



An Intelligent Semantic Orientation Identification Framework on Economic Text Using Q-Neutrosophic Soft Matrix under Interval-Valued for Financial Sentiment Analysis

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Abstract

Neutrosophic Logic is a neonate field of research in which all propositions are considered to have the percentage of truth in a subset I, F, and T. Neutrosophic set (NS) has been positively utilized for indeterminate data processing, and proven benefits for addressing the indeterminacy data information and is still a method nominated for classification application and data analysis. Soft set (SS) is a powerful device for handling the uncertainty of information in a parametric situation. On the other hand, the concept of interval-valued neutrosophic soft sets (IVNSSs) is a novel generality of the neutrosophic soft sets (NSSs) to the NSs once the authors incorporate the important features of IVNS and soft sets (SSs) in one method. Therefore, this method operated to offer decision-makers with flexibility in the procedure of understanding unclear information. From the scientific viewpoint, the procedure of estimating this higher performance IVNSS vanishes. Q-neutrosophic SSs are fundamentally NSSs considered by 3 independent 2D membership functions that represents indeterminacy, falsity and uncertainty. Therefore, it is used to 2D inconsistent, imprecise and indeterminate data, which seem in most real world challenges. The usage of robo-readers for analyzing news texts is the advanced technology trend in financial technology. A considerable effort has been invested to develop refined financial orientation that is applied to inspect how financial sentiments related to future performance of the company. Recently, the financial sentiment analysis (SA) has become a more and more related subfield within text analytics that addresses the computational analysis of subjectivity and opinion in texts. Most of the methods have concentrated on particular fields, utilizing type-based corpora as training data for machine learning (ML) methods that classify the input text as both negative and positive. In this manuscript, we develop a Semantic Orientation Identification Framework in Economic Text Using Q-neutrosophic soft matrix under Interval-valued (SOIFET-IVQNSM) model for financial SA. The aim of the paper is to propose an innovative approach for identifying semantic orientation in economic texts to enhance financial sentiment and prediction accuracy. Primarily, the input text data is preprocessed utilizing diverse preprocessing levels like removal of stop words, tokenization, stemming, spelling correction, and lemmatization to make it suitable for further processing. Besides, the word embedding process is mainly executed by the term frequency-inverse document frequency (TF-IDF) model to transform economic text into meaningful vector

representation. For classification purpose, the proposed SOIFET-IVQNSM model designs a Q-neutrosophic soft matrix under Interval-valued (IV-Q-NSM) model. The simulation validation of the SOIFET-IVQNSM algorithm is tested on a benchmark database, and the results are measured under several metrics. The simulation result highlighted the improvement of the SOIFET-IVQNSM system in semantic orientation identification.

Keywords: Neutrosophic Set; Semantic Orientation Identification; Economic Text; Interval-Valued Neutrosophic Set; Neutrosophic Logic; Financial Sentiment

1. Introduction

One of the theory is the fuzzy set (FS) that advanced as a mathematical process of describing and addressing vagueness in everyday life. The basic work in this field was recognized by Lotfi Zadeh, who presented the theory of fuzzy sets (FS), which acts as an expansion of classic crisp sets. In fuzzy set concept, all components are given a degree of membership between 0 and 1, permitting for a more subtle representation of uncertainty. This groundbreaking theory has urged a research wealth through several fields, as shown by much analysis. As daily life becomes more and more complex, there is a growing demand for novel mathematical devices or for the development of recent ones. In that regard, Florentin Smarandache presented neutrosophic set (NS) concept in 1998, which develops on Zadeh's fuzzy sets by giving 3 membership degrees to all components, each of them lie within the range [0, 1]. This permits for the rich uncertainty representation. NS expansions, namely complex NS (CNS), interval complex NS (ICNS) and interval NS (INS) are the efficacious devices for modelling vagueness in decision-making [1]. NS offers a robust framework for managing vagueness and uncertainty in decision-making, surpassing the capabilities of fuzzy, classical, and intuitionistic fuzzy sets. NS introduces three membership degrees, such as truth, indeterminacy, and falsehood, to represent the certainty of a statement, and they are utilized in several decision-making scenarios [2]. To handle more complex and real-world situations, CNS and INS are introduced as extensions of NS. Adam and Hassan recognized Q-fuzzy soft sets. The concept behind the expansion of Q-fuzzy soft sets is that in numerous samples a next element should be add to the look of the membership value of the element. This theory was prolonged to Q-intuitionistic fuzzy soft set by Broumi in added a 2D non-MF. Nevertheless, these techniques cannot tackle indeterminate information that seems in 2D universal sets. Therefore, the theory of the Q-NSSs is well known to incorporate the main attributes of soft sets and Q-NS. The Q-NSSs method is the enhanced method of NS that can characterize 2D information. The problem in the ongoing financial crisis has encouraged several researchers on market sentiments and how to quantify them appropriately and reliably. Conventional approaches like confidence indices obtained through standard surveys have limitations [3]. The structured nature of questionnaires restricts the depth and breadth of information gathered, and the data quickly becomes out-of-date. To address these limitations with survey-based sentiments, there is growing attention in methods that offer officials and investors a immediate view of economic progress [4]. An effective technique involves using media as an indicator of investor sentiment. Rather than relying on monthly surveys to gather opinions on the current economic developments, financial news can be employed to estimate shifts in market sentiment [5].

The employment of polarity lexicons is possibly the most frequently applied method for detecting semantic orientations (i.e., positive, negative, or neutral) in text. Nevertheless, it is well known that the performance of these methods depends on polarity-lexicons and is greatly influenced by the domain and context of the opinionated or subjective statement [6]. An expression that can be considered to have an effective semantic orientation in one domain may need to be interpreted differently in another context [7]. In addition to the necessity for being able to account for common polarity-bearing expressions appropriately, contextual knowledge and phrase-structure information are employed to enhance the precision of semantic orientation judgments [8]. Sentiment analysis (SA) examines individuals' attitudes, sentiments, emotions, opinions, appraisals, and evaluations towards numerous entities, namely topics, events, products, services, organizations, individuals, issues, and their traits [9]. The key motive of SA is to categorize the polarity of a provided text, which takes place at the sentence, document, or aspect level. Earlier investigations in financial SA mainly aimed at the sentence- or document-level sentiment polarities [10]. SA has become an intricate and highly domain-dependent task. In essence, deep learning (DL) is a method for deriving data patterns from empirical samples. It helps streamline high-dimensional, unstructured data into compact vector forms [11]. Deep neural networks (DNN) extract these patterns across various layers of abstraction by applying non-linear neural network (NN) methods [12]. Each layer in the network transforms the previous layer's output into a moderately more abstract version, utilizing trained parameters. These parameters are finetuned by reducing a loss function that determines the difference amid the model's output and the actual target values [13].

A. Paper Contributions

In this manuscript, we develop a Semantic Orientation Identification Framework in Economic Text Using Q-neutrosophic soft matrix under Interval-valued (SOIFET-IVQNSM) model for financial SA. The major contributions of the paper are summarized as demonstrated:

- Proposes an advanced method to identify semantic orientation in economic texts.
- The input text data is preprocessed utilizing diverse preprocessing levels namely removal of stop word, stemming, tokenization, lemmatization, spelling correction, and making it appropriate for further processing.
- The word embedding model is mainly executed by the term frequency-inverse document frequency (TF-IDF) for converting economic text into a meaningful vector model.
- The presented SOIFET-IVQNSM model designs IV-Q-NSM approach for the classification process.
- The empirical validation of the SOIFET-IVQNSM approach is shown on the benchmark database and the results are measured under various metrics.

2. Literature Survey on Semantic Orientation Identification Framework

Liu et al. [14] presented Multi-Level SA that depends on pretrained language models (PLMs) and LLM, a new method that systematically combines industry-specific meso-level sentiment, firm-specific micro-level sentiment, and duration-aware smoothing for modeling the latency and persistence of textual impact. This method offers a more nuanced understanding of sentiment among various market levels, although accounting for the temporal advancement of sentiment effects. Cai et al. [15] presented an approach for financial customer services, involving semi-supervised learning, text classification, label semantic inference and data augmentation. This learning model is leveraged for augmenting restricted corpus data, which merges back-translation with BERT techniques. At last, a BERT-driven text classification method is employed for recognizing financial customer service motives, including multilevel feature fusion for label semantics and corpus information.

