Exploring Intuitionistic Fuzzy-Valued Neutrosophic Multiset Technique for High-Dimensional Financial Data Classification in Complex Systems

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Abstract

In decision-making, neutrosophic set allows for the information representation with three membership functions: truth (T), indeterminacy (I), and false (F). Each component in a neutrosophic set has membership, non-membership, and indeterminacy degrees that are independent and range from 0 to 1. This makes neutrosophic set especially suitable in complex decision-making scenarios where information is contradictory, incomplete, or ambiguous, which enables robust and more nuanced analysis and solutions. A large portion of finance companies experience problems handling vast amounts of data. These data are often left unstructured and unorganized. Therefore, it is necessary to classify them to exploit it. Data classification also simplifies to use, locating, and retrieval of information. It becomes vital while handling risk management, legal discovery, data security, and compliance. Therefore, this manuscript presents an Intuitionistic Fuzzy-Valued Neutrosophic Multiset based Financial Data Classification (IFVNMS-FDC) technique in Complex Systems. The main aim of the IFVNMS-FDC technique is to recognize and categorize the financial data into respective classes. To do so, the IFVNMS-FDC technique initially uses min-max scalar as a pre-processing step. Besides, the high-dimensional financial data can be handled by the design of whale optimization algorithm (WOA) based feature selection. Finally, the IFVNMS-FDC technique derives IFVNMS technique for the identification of various classes related to the financial data. A wide-ranging experiments were involved in exhibiting the performance of the IFVNMS-FDC technique. The experimental values depicted that the IFVNMS-FDC method obtains reasonable performance on financial data recognition.

Keywords: Financial Data Classification; Neutrosophic Logic; Whale Optimization Algorithm; Intuitionistic Fuzzy Set; Intuitionistic Fuzzy Value

1. Introduction

Neutrosophic Logic is a developing research field in which every proposal is assessed to have the proportion of truth (T), the proportion of uncertainty (I), and the proportion of falsity (F) [1]. Neutrosophic set (NS) was effectively used for an indeterminate data process and shows benefits to handling the indeterminacy information of data and a method encouraged for classification application and data analysis [2]. NS offers an effective and exact method to describe imbalanced data based on the features of the data. Financial service departments, customers, and especially regulators rapidly concluded that obvious and related data was essential to risk reduction [3]. So, now we see current efforts by regulators to confirm that businesses functioning in financial services

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produce comprehensible information and comprehensive [4]. Those financial difficulties are of specific interest to the financial business for fund managers always searching to build complex and strict credit scoring systems for joint companies and persons to reduce credit risk and develop capital allocation [5]. In this respect, credit scoring and bankruptcy risk evaluation are used to evaluate the applicant's probability of corporate company in the future, which is mostly a classification problem [6]. Precise forecasts help choose good clients and enhance financial and banking business methods.

In financial applications, Machine learning (ML) varies from other sectors in just how the feature of a method is measured [7]. In numerous applications, "accuracy of prediction" is frequently employed, in financial applications, transparency, and interpretability are also significant and occasionally a requirement [8]. In financial applications, accuracy is not an important problem. There is a developing interest in having higher levels of model transparency that is the capability to offer an obvious clarification of the output result [9]. By leveraging progressive data analytics methods, including ML algorithms and clustering methods, the study intends to improve the precision and effectiveness of identifying suspect financial transactions [10]. Through the progress and execution of innovative detection frameworks, the research goal is to contribute to the creation of a reliable and safer transaction environment inside the global financial system. This manuscript presents an Intuitionistic Fuzzy-Valued Neutrosophic Multiset based Financial Data Classification (IFVNMS-FDC) technique in Complex Systems. The main aim of the IFVNMS-FDC technique is to recognize and categorize the financial data into respective classes. To do so, the IFVNMS-FDC technique initially uses min-max scalar as a pre-processing step. Besides, the high-dimensional financial data can be handled by the design of whale optimization algorithm (WOA) based feature selection. Finally, the IFVNMS-FDC technique derives IFVNMS technique for the identification of various classes related to the financial data. The experimental values represented that the IFVNMS-FDC method obtains reasonable performance on financial data recognition.

2. Literature Survey

Huang et al. [11] introduce an ML-based K-means clustering algorithm. Anomalous behaviors and patterns can be promptly detected by clustering large quantities of financial information, thus effectively identifying suspected counterfeits. In addition, K-means clustering helps to optimize resource allocation in finance sectors by facilitating monitoring and prevention efforts in critical regions, thereby alleviating the impacts of fraud on the finance system. Balmaseda et al. [12] present Graph Neural Network (GNN) for the analysis of systemic risks. GNN uses the feature information and network structure to handle wide-ranging financial networks, which provide the benefits of ML methodology over the available data. Also, the study proposes a C2R model to alleviate the pre-labelling efforts for high systemic risks by pre-labelling into a limited amount of classes while continuously analyzing the risk score.

Mitsuda et al. [13] extend the work of approximate amplitude encoding (AAE) system such that it can manipulate multifaceted data vectors. The basic concept is to apply the reliability distance as a cost function, where the conventional shadow techniques are used to effectively estimate the gradient and fidelity. Also, the study uses this technique for realizing the complex kernel binary classifier known as the compact Hadamard classifier, and later the model presents a computational analysis showing that it allows credit card fraud detection and Iris dataset classification. Noviandy et al. [14] propose the potential of ML, especially the XGBoost model, integrated with data augmentation method, to improve the recognition of credit card fraud. The proposed model includes fraud recognition using approaches such as Synthetic Minority Over-sampling Technology-Edited Nearest Neighbor (SMOTE-ENN) and leveraging historical transaction information.

