nitrosophic group. Accordingly, the nitrosophic group was defined as $< T, I, F >$, as each element of the previous group is denoted by the form [21]:

$$\forall x(t, i, f) \in < T, I, F >$$

i: represents neutrality, t: represents the degree of organicity, f: represents the degree of inorganicity, t,i,f are real numbers of T,I,F, respectively.

As we know that one of the disadvantages of the SVM algorithm is that it is very sensitive to outliers, and to solve this problem, we reformulated the nitrosophic group for the input samples based on the distances between the samples.

The neutrosophic group helps solve the problem of outliers when combined with the reformatted SVM.

And using the same previous symbols that express the data representation, we can know the input samples associated with the nitrosophic group with a set of points as follows:

$$(x_j, y_j, t_j, i_j, f_j); j = 1,2,3, \dots, n$$

$$g_j = t_j + i_j - f_j$$

For the set of points on the line $y = 1$

$$t_j = 1 - \frac{\|x_j - s^+\|}{max_{x_{k \in N}} \|x_k - s^+\|}$$

$$i_j = 1 - \frac{\|x_j - s^{all}\|}{max_{x_{k \in N}} \|x_k - s^{all}\|}$$

$$f_j = 1 - \frac{\|x_j - s^-\|}{max_{x_{k \in N}} \|x_k - s^-\|}$$

For the set of points on the line y = -1

$$t_j = 1 - \frac{\|x_j - s^-\|}{max_{x_{k \in N}} \|x_k - s^-\|}$$

$$i_j = 1 - \frac{\|x_j - s^{all}\|}{max_{x_{k \in N}} \|x_k - s^{all}\|}$$

$$f_j = 1 - \frac{\|x_j - s^+\|}{max_{x_{k \in N}} \|x_k - s^+\|}$$

where s^+ is the inverse Lagrangian interpolation of the data set on the line $y = 1$

Where s^- is the inverse Lagrangian interpolation of the data set on the line $y = -1$

where s^{all} is the inverse Lagrangian interpolation of the whole data set.

s is calculated as in stage 2.

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6. Support vector machine algorithm with orthogonal legend kernel according to the nitrosophilic group

In this research, we categorized the points that are distributed uniformly over the range [-1,1] using the legendar kernel function orthogonal to the input. We were able to achieve more accurate results with fewer support beams. By adding a neutrosophilic value to determine the degree of belonging of each entry to the desired variety, the set of training points became as follows [21,27,28,29,30]

$$(\Phi(x_1), y_1, g_1), (\Phi(x_2), y_2, g_2), \ldots, (\Phi(x_n), y_n, g_n)$$

We are looking for the best super surface that classifies points into two classes. Adding the neutrosophilic value g, then the problem becomes:

$$\frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} g_i\,\epsilon_i$$

where C is a qualitative constant associated with g.

And the Lagrangian equation becomes:

$$L(w,b,\epsilon,\lambda,\beta) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} g_i\,\epsilon_i - \sum_{i=1}^{n} \lambda_i(y_i(w.\Phi(x_i)+b) - 1 + \epsilon_i) - \sum_{i=1}^{n} \beta_i\,\epsilon_i$$

To search for the optimal solution, we derive with respect to w, b, ϵ_i

$$\frac{\partial L(w,b,\epsilon,\lambda,\beta)}{\partial w} = w - \sum_{i=1}^{n} \lambda_i\, y_i\, \Phi(x_i) = 0$$

$$\frac{\partial L(w,b,\epsilon,\lambda,\beta)}{\partial b} = -\sum_{i=1}^{n} \lambda_i y_i = 0$$

$$\frac{\partial L(w,b,\epsilon,\lambda,\beta)}{\partial \epsilon_i} = g_i C - \lambda_i - \beta_i = 0$$

We find the question of optimization:

$$W(\lambda) = \sum_{i=1}^{n} \lambda_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \lambda_i\,\lambda_j y_i\, y_j\, K(x_i\,, x_j)$$

within the terms $\sum_{i=1}^{l} y_i\lambda_i = 0$

$$0 \le \lambda_i \le g_i C \quad , i = 1, \ldots, n$$

$$K(x,z) = \sum_{i=0}^{n} P_i(x).P_i(z)$$

After we finish the algorithm training phase, any new input is tested by applying the following sign function:

$$sign(w\Phi(x)+b) = \{The\ resulting \ge 0 \Rightarrow y = +1 \qquad The\ resulting < 0 \Rightarrow y = -1$$

Thus, any new input is classified into its appropriate output.

7. Conclusion and results:

In this research, we presented a study to classify breast cancer by obtaining study data from Al-Bayrouni Hospital. The data we used was distorted and contained abnormal and missing values.We corrected and processed the data through nitrosophic logic and inverse Lagrangian interpolation, and then we formulated a support vector machine algorithm with two kernels. Legender orthogonal according to the nitrosophic logic, and we trained it on the data, so the result was that our proposed algorithm is superior to the classical support vector machine algorithm. We were able to correlate the inputs of this algorithm, which is calculated based on the

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inverse Lagrangian interpolation, in order to determine the degree of belonging to each class. We got the results as follow:

	precision	recall	f1-score	support
0	0.97	0.99	0.98	72
1	0.98	0.95	0.96	42
accuracy			0.97	114
macro avg	0.97	0.97	0.97	114
weighted avg	0.97	0.97	0.97	114

Confusion matrix:

[[71 1]
 [2 40]]

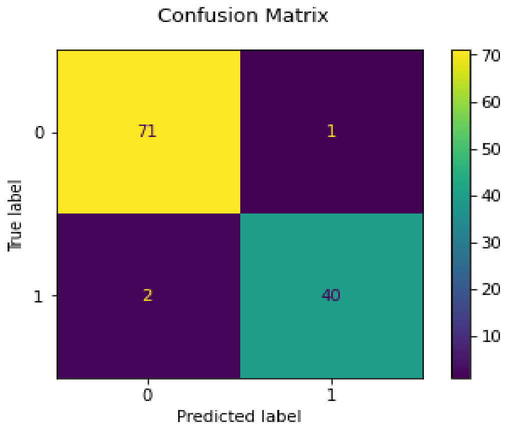

Figure 3: Confusion matrix with the predicted label

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