Hosain et al. [16] presented xFiTRNN, a hybrid approach that combines contextualized transformer-based RNN, linearized phrase structure, and self-attention mechanisms to improve model performance as well as explain ability in predicting financial sentences. This approach extracts delicate contextual details from financial texts, although upholding explainability. In [17], an optimized stacked-LSTM-empowered SA technique has been presented for cryptocurrency price prediction. This technique can identify the dependencies of co-occurrence statistical and latent contextual semantic features between phrases in a sentence. Moreover, this technique encompasses several LSTM layers, and all layers are enhanced through the Particle Swarm Optimizer (PSO) model for learning hyperparameters. Shang et al. [18] suggested an innovative Lexicon Enhanced Collaborative Network (LECN) for TSA in financial texts. Generally, this paradigm developed an integrated approach that extracts the connections to improve TSA's execution. Furthermore, this paradigm adaptively integrates sentiment lexicons for guiding the sentiment classification that supports the paradigm's ability to understand financial expressions. Additionally, this paradigm presents a message-selective-passing module for dynamically managing information flows between two tasks, thus refining the collaborative results.

Vijay et al. [19] presented FSOL, a semantic method to recommend financial documents, which employs dense auxiliary knowledge for semantic and epistemic reasoning. Financial documents undergo classification utilizing logistic regression classifiers; leveraging features extracted from context trees related information are obtained. Zhang et al. [20] introduced an efficient instruction tuning technique to tackle these concerns. Even though LLMs have remarkable abilities in financial NLP, they still have difficulty in understanding financial context and numerical values, restraining their efficiency in financial sentiment prediction.

3. Materials and Methods

This paper proposes a SOIFET-IVQNSM model for financial SA. The major objective of this study is to suggest an advanced methodology to recognize semantic orientation in economic texts to improve prediction precision and financial sentiment.

A. Method Overview

To attain this, the presented model has the input text data is initially pre-processed using different pre-processing levels like removal of stop words, tokenization, stemming, spelling correction, and lemmatization making it suitable for further processing. Additionally, the word-embedding model is mainly performed by the TF-IDF method for converting economic text into an important vector representation. For classification purposes, the presented SOIFET-IVQNSM method designs an IV-Q-NSM approach. Fig. 1 illustrate the overall process of SOIFET-IVQNSM model.

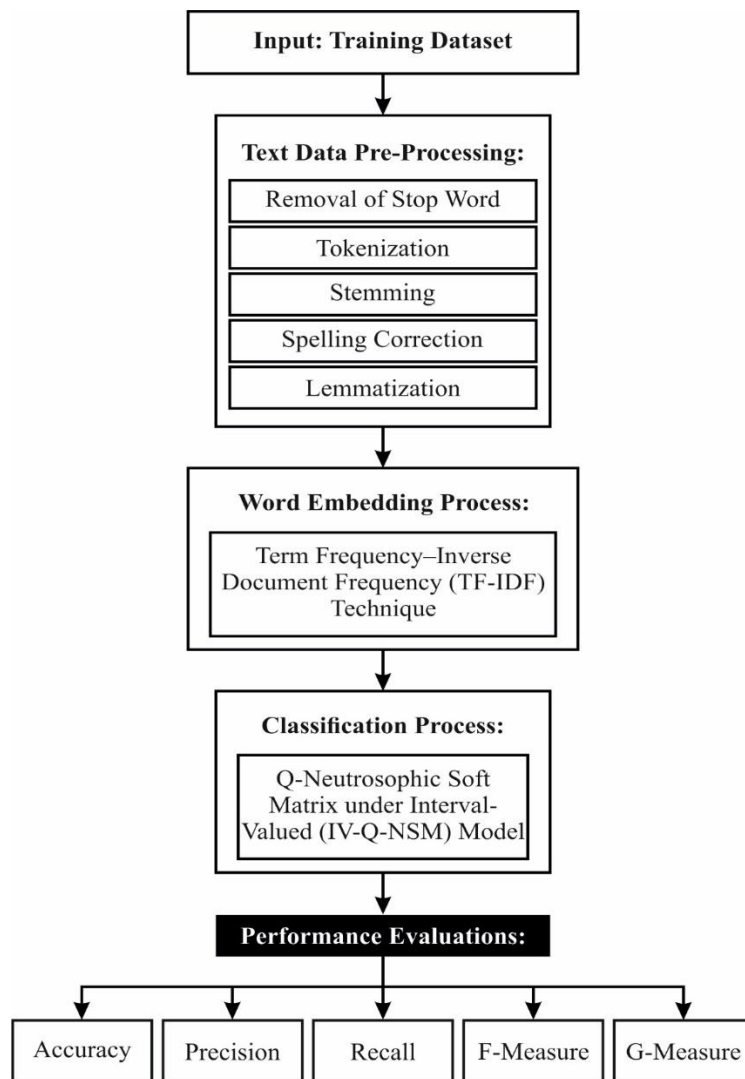


Figure 1. Overall process of the SOIFET-IVQNSM model

B. Various Pre-processing Levels

Primarily, the input text data is pre-processed utilizing diverse pre-processing levels like removal of stop word, spelling correction, tokenization, lemmatization, and stemming to make it appropriate for additional processing. Here, the input data are collected from the dataset [21]. The input data's text format is pre-processed utilizing the dissimilar text pre-processing models: stemming, tokenization, stop word removal, lemmatization, and spelling correction. The pre-processing methods are explained in the succeeding sub-sections. Using preprocessing, the dimension of the data is reduced, and it is well trained for recommended tasks.

1. Stop Word Removal

The procedure of removing the stop words lowers the data dimensionalities. For example: "The," "an," "At," "a," "that," etc., in this process, eliminating those words does not change the meanings of the word.

2. Tokenization

This process breaks the longest paragraphs into broken texts called tokens. It is the process of breaking the larger paragraph into smaller sentence and also breaking the sentences into tokens. The chunks of words are named tokens.

3. Stemming

This process converts many tenses of words into their common root format. It is essential to remove the unwanted calculation of words. Furthermore, this procedure will decrease the size of the word. For example: "arguing" to "argue."

4. Spelling Correction

This procedure is applied to correct errors. It is used for data cleaning. This model forecasts the incorrect words and outcomes in the modified word form. The misspelt words change the meaning of the correct word. For example: “b4” to “before,” “tmrw” to “tomorrow.”

5. Lemmatization

It is the procedure of combining more than one words into particular words. This reprocessing model forecasts the word morphology. Furthermore, this procedure extracts the final words such as “impressed” to “impress,” “catch” to “caught,” and so forth.

C. Word Embedding using TF-IDF Model

Besides, the word embedding process is mainly executed by TF-IDF model to transform economic text into a meaningful vector representation. TF-IDF model tackling this by weighting words depend upon their significance through the dataset [22]. It evaluates the relative frequencies of the word in particular documents, modified by its inverse frequency through every document, entailing a matrix of term-document of TF-IDF scores. It allocates superior weight in words that arise frequently in particular documents.

$$TF - IDF(t, d) = TF(t, d) * IDF(t) = TF(t, d) * \log \quad (1)$$

Now, N signified entire document counts, $df(t)$ represent document frequency, depicting the document counts comprising the term t , and $TF(t, d)$ signifies the TF t in document d .

While, term occurs in all documents, it leads to $IDF(t)$ of 0, a value of 1 is add with the term of logarithmic in $IDF(t)$ computation.

D. IV-Q-NSM-based Classification Process

For the classification purpose, the proposed SOIFET-IVQNSM technique intends IV-Q-NS Matrix model. In this section, retaining some important concepts associated with the presented method like FS , $Q-FS$, SS , and NS [23].