Emmanuel et al. [15] introduced a stack of classifier technique combined with the filter-based FS method. The study presents the baseline estimate as follows: Random Forest (RF), GB, and XGB. In addition, the estimator in the stacked structural design was sequentially connected to extract the higher performance. In this research, the filter-based FS technique is utilized based on theory of information gain (IG). Vishwakarma and Kesswani [16] proposed a two-stage IDS for the IoT systems. Initially, the method classifies dataset into four different sections based on the data types (viz., float, nominal, binary, and integer). Then, the model categorizes those using divergent types of the NB classifier. Next, majority voting is used for choosing the outcome of the classification. Secondly, the method passes the information that is benign at the initial stage or behaves normally and categorizes them through the unsupervised elliptic envelope.

3. Methodology

In this manuscript, we have presented an IFVNMS-FDC technique in complex systems. The main aim of the IFVNMS-FDC technique is to recognize and categorize the financial data into respective classes. It comprises three various phases involved as data normalization, feature selection, and classification phases are demonstrated in Fig. 1.

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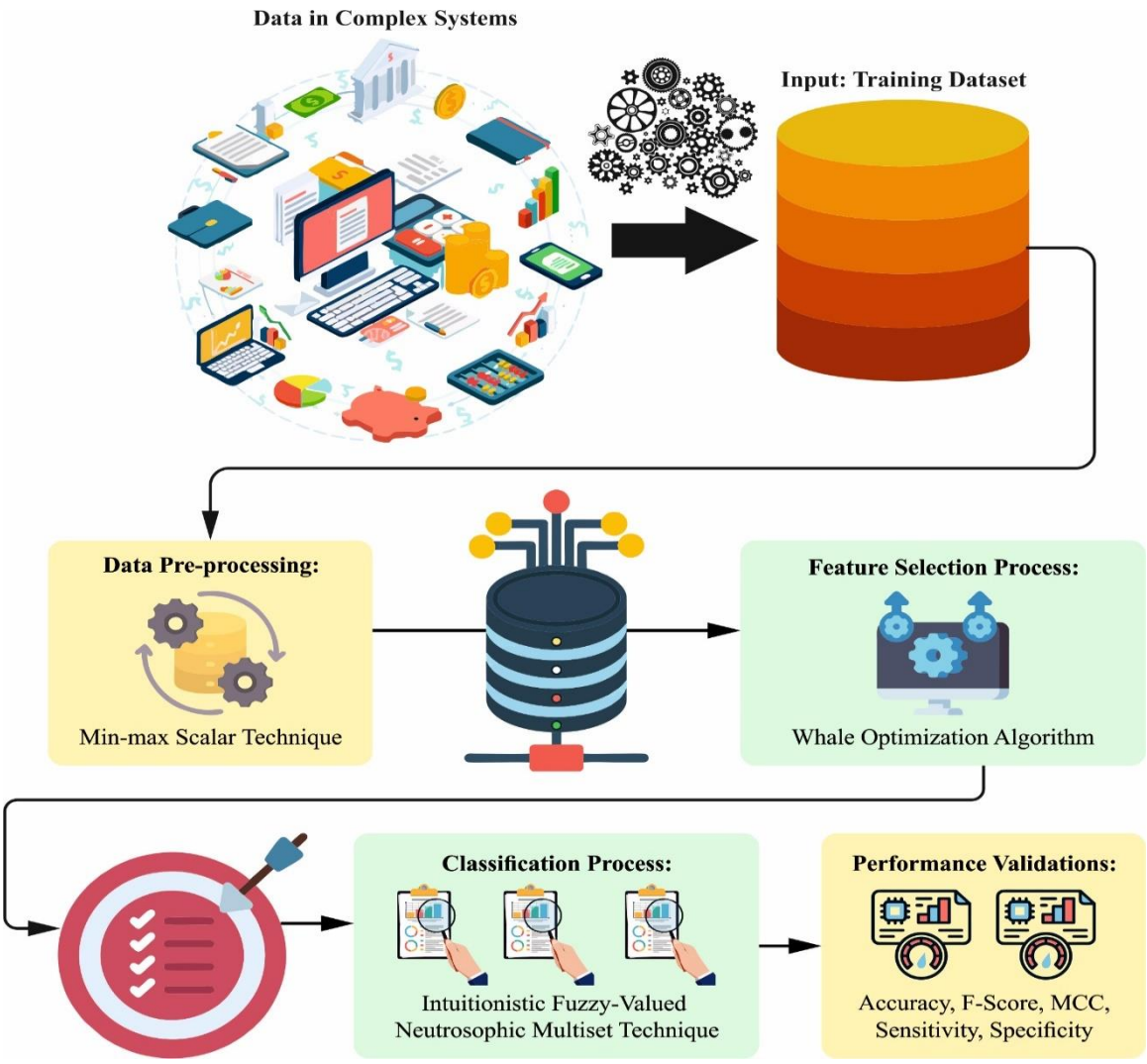

Fig. 1. Overall process of IFVNMS-FDC method

A. Data Normalization

Initially, the IFVNMS-FDC technique uses min-max scalar as a pre-processing step. MinMax Scaler shrinks the data in the interval of 0 and 1 [17]. It converts dataset via scaling features. It also scales the value to certain values without altering the shape of original distribution.

B. Feature Selection using WOA

Next, the high-dimensional financial data can be handled by the design of WOA-based feature selection. The main inspiration for WOA comes from the hunting behaviors of humpback whales [18]. The prey encircling, spiral bubble-net attacking, and prey searching are three key components of humpback whales in WOA.

Prey encircling:

Assume the present optimum candidate solution as a prey. Agent updates the position to the optimum search agent:

$$\vec{D} = \left|\vec{C} \cdot \vec{X}^*(t) - \vec{X}(t)\right| \tag{1}$$

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \cdot \vec{D} \tag{2}$$

Here coefficients $\vec{A}$ and $\vec{C}$ are used for updating location, are evaluated by Eqs. (3) and (4):

$$\vec{A} = 2\vec{a} \cdot \vec{r} - \vec{a} \tag{3}$$

$$\vec{C} = 2 \cdot \vec{r} \tag{4}$$

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In the equations, $\vec{a}$ is a parameter linearly dropped from 2 to 0 through iteration, which facilitates exploration and exploitation.

Exploitation stage (Bubble-net attacking strategy):

This stage has two different strategies namely spiral position update and shrinking encircling strategies. The spiral position update mechanism evaluates the distance between the target prey and the humpback whales, with a spiral or helix whale movement as in Eq. (5) and shrinking encircling can be achieved by reducing the $\vec{a}$ value in (3).

$$\vec{X}(t+1) = \vec{D}' \cdot e^{bl}\cos(2\pi l) + \vec{X}^*(t) \tag{5}$$

The selection probability between the spiral model or the shrinking encircling mechanism is considered for mimicking the behaviors of whales and the position updating of whales can be given below:

$$\vec{X}(t+1) = \begin{cases} \vec{X}^*(t) - \vec{A} \cdot \vec{D} & ifp < 0.5 \\ \vec{D}' \cdot e^{bl}cos(2\pi l) + \vec{X}^*(t) & ifp \geq 0.5 \end{cases} \tag{6}$$

Prey searching:

The whales randomly find the prey based on the location. $\vec{A}$ with arbitrary value less than -1 or greater than 1 induces search agent to move away from the whale position. Compared to the exploitation stage, the exploration stage updates the location of search agents based on the randomly selected search agent in place of the optimum search agents. This strategy, coupled with $|\vec{A}| > 1$, highlights and permits WOA to carry out global search.

$$\vec{D} = |\vec{C} \cdot \vec{X}_{\text{rand}} - \vec{X}| \tag{7}$$

$$\vec{X}(t+1) = \vec{X}_{\text{rand}} - \vec{A} \cdot \vec{D} \tag{8}$$

The FF deliberates the classifier accurateness and the quantity of designated attributes. It diminishes the proportions of the designated attributes and improves the classifier correctness. Consequently, the subsequent FF is used to estimate single solution.

$$Fitness = \alpha * ErrorRate + (1-\alpha) * \frac{\#SF}{\#All_F} \tag{9}$$

Here, $ErrorRate$ implies the classifier error rate and is considered as the proportion of improper classified to the quantity of classifications completed wihtin [0,1], $\#SF$ shows the quantity of designated attributes and $\#All_F$ refers to the complete sum of attributes in the new dataset. α controls the significance of classifier superiority and subset distance.

C. Financial Data Classification using IFVNMS

Finally, the IFVNMS-FDC technique derives IFVNMS technique for the identification of various classes related to the financial data. The conceptions of triangular norms (t-conorm) and (t-norm) have considerable significance in the depiction of combination operators and numerical operations for the fuzzy set [19]. A triangular norm a are tasks that plan couples of statistics in [0,1]. Deschrijver et al. protracted the ideas of both functions to the IF set by describing these tasks from the area of $I^* \times I^*$ to I^* where $I^* := \{(x_1, x_2) : x_1, x_2 \in [0,1] \text{ and } x_1 + x_2 \leq 1\}$. Beforehand remembering these notions, we remember a fractional direction for IFVs.

Assume $x = (x, x)$ and $y = (y_1, y_2)$ as IFVs. As stated by the fractional order presented by Atanassov $x \leq (int)\, y$ if and only if $x_1 \leq y_1$ and $x_2 \geq y_2$.

An operator $\mathcal{T} : I^* \times I^* \to I^*$ is known as an IF t-norm when $T = x$ edge criteria),

If $x \in I^*, \mathcal{T}\big(x, (1,0)\big) = x$,

If $x, y \in I^*, \mathcal{T}(x, y) = \mathcal{T}(y, x)$,

If $x, y, z \in I^*, \mathcal{T}(x, \mathcal{I}(y, z)) = \mathcal{T}\big(y, \mathcal{I}(x, z)\big)$,

If $x = (x_1, x_2), x' = (x_1', x_2\ y = (y_1, y_2), y' = (y_1', y_2') \in I^*, \mathcal{T}(x, y) \leq (int)\mathcal{T}(x', y')$ when $(x, x) \leq (int)(x_1', x_2')$ and $(y_1, y_2) \leq (int)(y_1', y_2')$.