Definition2.1. [1] Let $\mathcal{U} = \{u_1, u_2, u_3, \dots, u_n\}$ refers to primary points area (nonempty universal set). Next, the FS \mathcal{F} on \mathcal{U} was described by succeeding type:

$$\mathcal{F} = \{u_j, \hat{P}^t(u_j) | u_j \in \mathcal{U}\}$$

Whereas \mathcal{F} represent mapping described as $\mathcal{F}: \mathcal{U} \rightarrow [0,1]$ like $\hat{P}^t \in [0,1]$ and named truth membership function (TMF).

Definition2.2. Presume that $\mathcal{U} = \{u_1, u_2, u_3, \dots, u_n\}$ refers to primary point's area (non-empty universal set) and $\mathcal{Q} = \{q_1, q_2, q_3, \dots, q_n\}$ denote non-empty set. Next, the Q-FS $\mathcal{F}_{\mathcal{Q}}$ on the pair of order $(\mathcal{U}, \mathcal{Q})$ can be characterized by subsequent type:

$$\mathcal{F}_{\mathcal{Q}} = \{(u, q), \hat{P}^t(u, q) | (u, q) \in \mathcal{U} \times \mathcal{Q}\}$$

Here, \mathcal{F} refers to mapping described as $\mathcal{F}_{\mathcal{Q}}: \mathcal{U} \times \mathcal{Q} \rightarrow [0,1]$ like $\hat{P}_{\mathcal{Q}}^t \in [0,1]$ and named Q-truth MF (TMF).

Definition2.3. Suppose $\mathcal{U} = \{u_1, u_2, u_3, \dots, u_n\}$ consider primary points area (non-empty universal set). Formerly, the NS N on \mathcal{U} was well defined by subsequent variety:

$$N = \{u_j, \hat{P}^t(u_j), \hat{P}^i(u_j), \hat{P}^f(u_j) | u_j \in \mathcal{U}\}$$

Now, N stands for mapping labelled as $N: \mathcal{U} \rightarrow [0,1]$ like $\hat{P}^t(u_j), \hat{P}^i(u_j), \hat{P}^f(u_j) \in [0,1]$ and called TMF, neutrality MF (NMF), and falsity MF (FMF) with stander state $0 \leq \hat{P}_{\mathcal{Q}}^t(u_j) + \hat{P}^i(u_j) + \hat{P}^f(u_j) \leq 1$.

Definition2.4. Let $\mathcal{U} = \{u_1, u_2, u_3, \dots, u_n\}$ consider primary point's area (non-empty universal set). Next, the Q-NS N on $(\mathcal{U} \times \mathcal{Q})$ can be specified by succeeding type:

$$N_{\mathcal{Q}} = \{u_j, \hat{P}_{\mathcal{Q}}^t(u, q), \hat{P}_{\mathcal{Q}}^i(u, q), \hat{P}_{\mathcal{Q}}^f(u, q) | (u, q) \in \mathcal{U} \times \mathcal{Q}\}$$

Whereas $N_{\mathcal{Q}}$ indicate mapping described as $N_{\mathcal{Q}}: \mathcal{U} \times \mathcal{Q} \rightarrow [0,1]$ like $\hat{P}_{\mathcal{Q}}^t(u, q), \hat{P}_{\mathcal{Q}}^i(u, q), \hat{P}_{\mathcal{Q}}^f(u, q) \in [0,1]$ and named TMF, NMF, and FMF with stander state $0 \leq \hat{P}_{\mathcal{Q}}^t(u, q), \hat{P}_{\mathcal{Q}}^i(u, q), \hat{P}_{\mathcal{Q}}^f(u, q) \leq 1$.

Definition2.5. Suppose $\mathcal{U} = \{u_1, u_2, u_3, \dots, u_n\}$ consider primary point's space (non-empty universal set). At that time, the IVNS N on \mathcal{U} is specified by succeeding type:

$$N = \{u_j, \hat{P}^t(u_j), \hat{P}^i(u_j), \hat{P}^f(u_j) | u_j \in \mathcal{U}\}$$

Whereas $\hat{P}^t(u_j) = [\hat{P}^{t,l}(u_j), \hat{P}^{t,u}(u_j)]$, $\hat{P}^i(u_j) = [\hat{P}^{i,l}(u_j), \hat{P}^{i,u}(u_j)]$ and $\hat{P}^f(u_j) = [\hat{P}^{f,l}(u_j), \hat{P}^{f,u}(u_j)]$

In such a manner the domain of these terms is \mathcal{U} and the co-domain is $[0,1]$ and $\hat{P}^{t,l}(u_j), \hat{P}^{t,u}(u_j)$ are upper and lower of TMF, $\hat{P}^{i,l}(u_j), \hat{P}^{i,u}(u_j)$ represent upper and lower of IMF and $\hat{P}^{f,l}(u_j), \hat{P}^{f,u}(u_j)$ are upper and lower of FMF, with 2 stander states $0 \leq \hat{P}^{t,l}(u_j), \hat{P}^{i,l}(u_j) + \hat{P}(u_j) \leq 1$ and $0 \leq \hat{P}(u_j) + \hat{P}(u_j) + \hat{P}(u_j) \leq 1$.

Definition2.6. Let $N_1 = \{u_j, \hat{P}_1^t(u_j), \hat{P}_1^i(u_j), \hat{P}_1^f(u_j) | u_j \in \mathcal{U}\}$, $N_2 = \{u_j, \hat{P}_2^t(u_j), \hat{P}_2^i(u_j), \hat{P}_2^f(u_j) | u_j \in \mathcal{U}\}$ consider dual INS on primary points area (nonempty universal set) \mathcal{U}

Whereas $\hat{P}_1^t(u_j) = [\hat{P}_1^{t,l}(u_j), \hat{P}_1^{t,u}(u_j)]$, $\hat{P}_1^i(u_j) = [\hat{P}_1^{i,l}(u_j), \hat{P}_1^{i,u}(u_j)]$ and $\hat{P}_1^f(u_j) = [\hat{P}_1^{f,l}(u_j), \hat{P}_1^{f,u}(u_j)]$ and $\hat{P}_2^t(u_j) = [\hat{P}_2^{t,l}(u_j), \hat{P}_2^{t,u}(u_j)]$, $\hat{P}_2^i(u_j) = [\hat{P}_2^{i,l}(u_j), \hat{P}_2^{i,u}(u_j)]$ and $\hat{P}_2^f(u_j) = [\hat{P}_2^{f,l}(u_j), \hat{P}_2^{f,u}(u_j)]$ Formerly,

- i. Complement $N_1^c = \{u_j, \hat{P}_1^f(u_j), 1 - \hat{P}_1^i(u_j), \hat{P}_1^t(u_j) | u_j \in \mathcal{U}\}$
- ii. Union: $N_1 \cup N_2 = \{u_j, \max[\hat{P}_1^t(u_j), \hat{P}_2^t(u_j)], \min[\hat{P}_1^i(u_j), \hat{P}_2^i(u_j)], \min[\hat{P}_1^f(u_j), \hat{P}_2^f(u_j)] | u_j \in \mathcal{U}\}$.
- iii. Intersection $N_1 \cap N_2 = \{u_j, \min[\hat{P}_1^t(u_j), \hat{P}_2^t(u_j)], \max[\hat{P}_1^i(u_j), \hat{P}_2^i(u_j)], \max[\hat{P}_1^f(u_j), \hat{P}_2^f(u_j)] | u_j \in \mathcal{U}\}$.
- iv. Subset $N_1 \subseteq N_2$ if $\hat{P}_1^t(u_j) \leq \hat{P}_2^t(u_j)$, $\hat{P}_1^i(u_j) \geq \hat{P}_2^i(u_j)$, $\hat{P}_1^f(u_j) \geq \hat{P}_2^f(u_j)$.

Definition2.7. A pair $(\mathcal{F}, \bar{A} \subseteq \mathcal{E})$ called SSs across the nonempty universe of discourse \mathcal{U} if $\mathcal{F}: \bar{A} \subseteq \mathcal{E} \rightarrow P(\mathcal{U})$, like $P(\mathcal{U})$ specify the power group of \mathcal{U} .

Definition3.1: $N = \{v_j, \hat{P}^t(v_j), \hat{P}^i(v_j), \hat{P}^f(v_j) | v_j \in V\}$ named NS on the universal set V [24].