An operator $S : I^* \times I^* \to I^*$ is known as an IF t-conorm when

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If $x \in I^*, S(x,(0,1)) = x$,

If $x, y \in I^*, S(x,y) = S(y,x)$,

If $x, y, z \in I^*, S(x, S(y,z)) = S(y, S(x,z))$,

If $x = (x,x), x' = (x_1', x_2\ y = (y_1, y_2), y' = (y_1', y_2') \in I^*$, $S(x,y) \leq (int)$ $S(x',y')$ when $(x_1, x_2) \leq (int)(x_1', x_2')$ and $(y_1, y_2) \leq (int)(y_1', y_2')$

An operator $N: I^* \to I^*$ then

If $x = (x_1, x_2), y = (y_1, y_2) \in I^*, N(x) \leq (int)N(y)$ when $x \geq (int)y$, viz., N is declining,

$N((O,1)) = (1,0)$ and $N((1,0)) = (0,1)$.

State 1 the planning N_s definite as $N_s((x_1, x_2)) = (xx)$ refers to fuzzy negators and it is known as the average negator.

Assume $\mathcal{J}$ as an IF t-norm and N as a fuzzy negator.

Assume T as a t-norm and S as a t-conorm in the regular sense. If

$T(a,b) \leq 1 - S(1-a, 1b)$ if $a, b \in [0,1]$, (2.1)

then the planning $\mathcal{T} : I^* \times I^* \to I^*$is $\mathcal{T}(x,y) = (T(x1, y_{12}), S(x, y_2))$ defined by an IF t-norm and the plotting $\mathcal{J}^* : I^* \times I^* \to I^*$ is $\mathcal{J}^*(x,y) = (S(x_1, y_1), T(x_2, y))$ remains the twofold IF t-conorm of $\mathcal{J}$ regarding N_s.

State 2 additional generators of triangular norms are crucial while determining the arithmetical operator. Here, we produce an IF t-norm and t-conorm using generator. Assume $: [0,1] \to [0,\infty]$ as the additional generator of a t-norm T and Assume S as the twofold t-conorm of T. In such cases, we find out if$h(t) = g(1-t)$. Later, (2.1) is fulfilled. Therefore, with (iii) of State 1 we attain an IF t-norm $\mathcal{T}$ is

$\mathcal{T}(x,y) = (g^{-1}(g(x_1) + g(y_1)), h^{-1}(h(x_2) + h(y_2)))$ and its twofold t-conorm

$\mathcal{T}^*(x,y) = (h^{-1}(h(x1) + h(y_1)), g^{-1}(g(x2) + g(y_2)))$

regarding $\mathcal{N}_s$. In such cases, it is said that $\mathcal{T}$ refers to the IF t-norm produced by g.

Assume g, h:$[0,1] \to [0,\infty]$ as $g(t) = -\log t$ and $h(t) = -\log(1-t)$. Now, we attain the arithmetical IF t-norm

$$\mathcal{J}(x,y) = (x_1 y_1, x_2 + y_2 - x_2 y_2)$$

its twofold IF dual t-conorm

$\mathcal{J}^*(x,y) = (x_1 + y_1 - x_1 y_1, x_2 y_2)$.

Assume $\alpha, \beta \in [0,1]$ thus $\alpha + \beta \leq 1$. Now, the pair (α, β) is known as an IFV.

Consider $X = \{x_1, \dots, x_n\}$ as a fixed set. An IFVNMS determined on X is shown below

$A = \{\{x_i, ((\mathbb{T}_A^{i,j})_{j=1}^{p_i}, (\mathbb{I}_A^{i,j})_{j=1}^{p_i}, (\mathbb{F}_A^{i,j})_{j=1}^{p_i})\}: i = 1, \dots n\}$ (2.2)

Where $(\mathbb{T}_A^{i,j})_{j=1}^{p_i}, (\mathbb{I}_A^{i,j})_{j=1}^{p_i}$ and $(\mathbb{F}_A^{i,j})_{j=1}^{p_i}$ are the trust, indeterminacy and false degrees of IFVs, correspondingly, viz., $i = 1, n, j = 1, p_i$

$\mathbb{T}_A^{i,j} = \left(\mathbb{T}_A^{j,t_i}, \mathbb{T}_A^{j,f_i}\right)$, with $\mathbb{T}_A^{j,t_i}, \mathbb{T}_A^{j,f_i} \in [0,1]$

thus $0 \leq T_A^{j,t_i} + T_A^{j,f_i} \leq 1$ (2.3)

$\mathbb{I}_A^{i,j} = (I_A^{j,t_i}, I_A^{j,f_i})$, with $I_A^{j,t_i}, I_A^{j,f_i} \in [0,1]$ thus

$0 \leq I_A^{j,t_i} + I_A^{j,f_i} \leq 1$ (2.4)

and

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$\mathbb{F}_A^{i,j} = \left(F_A^{j,t_i}, F_A^{j,f_i}\right)$, with $F_A^{j,t_i}, F_A^{j,f_i} \in [0,1]$

thus $0 \leq F_A^{j,t_i} + F_A^{j,f_i} \leq 1$. (2.5)

If $i = 1, \dots, n$ then the formula is

$$\alpha = \{(\mathbb{T}_\alpha^j)_{j=1}^p, (\mathbb{I}_\alpha^j)_{j=1}^p, (\mathbb{F}_\alpha^j)_{j=1}^p\}$$

$$:= \{x_i, ((\mathbb{T}_A^{i,j})_{j=1}^{p_i}, \left(\mathbb{I}_A^{i,j})_{j=1}^{p_i}, \left(\mathbb{F}_A^{i,j})_{j=1}^{p_i}\right)\}$$

represents an IFVNMV $(\mathbb{I}_A^{i,j} \cap_{(int)} \mathbb{I}_B^{i,j})_{j=1}^{p_i} = (\min(I_A^{j,t_i}, I_B^{j,t_i}), \max(I_A^{j,f_i}, I_B^{j,f_i}))_j^{p_i} j$

Consider $X = \{x_{1,2}x\}$. The IFVNMS is:

$$A = \begin{Bmatrix} \langle x_1, ((0.5,0.4), (0.7,0.1)), ((0.3,0.2), (0.1,0.1)), ((0.9,0.1), (0.2,0.6))) \rangle \\ \langle x_2 \begin{matrix} ((0.3,0.5), (0..4,0.2), (0.1,0.2)), \left((0.1,0.9), (0.5,0.5), (0.7,0.2)\right) \\ \left((0.0,0.8), (03,0.6), (0.5,0.2)\right) \end{matrix} \rangle \end{Bmatrix}.$$

Here, we present a set of theoretical functions amongst IFVNMSs. " $\subset (int), \cap_{(int)}, \cup_{(int)}, (\cdot)^{c(int)}$ is the sequence operation for IFSs.

Consider $X = \{x1, x_n\}$ as a fixed set and A and B as two IFVNMSs in X. Sequence operation amongst IFVNMSs is given below:

a) $A \subset B$ given that

(i) $\mathbb{T}_A^{i,j} \subset (int)\mathbb{T}_B^{i,j}$ i.e., $T_A^{j,t_i} \leq T_B^{j,t_i}$ and $T_A^{j,f_i} \geq T_B^{j,f_i}$

(ii) $\mathbb{I}_A^{i,j} \supset (int)\mathbb{I}_B^{i,j}$ viz., $I_A^{j,t_i} \geq I_B^{j,t_i}$ and $I_A^{j,f_i} \leq I_B^{j,f_i}$

(iii) $\mathbb{F}_A^{i,j} \supset (int)\mathbb{F}_B^{i,j}$ viz., $F_A^{j,t_i} \geq F_B^{j,t_i}$ and $F_A^{j,f_i} i \leq F_B^{j,f_i}$

for $j = 1,2, \dots p_i$ and $i = 1,2, n$.

(b) $A = B$ given that $A \subset B$ and $A \supset B$.

(c) $A^c = \{\{x_i, ((\mathbb{F}_A^{i,j})_{j=1}^{p_i}, ([\mathbb{I}_A^{i,j}]^{c(int)})_{j=1}^{p_i}, (\mathbb{T}_A^{i,j})_{j=1}^{p_i})):$

$i = 1,2, \dots n\}$

(d) $A \cup B = \{\{x_i, (\left(\mathbb{T}_A^{i,j} \cup_{(int)} \mathbb{T}_B^{i,j})_{j=1}^{p_i}, \left(\mathbb{I}_A^{i,j} \cap_{(int)} \mathbb{I}_B^{i,j})_{j=1}^{p_i}, \left(\mathbb{F}_A^{i,j} \cap_{(int)} \mathbb{F}_B^{i,j})_{j=1}^{p_i}\right)\}: i = 1,2, \dots n\}$ where

$(\mathbb{T}_A^{i,j} \cup_{(int)} \mathbb{T}_B^{i,j})_{j=1}^{p_i} = (\max(\mathbb{T}_A^{j,t_i}, \mathbb{T}_B^{j,t_i})j, \min(\mathbb{T}_A^{j,f_i}, \mathbb{T}_B^{j,f_i}))_j^{p_i}$,

and

$(\mathbb{F}_A^{i,j} \cap_{(int)} \mathbb{F}_B^{i,j})_{j=1}^{p_i} = (\min(\mathbb{F}_A^{j,t_i}, \mathbb{F}_B^{j,t_i}), \max(\mathbb{F}_A^{j,f_i}, \mathbb{F}_B^{j,f_i}))_j^{p_i} j$.

(e) $A \cap B = \{\{x_i, ((\mathbb{T}_A^{i,j} \cap_{(int)} \mathbb{T}_B^{i,j})_{j=1}^{p_i}, (\mathbb{I}_A^{i,j} \cup_{(int)} \mathbb{I}_B^{i,j})_{j=1}^{p_i}, (\mathbb{F}_A^{i,j} \cup_{(int)} \mathbb{F}_B^{i,j})_{j=1}^{p_i})) : i = 1,2, \dots, n\}$ where

$(\mathbb{T}_A^{i,j} \cap_{(int)} \mathbb{T}_B^{i,j})_{j=1}^{p_i} = (\min(\mathbb{T}_A^{j,t_i}, \mathbb{T}_B^{j,t_i}), \max(\mathbb{T}_A^{j,f_i}, \mathbb{T}_B^{j,f_i}))_j^{p_i} j$'

$(\mathbb{I}_A^{i,j} \cup_{(int)} \mathbb{I}_B^{i,j})_{j=1}^{p_i} = (\max(\mathbb{I}_A^{j,t_i}, \mathbb{I}_B^{j,t_i})j$'min $(\mathbb{I}_A^{j,f_i}, \mathbb{I}_B^{j,f_i}))_j^{p_i}$,

and

$(\mathbb{f}_A^{i,j} \cup_{(int)} \mathbb{F}_B^{i,j})_{j=1}^{p_i} = (\max(\mathbb{F}_A^{j,t_i}, \mathbb{F}_B^{j,t_i})j$'$\min(\mathbb{F}_A^{j,f_i}, \mathbb{F}_B^{j,f_i}))_j^{p_i}$.