Assume that $N = \hat{P}^t(v_j), \hat{P}^i(v_j), \hat{P}^f(v_j): V \rightarrow [0,1]$ and $\hat{P}^t(v_j), \hat{P}^i(v_j), \hat{P}^f(v_j) \in [0,1]$.

Definition3.2: $N_{\mathcal{Q}} = \{v_j, \hat{P}_{\mathcal{Q}}^t(v, q), \hat{P}_{\mathcal{Q}}^i(v, q), \hat{P}_{\mathcal{Q}}^f(v, q) | (v, q) \in V \times \mathcal{Q}\}$ known as Q-NS on $Q \times V$.

Let $N_{\mathcal{Q}} = \hat{P}_{\mathcal{Q}}^t(v, q), \hat{P}_{\mathcal{Q}}^i(v, q), \hat{P}_{\mathcal{Q}}^f(v, q): V \rightarrow [0,1]$ and $\hat{P}_{\mathcal{Q}}^t(v, q), \hat{P}_{\mathcal{Q}}^i(v, q), \hat{P}_{\mathcal{Q}}^f(v, q) \in [0,1]$.

Definition3.3: $IVN_{\mathcal{Q}} = \{e \in \bar{A}, < \hat{P}_{\mathcal{Q}}^t(v, q)(e), \hat{P}_{\mathcal{Q}}^i(v, q)(e), \hat{P}_{\mathcal{Q}}^f(v, q)(e) > | (v, q) \in V \times \mathcal{Q}\}$

Now

$$\begin{aligned} \hat{P}_{\mathcal{Q}_A}^t(v, Q)(e) &= [\hat{P}_{\mathcal{Q}_A}^{t,l}(v, q)\{e\}, \hat{P}_{\mathcal{Q}_A}^{t,u}(v, q)(e)] \\ \hat{P}_{\mathcal{Q}_A}^i(v, q)\{e\} &= [\hat{P}_{\mathcal{Q}_A}^{i,l}(v, q)(e), \hat{P}_{\mathcal{Q}_A}^{i,u}(v, q)(e)] \\ \hat{P}_{\mathcal{Q}_A}^f(v, q)(e) &= [\hat{P}_{\mathcal{Q}_A}^{f,l}(v, q)(e), \hat{P}_{\mathcal{Q}_A}^{f,u}(v, q)\{e\}] \end{aligned}$$

named IV-Q-NS on $Q \times V$. Assume $\hat{P}_{\mathcal{Q}}^t(v, q), \hat{P}_{\mathcal{Q}}^i(v, q), \hat{P}_{\mathcal{Q}}^f(v, q): V \rightarrow [0,1]$ and $\hat{P}_{\mathcal{Q}}^t(v, q), \hat{P}_{\mathcal{Q}}^i(v, q), \hat{P}_{\mathcal{Q}}^f(v, q) \in [0,1]$.

Sample3.4: Assume that $\mathfrak{F}_{\mathcal{Q}_A} =$

$$\begin{aligned} &\{(e_{12} \frac{\langle [0.2,0.8], [0.1,0.7], [0.4,0.8] \rangle}{(v_1, cb_1)}, \frac{\langle [0.1,0.4], [0.5,0.8], [0.7,0.8] \rangle}{(v_1, cb_2)}, \frac{\langle [0.3,0.6], [0.2,0.7], [0.5,0.8] \rangle}{(v_2, cb_1)}, \frac{\langle [0.4,0.6], [0.2,0.9], [0.5,0.7] \rangle}{(v_2, cb_2)}, \\ &\quad \frac{\langle [0.1,0.5], [0.3,0.7], [0.2,0.8] \rangle}{(v_3, cb_1)}, \frac{\langle [0.4,0.8], [0.4,0.6], [0.2,0.8] \rangle}{(v_3, cb)}\} \\ &(e_{22} \frac{\langle [0.1,0.8], [0.5,0.7], [0.3,0.4] \rangle}{(v_1, q_1)}, \frac{\langle [0.1,0.8], [0.4,0.7], [0.2,0.6] \rangle}{(v_1, q_2)}, \frac{\langle [0.5,0.8], [0.4,0.9], [0.2,0.7] \rangle}{(v_2, cb_1)}, \frac{\langle [0.1,0.2], [0.2,0.5], [0.4,0.7] \rangle}{(v_2, cb_2)}, \\ &\quad \frac{\langle [0.1,0.4], [0.2,0.5], [0.3,0.7] \rangle}{(v_1, q_1)}, \frac{\langle [0.1,0.6], [0.4,0.5], [0.5,0.7] \rangle}{(v_3, q_2)}) \\ &(e_{32} \frac{\langle [0.7,0.9], [0.2,0.8], [0.3,0.6] \rangle}{(v_1, q_1)}, \frac{\langle [0.4,0.7], [0.2,0.5], [0.1,0.7] \rangle}{(v_1, q_2)}, \frac{\langle [0.1,0.8], [0.1,0.4], [0.3,0.6] \rangle}{(v_2, q_1)}, \frac{\langle [0.5,0.6], [0.3,0.6], [0.2,0.7] \rangle}{(v_2, q_2)}, \\ &\quad \frac{\langle [0.4,0.6], [0.2,0.7], [0.3,0.6] \rangle}{(v_3, q_1)}, \frac{\langle [0.4,0.8], [0.8,0.9], [0.3,0.7] \rangle}{(v_3, q_2)}) \} \end{aligned}$$

An IV-Q-NSs in Form of Matrix

To establish the algebraic capability with a matrix system.

Definition4.1: Like $\hat{P}_{\mathcal{Q}_A} = \{e \in \bar{A} < \hat{P}_{\mathcal{Q}}^t(\hat{v}, \hat{q})(e) > | (\hat{v}, \hat{q}) \in V \times \mathcal{Q}\} \in IV - Q -NSS(V)$.

$$[\hat{P}_{\bar{A}}]_{m \times n} = \begin{bmatrix} & \backslash & e_1 & e_1 \dots & e_m \\ (\hat{v}_1, \hat{q}_1) & \hat{P}_{\bar{A}_{1,1}} & \hat{P}_{\bar{A}_{1,2}} & \dots & \hat{P}_{\bar{A}_{1,j}} \\ (\hat{v}_2, \hat{q}_2) & \hat{P}_{\bar{A}_{2,1}} & \hat{P}_{\bar{A}_{2,2}} & \dots & \hat{P}_{\bar{A}_{2,j}} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ (\hat{v}_n, \hat{q}_j) & \hat{P}_{\bar{A}_{i,1}} & \hat{P}_{\bar{A}_{i,2}} & \dots & \hat{P}_{\bar{A}_{i,j}} \end{bmatrix}, \quad i = 1, 2, 3, \dots, n \text{ is Row counts and } j = 1, 2, 3, \dots, m \text{ is}$$

Column counts.

Sample4.2: Let the values are offered in the sample 2.4 is specified:

Definition4.2: Assume that $[\hat{P}_{\bar{A}_{i,j}}]_{m \times n}$ and $[\hat{P}_{\bar{B}_{i,j}}]_{m \times n}$ be two IV-Q-NS matrix, here $[\hat{P}_{\bar{A}_{i,j}}]_{m \times n} =$

$$\left\langle \left[\hat{P}_{\bar{A}_{i,j}}^{t,l}, \hat{P}_{\bar{A}_{i,j}}^{t,u} \right], \left[\hat{P}_{\bar{A}_{i,j}}^{i,l}, \hat{P}_{\bar{A}_{i,j}}^{i,u} \right], \left[\hat{P}_{\bar{A}_{i,j}}^{f,l}, \hat{P}_{\bar{A}_{i,j}}^{f,u} \right] \right\rangle_{m \times n} \quad \text{and} \quad [\hat{P}_{\bar{B}_{i,j}}]_{m \times n} =$$

$$\left\langle \left[\hat{P}_{\bar{B}_{i,j}}^{t,l}, \hat{P}_{\bar{B}_{i,j}}^{t,u} \right], \left[\hat{P}_{\bar{B}_{i,j}}^{i,l}, \hat{P}_{\bar{B}_{i,j}}^{i,u} \right], \left[\hat{P}_{\bar{B}_{i,j}}^{f,l}, \hat{P}_{\bar{B}_{i,j}}^{f,u} \right] \right\rangle_{m \times n} \quad \text{for all } i = 1, 2, 3, \dots, r, j = 1, 2, \dots, s.$$

Afterwards, utilizing resultant points:

1. $[\hat{P}_{\bar{A}_{i,j}}]_{m \times n}$ is named zero-IV-Q-NS Matrix if $[\hat{P}_{\bar{A}_{i,j}}]_{m \times n} = \langle [0,0], [1,1], [1,1] \rangle_{m \times n}$.
2. $[\hat{P}_{\bar{A}_{i,j}}]_{m \times n}$ is total-IV-Q-NS Matrix if $[\hat{P}_{\bar{A}_{i,j}}]_{m \times n} = \langle [1,1], [0,0], [0,0] \rangle_{m \times n}$.
3. An IV-Q-NSM $[\hat{P}_{\bar{A}_{i,j}}]_{m \times n}$ is IV-Q-NS-submatrix $[\hat{P}_{\bar{A}_{i,j}}]_{m \times n}$ and depicted as $[\hat{P}_{\bar{A}_{i,j}}]_{m \times n} \subseteq [\hat{P}_{\bar{A}_{i,j}}]_{m \times n}$ if the degrees: $\hat{P}_{\bar{A}_{i,j}}^{t,l} \leq \hat{P}_{\bar{B}_{i,j}}^{t,l}, \hat{P}_{\bar{A}_{i,j}}^{t,u} \leq \hat{P}_{\bar{B}_{i,j}}^{t,u}, \hat{P}_{\bar{A}_{i,j}}^{i,l} \geq \hat{P}_{\bar{B}_{i,j}}^{i,l}, \hat{P}_{\bar{A}_{i,j}}^{i,u} \geq \hat{P}_{\bar{B}_{i,j}}^{i,u}$ and $\hat{P}_{\bar{A}_{i,j}}^{f,l} \geq \hat{P}_{\bar{B}_{i,j}}^{f,l}, \hat{P}_{\bar{A}_{i,j}}^{f,u} \geq \hat{P}_{\bar{B}_{i,j}}^{f,u}$.
4. A square IV-Q-NS Matrix $[\hat{P}_{\bar{A}_{i,j}}]_{m \times n}$ has a transpose to exchange row and column of $[\hat{P}_{\bar{A}_{i,j}}]_{m \times n}$ and it is specified as $[\hat{P}_{\bar{A}_{i,j}}]_{m \times n}^t$ Let

$$[\hat{P}_{\bar{A}_{i,j}}]_{m \times n}^t = \left\langle \left[\hat{P}_{\bar{A}_{i,j}}^{t,l}, \hat{P}_{\bar{A}_{i,j}}^{t,u} \right], \left[\hat{P}_{\bar{A}_{i,j}}^{i,l}, \hat{P}_{\bar{A}_{i,j}}^{i,u} \right], \left[\hat{P}_{\bar{A}_{i,j}}^{f,l}, \hat{P}_{\bar{A}_{i,j}}^{f,u} \right] \right\rangle_{m \times n}^t$$

$$= \left\langle \left[\hat{P}_{\bar{A}_{i,j}}^{t,l}, \hat{P}_{\bar{A}_{i,j}}^{t,u} \right], \left[\hat{P}_{\bar{A}_{i,j}}^{i,l}, \hat{P}_{\bar{A}_{i,j}}^{i,u} \right], \left[\hat{P}_{\bar{A}_{i,j}}^{f,l}, \hat{P}_{\bar{A}_{i,j}}^{f,u} \right] \right\rangle_{m \times n}^t$$

5. If $\hat{P}_{\bar{A}_{i,j}} = \hat{P}_{\bar{A}_{i,j}}$ which means square IV-Q-NS Matrix $[\hat{P}_{\bar{A}_{i,j}}]_{m \times n}$ is signified by symmetric square IV-Q-NS Matrix.

$$[\hat{P}_{\bar{A}_{i,j}}]_{m \times n} = [\hat{P}_{\bar{A}_{i,j}}]_{m \times n}^{ts}$$

Definition4.4: Assume that $[\hat{P}_{\bar{A}_{i,j}}]_{m \times n}$ and $[\hat{P}_{\bar{B}_{i,j}}]_{m \times n}$ be dual IV-Q-NS Matrix, here $[\hat{P}_{\bar{A}_{i,j}}]_{m \times n} =$

$$\left\langle \left[\hat{P}_{\bar{A}_{i,j}}^{t,l}, \hat{P}_{\bar{A}_{i,j}}^{t,u} \right], \left[\hat{P}_{\bar{A}_{i,j}}^{i,l}, \hat{P}_{\bar{A}_{i,j}}^{i,u} \right], \left[\hat{P}_{\bar{A}_{i,j}}^{f,l}, \hat{P}_{\bar{A}_{i,j}}^{f,u} \right] \right\rangle_{m \times n}, \quad [\hat{P}_{\bar{B}_{i,j}}]_{m \times n} =$$

$$\left\langle \left[\hat{P}_{\bar{B}_{i,j}}^{t,l}, \hat{P}_{\bar{B}_{i,j}}^{t,u} \right], \left[\hat{P}_{\bar{B}_{i,j}}^{i,l}, \hat{P}_{\bar{B}_{i,j}}^{i,u} \right], \left[\hat{P}_{\bar{B}_{i,j}}^{f,l}, \hat{P}_{\bar{B}_{i,j}}^{f,u} \right] \right\rangle_{m \times n} \quad \text{and} \quad [\hat{P}_{\bar{C}_{i,j}}]_{m \times n} =$$

$$\left\langle \left[\hat{P}_{\bar{C}_{i,j}}^{t,l}, \hat{P}_{\bar{C}_{i,j}}^{t,u} \right], \left[\hat{P}_{\bar{C}_{i,j}}^{i,l}, \hat{P}_{\bar{C}_{i,j}}^{i,u} \right], \left[\hat{P}_{\bar{C}_{i,j}}^{f,l}, \hat{P}_{\bar{C}_{i,j}}^{f,u} \right] \right\rangle_{m \times n}$$

The algebraic operations of IV-Q-NS Matrix are explained:

Addition: This operation utilizes dual IV-Q-NS Matrix:

$$[\hat{P}_{\bar{A}_{i,j}}]_{m \times n} + [\hat{P}_{\bar{B}_{i,j}}]_{m \times n} = [\hat{P}_{\bar{C}_{i,j}}]_{m \times n} = \left\langle \left[\hat{P}_{\bar{C}_{i,j}}^{t,l}, \hat{P}_{\bar{C}_{i,j}}^{t,u} \right], \left[\hat{P}_{\bar{C}_{i,j}}^{i,l}, \hat{P}_{\bar{C}_{i,j}}^{i,u} \right], \left[\hat{P}_{\bar{C}_{i,j}}^{f,l}, \hat{P}_{\bar{C}_{i,j}}^{f,u} \right] \right\rangle_{m \times n}$$

Now

$$\hat{P}_{\bar{C}_{i,j}}^{t,l} = \hat{P}_{\bar{A}_{i,j}}^{t,l} + \hat{P}_{\bar{B}_{i,j}}^{t,l} - \hat{P}_{\bar{A}_{i,j}}^{t,l} \times \hat{P}_{\bar{B}_{i,j}}^{t,l}, \quad \hat{P}_{\bar{C}_{i,j}}^{t,u} = \hat{P}_{\bar{A}_{i,j}}^{t,u} + \hat{P}_{\bar{B}_{i,j}}^{t,u} - \hat{P}_{\bar{A}_{i,j}}^{t,u} \times \hat{P}_{\bar{B}_{i,j}}^{t,u},$$

$$\hat{P}_{\bar{C}_{i,j}}^{i,l} = \hat{P}_{\bar{A}_{i,j}}^{i,l} \times \hat{P}_{\bar{B}_{i,j}}^{i,l}, \hat{P}_{\bar{C}_{i,j}}^{i,u} = \hat{P}_{\bar{A}_{i,j}}^{i,u} \times \hat{P}_{\bar{B}_{i,j}}^{i,u}$$

$$\hat{P}_{\bar{C}_{i,j}}^{f,l} = \hat{P}_{\bar{A}_{i,j}}^{f,l} \times \hat{P}_{\bar{B}_{i,j}}^{f,l}, \hat{P}_{\bar{C}_{i,j}}^{f,u} = \hat{P}_{\bar{A}_{i,j}}^{f,u} \times \hat{P}_{\bar{B}_{i,j}}^{f,u}$$