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4. Experimental Validation

The experimental analysis of the IFVNMS-FDC method can be inspected utilizing German credit dataset [20] as demonstrated in Table 1.

Table 1: Details of dataset

German Credit				
Source	# of Instances	# of Attributes	# of Class	Bankrupt/Non-Bankrupt
UCI	1000	24	2	300/700

In Table 2, detailed recognition results of the IFVNMS-FDC method are depicted for 70:30 of TRP/TSP. The tabulated values inferred that the IFVNMS-FDC method proficiently identifies two classes.

The average recognition results of the IFVNMS-FDC system on 70%TRP are established in Fig. 2. The outcomes specify that the IFVNMS-FDC method can efficaciously identify the samples. It is also noticed that the IFVNMS-FDC system gains average $accu_y$, $sens_y$, $spec_y$, F_{score}, and MCC of 92.00%, 87.12%, 87.12%, 89.78%, and 81.16%, correspondingly.

The average recognition results of the IFVNMS-FDC system on 30%TSP are validated in Fig. 3. The outcomes specify that the IFVNMS-FDC method can efficaciously identify the samples. It is also noticed that the IFVNMS-FDC system gains average $accu_y$, $sens_y$, $spec_y$, F_{score}, and MCC of 89.33%, 82.97%, 82.97%, 85.78%, and 73.46%, correspondingly.

Table 2: Recognition outcome of IFVNMS-FDC method on 70%TRP and 30%TSP

Class	$Accu_y$	$Sens_y$	$Spec_y$	F_{Score}	MCC
TRP (70%)					
Bankrupt	92.00	74.65	99.59	85.03	81.16
Non-Bankrupt	92.00	99.59	74.65	94.54	81.16
Average	92.00	87.12	87.12	89.78	81.16
TSP (30%)					
Bankrupt	89.33	67.82	98.12	78.67	73.46
Non-Bankrupt	89.33	98.12	67.82	92.89	73.46
Average	89.33	82.97	82.97	85.78	73.46

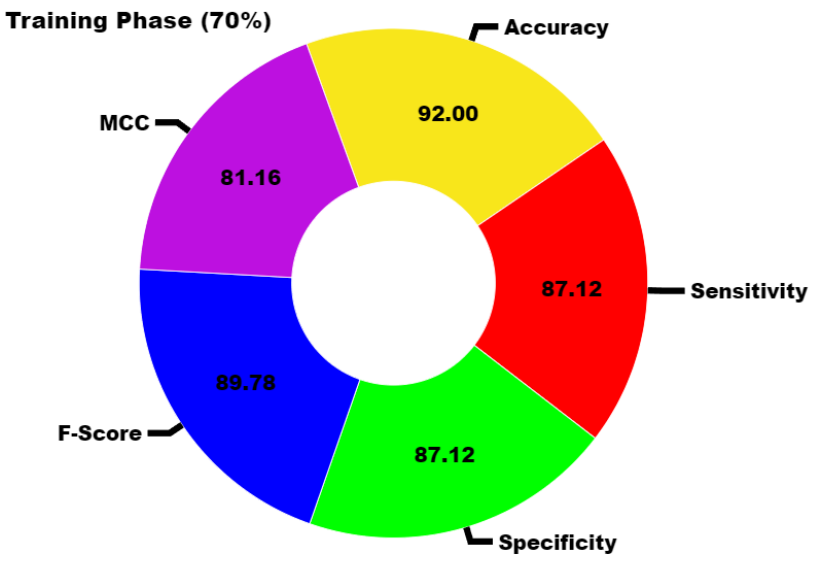

Figure 2. Average outcome of IFVNMS-FDC technique under 70%TRP

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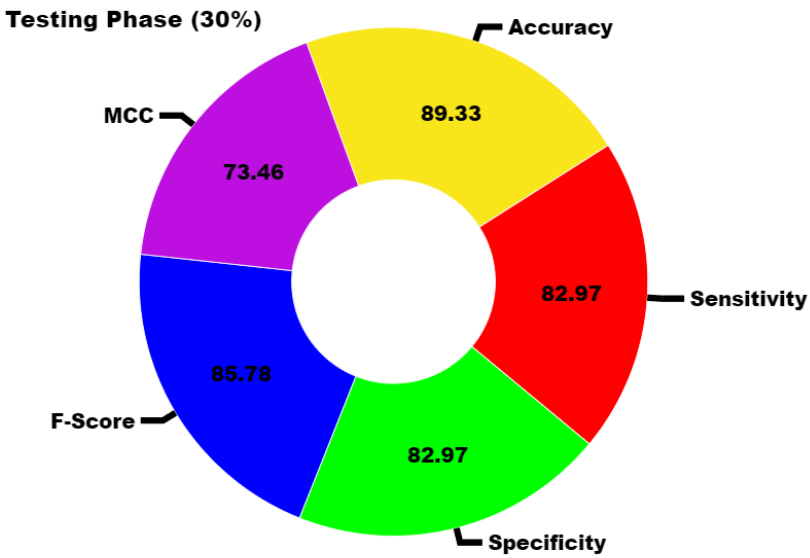