Subtraction: It employs in dual IV-Q-NS Matrix:

$$[\hat{P}_{\bar{A}_{i,j}}]_{m \times n} - [\hat{P}_{\bar{B}_{i,j}}]_{m \times n} = [\hat{P}_{\bar{C}_{i,j}}]_{m \times n} = \left[\left\langle [\hat{P}_{\bar{C}_{i,j}}^{t,l}, \hat{P}_{\bar{C}_{i,j}}^{t,u}], [\hat{P}_{\bar{C}_{i,j}}^{i,l}, \hat{P}_{\bar{C}_{i,j}}^{i,u}], [\hat{P}_{\bar{C}_{i,j}}^{f,l}, \hat{P}_{\bar{C}_{i,j}}^{f,u}] \right\rangle \right]_{m \times n}$$

Here

$$\hat{P}_{\bar{C}_{i,j}}^{t,l} = \left| \hat{P}_{\bar{A}_{i,j}}^{t,l} - \hat{P}_{\bar{B}_{i,j}}^{t,l} \right|, \hat{P}_{\bar{C}_{i,j}}^{t,u} = \left| \hat{P}_{\bar{A}_{i,j}}^{t,u} - \hat{P}_{\bar{B}_{i,j}}^{t,u} \right|,$$

$$\hat{P}_{\bar{C}_{i,j}}^{i,l} = \max \left(\hat{P}_{\bar{A}_{i,j}}^{i,l}, \hat{P}_{\bar{B}_{i,j}}^{i,l} \right), \hat{P}_{\bar{C}_{i,j}}^{i,u} = \max \left(\hat{P}_{\bar{A}_{i,j}}^{i,u}, \hat{P}_{\bar{B}_{i,j}}^{i,u} \right)$$

$$\hat{P}_{\bar{C}_{i,j}}^{f,l} = \left| \hat{P}_{\bar{A}_{i,j}}^{f,l} - \hat{P}_{\bar{B}_{i,j}}^{f,l} \right|, \hat{P}_{\bar{C}_{i,j}}^{f,u} = \left| \hat{P}_{\bar{A}_{i,j}}^{f,u} - \hat{P}_{\bar{B}_{i,j}}^{f,u} \right|$$

Multiplication: It leverages dual IV-Q-NS Matrix:

$$[\hat{P}_{\bar{A}_{i,j}}]_{m \times n} \times [\hat{P}_{\bar{B}_{i,j}}]_{m \times n} = [\hat{P}_{\bar{C}_{i,j}}]_{m \times n} = \left[\left\langle [\hat{P}_{\bar{C}_{i,j}}^{t,l}, \hat{P}_{\bar{C}_{i,j}}^{t,u}], [\hat{P}_{\bar{C}_{i,j}}^{i,l}, \hat{P}_{\bar{C}_{i,j}}^{i,u}], [\hat{P}_{\bar{C}_{i,j}}^{f,l}, \hat{P}_{\bar{C}_{i,j}}^{f,u}] \right\rangle \right]_{m \times n}$$

Here

$$\hat{P}_{\bar{C}_{i,j}}^{t,l} = \hat{P}_{\bar{A}_{i,j}}^{t,l} \times \hat{P}_{\bar{B}_{i,j}}^{t,l}, \hat{P}_{\bar{C}_{i,j}}^{t,u} = \hat{P}_{\bar{A}_{i,j}}^{t,u} \times \hat{P}_{\bar{B}_{i,j}}^{t,u}$$

$$\hat{P}_{\bar{C}_{i,j}}^{i,l} = \hat{P}_{\bar{A}_{i,j}}^{i,l} + \hat{P}_{\bar{B}_{i,j}}^{i,l} - \hat{P}_{\bar{A}_{i,j}}^{i,l} \times \hat{P}_{\bar{B}_{i,j}}^{i,l}, \hat{P}_{\bar{C}_{i,j}}^{i,u} = \hat{P}_{\bar{A}_{i,j}}^{i,u} + \hat{P}_{\bar{B}_{i,j}}^{i,u} - \hat{P}_{\bar{A}_{i,j}}^{i,u} \times \hat{P}_{\bar{B}_{i,j}}^{i,u}$$

$$\hat{P}_{\bar{C}_{i,j}}^{f,l} = \hat{P}_{\bar{A}_{i,j}}^{f,l} + \hat{P}_{\bar{B}_{i,j}}^{f,l} - \hat{P}_{\bar{A}_{i,j}}^{f,l} \times \hat{P}_{\bar{B}_{i,j}}^{f,l}, \hat{P}_{\bar{C}_{i,j}}^{f,u} = \hat{P}_{\bar{A}_{i,j}}^{f,u} + \hat{P}_{\bar{B}_{i,j}}^{f,u} - \hat{P}_{\bar{A}_{i,j}}^{f,u} \times \hat{P}_{\bar{B}_{i,j}}^{f,u}$$

Scalar Multiplication: This operation is used for dual IV-Q-NS Matrix:

$$K[\hat{P}_{\bar{A}_{i,j}}]_{m \times n} = \left[\left\langle [K\hat{P}_{\bar{A}_{i,j}}^{t,l}, K\hat{P}_{\bar{A}_{i,j}}^{t,u}], [K\hat{P}_{\bar{A}_{i,j}}^{i,l}, K\hat{P}_{\bar{A}_{i,j}}^{i,u}], [K\hat{P}_{\bar{A}_{i,j}}^{f,l}, K\hat{P}_{\bar{A}_{i,j}}^{f,u}] \right\rangle \right]_{m \times n}$$

Here $K \in R$.

Definition4.5: Assume that $[\hat{P}_{\bar{A}_{i,j}}]_{m \times n}$ and $[\hat{P}_{\bar{B}_{i,j}}]_{m \times n}$ be dual IV-Q-NS Matrix, now $[\hat{P}_{\bar{A}_{i,j}}]_{m \times n} =$

$$\left[\left\langle [\hat{P}_{\bar{A}_{i,j}}^{t,l}, \hat{P}_{\bar{A}_{i,j}}^{t,u}], [\hat{P}_{\bar{A}_{i,j}}^{i,l}, \hat{P}_{\bar{A}_{i,j}}^{i,u}], [\hat{P}_{\bar{A}_{i,j}}^{f,l}, \hat{P}_{\bar{A}_{i,j}}^{f,u}] \right\rangle \right]_{m \times n}, [\hat{P}_{\bar{B}_{i,j}}]_{m \times n} =$$

$$\left[\left\langle [\hat{P}_{\bar{B}_{i,j}}^{t,l}, \hat{P}_{\bar{B}_{i,j}}^{t,u}], [\hat{P}_{\bar{B}_{i,j}}^{i,l}, \hat{P}_{\bar{B}_{i,j}}^{i,u}], [\hat{P}_{\bar{B}_{i,j}}^{f,l}, \hat{P}_{\bar{B}_{i,j}}^{f,u}] \right\rangle \right]_{m \times n} \text{ and } [\hat{P}_{\bar{C}_{i,j}}]_{m \times n} =$$

$$\left[\left\langle [\hat{P}_{\bar{C}_{i,j}}^{t,l}, \hat{P}_{\bar{C}_{i,j}}^{t,u}], [\hat{P}_{\bar{C}_{i,j}}^{i,l}, \hat{P}_{\bar{C}_{i,j}}^{i,u}], [\hat{P}_{\bar{C}_{i,j}}^{f,l}, \hat{P}_{\bar{C}_{i,j}}^{f,u}] \right\rangle \right]_{m \times n} \text{ for all } i = 1, 2, \dots, r, j = 1, 2, \dots, s.$$

Sample1. Let $[\hat{P}_{\bar{A}_{i,j}}]_{m \times n} \leq [\hat{P}_{\bar{B}_{i,j}}]_{m \times n}$ then $\hat{P}_{\bar{A}_{i,j}}^{t,l} \leq \hat{P}_{\bar{B}_{i,j}}^{t,l}, \hat{P}_{\bar{A}_{i,j}}^{t,u} \leq \hat{P}_{\bar{B}_{i,j}}^{t,u}, \hat{P}_{\bar{A}_{i,j}}^{i,l} \geq \hat{P}_{\bar{B}_{i,j}}^{i,l}, \hat{P}_{\bar{A}_{i,j}}^{i,u} \geq \hat{P}_{\bar{B}_{i,j}}^{i,u}$ and $\hat{P}_{\bar{A}_{i,j}}^{f,l} \geq \hat{P}_{\bar{B}_{i,j}}^{f,l}, \hat{P}_{\bar{A}_{i,j}}^{f,u} \geq \hat{P}_{\bar{B}_{i,j}}^{f,u}$.

Now for $\alpha \in R$, afterward

$$\alpha \hat{P}_{\bar{A}_{i,j}}^{t,l} \leq \alpha \hat{P}_{\bar{B}_{i,j}}^{t,l}, \alpha \hat{P}_{\bar{A}_{i,j}}^{t,u} \leq \alpha \hat{P}_{\bar{B}_{i,j}}^{t,u}, \alpha \hat{P}_{\bar{A}_{i,j}}^{i,l} \geq \alpha \hat{P}_{\bar{B}_{i,j}}^{i,l}, \alpha \hat{P}_{\bar{A}_{i,j}}^{i,u} \geq \alpha \hat{P}_{\bar{B}_{i,j}}^{i,u} \text{ and } \alpha \hat{P}_{\bar{A}_{i,j}}^{f,l} \geq \alpha \hat{P}_{\bar{B}_{i,j}}^{f,l}, \alpha \hat{P}_{\bar{A}_{i,j}}^{f,u} \geq \alpha \hat{P}_{\bar{B}_{i,j}}^{f,u}$$

Subsequently $\alpha[\hat{P}_{\bar{A}_{i,j}}]_{m \times n} \leq \alpha[\hat{P}_{\bar{B}_{i,j}}]_{m \times n}$

Sample2. In $([\alpha \hat{P}_{\bar{A}_{i,j}}]_{m \times n})^t \in \text{IV-Q-NS Matrix}$, then

$$\begin{aligned}
 ([\alpha \hat{P}_{\bar{A}_{i,j}}]_{m \times n})^t &= \left[\left\langle \left[\alpha \hat{P}_{\bar{A}_{i,j}}^{t,l}, \alpha \hat{P}_{\bar{A}_{i,j}}^{t,u} \right], \left[\alpha \hat{P}_{\bar{A}_{i,j}}^{i,l}, \alpha \hat{P}_{\bar{A}_{i,j}}^{i,u} \right], \left[\alpha \hat{P}_{\bar{A}_{i,j}}^{f,l}, \alpha \hat{P}_{\bar{A}_{i,j}}^{f,u} \right] \right\rangle \right]_{m \times n} \\
 &= \alpha \left(\left\langle \left[\hat{P}_{\bar{A}_{i,j}}^{t,l}, \hat{P}_{\bar{A}_{i,j}}^{t,u} \right], \left[\hat{P}_{\bar{A}_{i,j}}^{i,l}, \hat{P}_{\bar{A}_{i,j}}^{i,u} \right], \left[\hat{P}_{\bar{A}_{i,j}}^{f,l}, \hat{P}_{\bar{A}_{i,j}}^{f,u} \right] \right\rangle \right) \\
 &= \alpha ([\alpha \hat{P}_{\bar{A}_{i,j}}]_{m \times n})^t
 \end{aligned}$$

4. Experimental Validation

A. Dataset Details

The experimental study of SOIFET-IVQNSM technique is examined under the Financial Sentiment Analysis database [25]. The sentiment analysis outcomes signify that out of 5,842 text samples, the majority falling under the neutral class, with 3,130 instances. This is succeeded by 1,852 positive text instances, exposing a substantial portion of the content that reflects a positive sentiment. At last, 860 negative text instances depict the smallest group. Generally, the data recommends that most of the text is both neutral and positive, with fewer samples of negative sentiment. Table 1 represents the sample texts.

Table 1: Sample Texts

Sentiment	Sample Text
Positive	“However, sales returned to growth in April-June 2010, CEO Pekka Eloholma said.”
Negative	“US sanctions put Gazprom-Shell alliance plans in jeopardy”
Neutral	“Viking Line has canceled some services.”

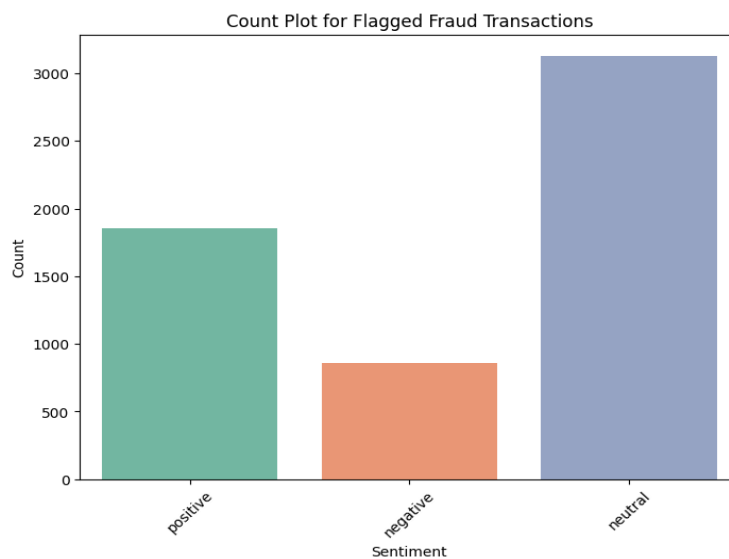


Figure 2. Count plot for flagged fraud transactions

Fig. 2 portrays the count plot for flagged fraud transactions of SOIFET-IVQNSM technique under 3 sentiments, like positive, negative, and neutral. The figure specifies that the neutral sentiment class has the maximum count, signifying that most flagged transactions are designated in a neutral tone. The positive sentiment has somewhat highest count, recommending a substantial part of flagged fraud-related interactions. Simultaneously, the negative sentiment has the minimum count that is typically expected in fraud-related discussions but appears less prevalent here.

B. Result Analysis

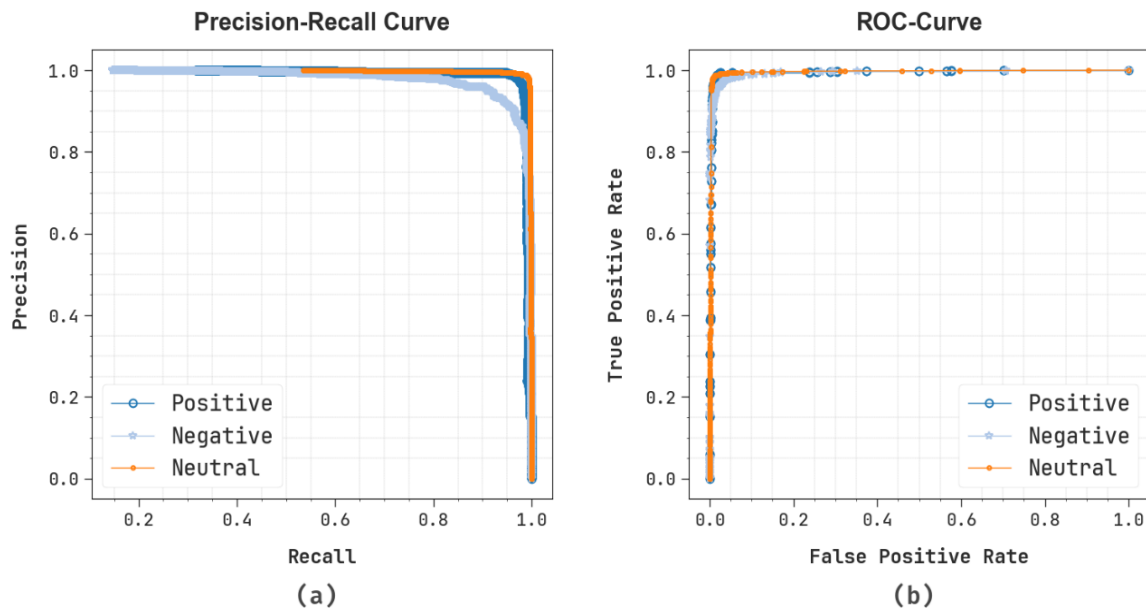


Figure 3. Classifier outcome of (a) PR and (b) ROC curves

Fig. 3 signifies the classifier solution of SOIFET-IVQNSM approach. Fig. 3a shows the PR analysis, depicting a greater outcome through each class. While, Fig. 3b demonstrates the study of ROC, displaying capable outcomes with superior values of ROC for distinct class labels.