Figure 3. Average outcome of IFVNMS-FDC technique under 30%TSP

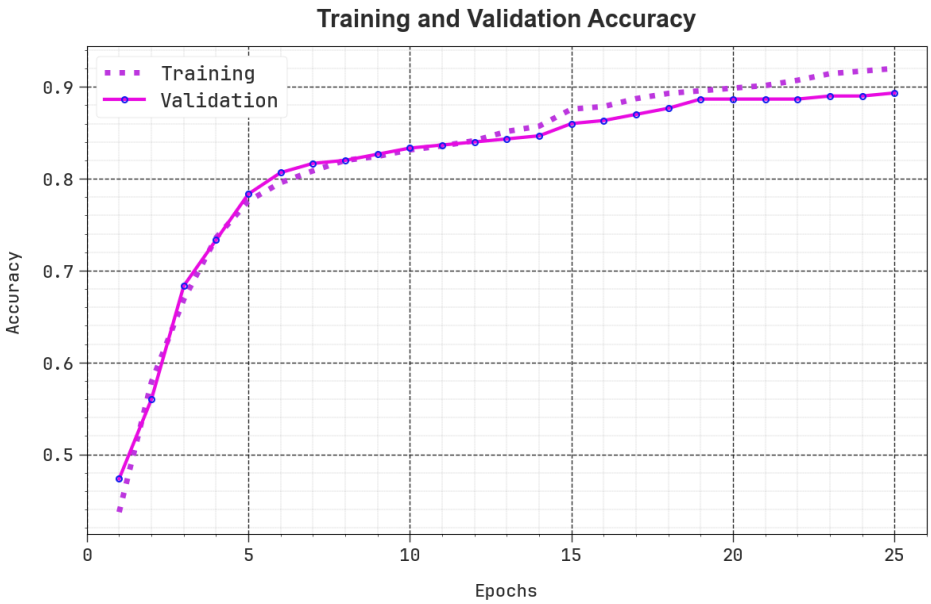

Figure 4. $Accu_y$ curve of the IFVNMS-FDC technique

In Fig. 4, the training and validation accuracy outcomes of the IFVNMS-FDC method are demonstrated. The accuracy values are calculated in the range of 0-25 epochs. The figure highlighted that the training and validation accuracy values display a growing tendency which notified the ability of the IFVNMS-FDC model with improved performance over several iterations. Furthermore, the training accuracy and validation accuracy remain closer over the epochs, which exhibits enhanced performance and indicates low minimal overfitting of the IFVNMS-FDC model, guaranteeing consistent prediction on unseen samples.

In Fig. 5, the training and validation loss graph of the IFVNMS-FDC method is demonstrated. The loss values are calculated in the range of 0-25 epochs. It is characterized that the training and validation accuracy values demonstrate a decreasing tendency, which notified the capability of the IFVNMS-FDC method in balancing a tradeoff between data fitting and generalization. The continual decrease in loss values further guarantees the enriched performance of the IFVNMS-FDC algorithm and tunes the prediction outcomes over time.

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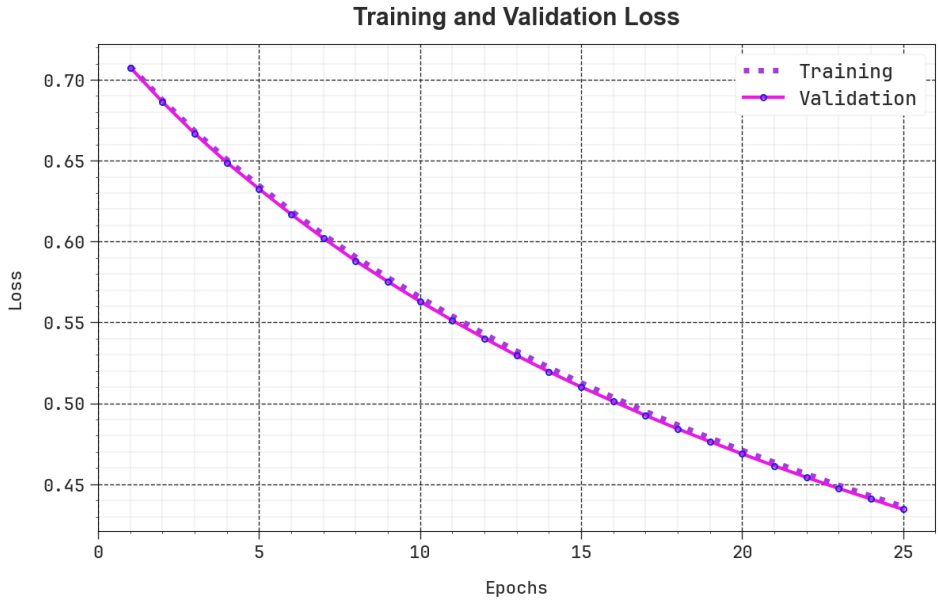

Figure 5. Loss curve of the IFVNMS-FDC technique

A detailed comparison study is made in Table 3 to demonstrate the proficiency of the IFVNMS-FDC technique [21].

In Fig. 6, a comparative $accu_y$ and F_{score} results of the IFVNMS-FDC technique are provided. The results indicate that the SVM, RBF, and Olex-GA models have shown worse values of $accu_y$ and F_{score}. Simultaneously, the DT and MLP methods have attained slightly improved $accu_y$ and F_{score}. Meanwhile, the ACO-DC and Bagging models have demonstrated closer values of $accu_y$ and F_{score}. Nevertheless, the IFVNMS-FDC technique results in improved performance with $accu_y$ and F_{score} of 92.00% and 89.78%, correspondingly.

Table 3: Comparative outcome of IFVNMS-FDC technique with existing approaches

Classifiers	$Accu_y$	$Sens_y$	$Spec_y$	F_{Score}
SVM Classifier	85.07	78.17	84.54	84.60
Bagging Model	86.95	84.44	81.91	85.53
Decision Tree	86.08	81.72	79.23	84.41
RBF Model	83.33	85.55	81.47	80.06
MLP Algorithm	85.79	82.55	83.80	84.39
Olex-GA	83.47	80.44	81.91	81.73
ACO-DC	89.28	83.43	85.15	88.07
IFVNMS-FDC	92.00	87.12	87.12	89.78

In Fig. 7, a comparative $sens_y$ and $spec_y$ outcomes of the IFVNMS-FDC method are demonstrated. The results indicate that the SVM, RBF, and Olex-GA methods have shown worse values of $sens_y$ and $spec_y$. Simultaneously, the DT and MLP methods have accomplished slightly improved $sens_y$ and $spec_y$. Meanwhile, the ACO-DC and Bagging models have demonstrated closer values of $sens_y$ and $spec_y$. Nevertheless, the IFVNMS-FDC technique results in superior performance with $sens_y$ and $spec_y$ of 87.12% and 87.12%, correspondingly.

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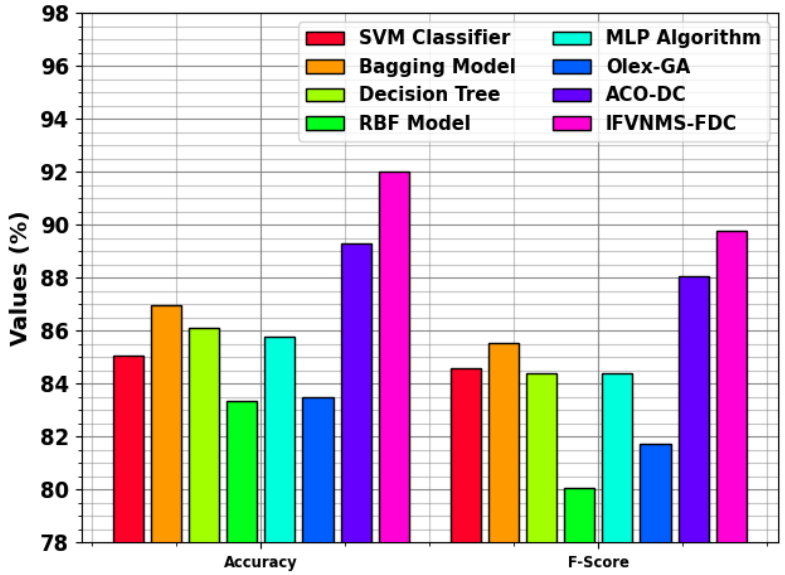

Figure 6. $Accu_y$ and F_{score} outcome of IFVNMS-FDC technique with existing approaches

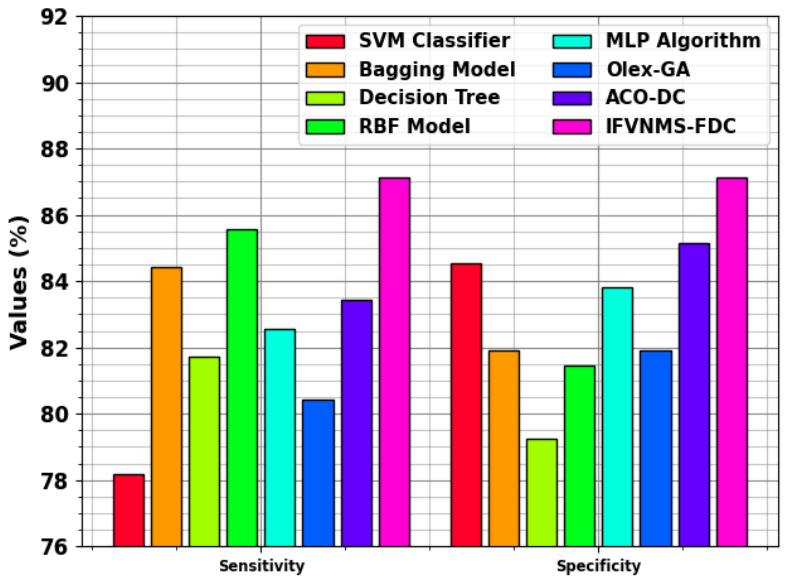

Figure 7. $Sens_y$ and $Spec_y$ outcome of IFVNMS-FDC method with existing techniques

5. Conclusion

In this study, we have presented an IFVNMS-FDC method in complex systems. The main aim of the IFVNMS-FDC technique is to recognize and categorize the financial data into respective classes. It comprises three various phases data normalization, feature selection, and classification phases. Initially, the IFVNMS-FDC technique uses min-max scalar as a pre-processing step. Besides, the high-dimensional financial data can be handled by the design of WOA-based feature selection. Finally, the IFVNMS-FDC technique derives IFVNMS technique for the identification of various classes related to the financial data. A wide-ranging experiments were involved for exhibiting the performance of the IFVNMS-FDC technique. The experimental values portrayed that the IFVNMS-FDC technique obtains reasonable performance on financial data recognition.

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