Table 2 denote the average value of SOIFET-IVQNSM method under the training phase (TRPHE) of 70%. The outcomes suggest that the SOIFET-IVQNSM method appropriately identified positive, negative and neutral samples. Although, the proposed SOIFET-IVQNSM model reaches an average $accu_y$, $prec_n$, $reca_l$, $F_{Measure}$, and $G_{Measure}$ of 98.26%, 96.51%, 96.07%, 96.28%, and 96.29%, correspondingly.

Table 2: Average values of the SOIFET-IVQNSM model under 70% TRPHE

Class	$Accu_y$	$Prec_n$	$Reca_l$	$F_{Measure}$	$G_{Measure}$
TRPHE (70%)					
Positive	98.29	96.52	98.03	97.27	97.27
Negative	97.90	94.30	91.53	92.89	92.90
Neutral	98.58	98.73	98.64	98.68	98.68
Average	98.26	96.51	96.07	96.28	96.29

Table 3 denote the average value of the SOIFET-IVQNSM methodology under testing phase (TSPHE) of 30%. In this stage, the proposed SOIFET-IVQNSM approach gains average $accu_y$ of 98.71%, $prec_n$ of 97.38%, $reca_l$ of 97.03%, $F_{Measure}$ of 97.20%, and $G_{Measure}$ of 97.20%.

Table 3: Average values of SOIFET-IVQNSM model under 30%TRPHE

Class	$Accu_y$	$Prec_n$	$Reca_l$	$F_{Measure}$	$G_{Measure}$
TSPHE (30%)					
Positive	98.57	96.95	98.79	97.87	97.87
Negative	98.52	95.83	93.50	94.65	94.66
Neutral	99.03	99.35	98.81	99.08	99.08
Average	98.71	97.38	97.03	97.20	97.20

C. Comparative Discussion

In Table 4, the comparative study of the SOIFET-IVQNSM approach with present approaches are revealed [26-28]. The proposed SOIFET-IVQNSM method has attained maximal result under several metrics.

The Fig. 4a indicates $accu_y$ and $prec_n$ performance of SOIFET-IVQNSM technique. Under $accu_y$, the SOIFET-IVQNSM methodology has got superior $accu_y$ of 98.71% while the present models like FinBERT, BART-Large, BiGRU, BiLSTM-Att, FastText-GB, GloVe-RF, and LFBP have attained minimal $accu_y$ of 90.60%, 97.40%, 97.06%, 95.93%, 85.27%, 97.41%, and 96.79%, correspondingly. Likewise, depend on $prec_n$, the SOIFET-IVQNSM model has got superior $prec_n$ of 97.38% whereas the present approaches namely FinBERT, BART-Large, BiGRU, BiLSTM-Att, FastText-GB, GloVe-RF, and LFBP have gained smaller $prec_n$ of 93.26%, 95.01%, 92.03%, 89.59%, 93.56%, 91.92%, and 95.91%, correspondingly.

Now, Fig. 4b reveals the $reca_l$ and $F_{Measure}$ of SOIFET-IVQNSM approach. Depend on $reca_l$, the SOIFET-IVQNSM method has got maximal $reca_l$ of 97.03% whereas the present models like FinBERT, BART-Large, BiGRU, BiLSTM-Att, FastText-GB, GloVe-RF, and LFBP have gained smaller $reca_l$ of 87.48%, 89.44%, 89.84%, 89.33%, 87.47%, 85.74%, and 89.72%, correspondingly. Eventualy, depend on $F_{Measure}$, the CMSGPTNLP-MAH model has got greater $F_{Measure}$ of 97.20% although the ResNet+Transformer/LSTM, CLIP+GPT, BERT, Vision Transformer, BioBERT, ClinicalBERT, and BiLSTM-BERT methodologies have reached smaller $F_{Measure}$ of 88.71%, 91.37%, 90.88%, 91.07%, 90.05%, 96.04%, and 89.86%, correspondingly.

Table 4: Comparative analysis of SOIFET-IVQNSM with recent techniques

Models	$Accu_y$	$Prec_n$	$Reca_l$	$F_{Measure}$
FinBERT	90.60	93.26	87.48	88.71
BART-Large	97.40	95.01	89.44	91.37
BiGRU	97.06	92.03	89.84	90.88
BiLSTM-Att	95.93	89.59	89.33	91.07
FastText-GB	85.27	93.56	87.47	90.05
GloVe-RF	97.41	91.92	85.74	96.04
LFBP	96.79	95.91	89.72	89.86
SOIFET-IVQNSM	98.71	97.38	97.03	97.20

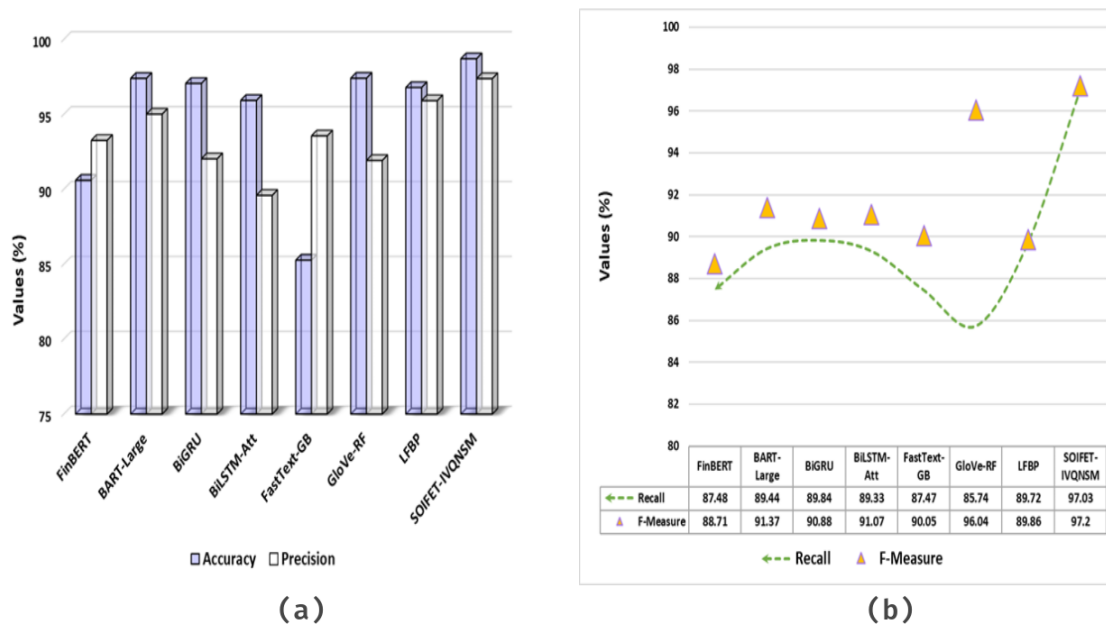


Figure 4. Average values of SOIFET-IVQNSM model (a) $Accu_y$ and $Prec_n$ and (b) $Recal_l$ and $F_{Measure}$

5. Conclusion

In this article, we have developed a SOIFET-IVQNSM technique for financial SA. The objective of the work is to recommend an advanced model for recognizing semantic orientation in economic texts to improve prediction precision and financial sentiment. At the primary stage, the input text data is pre-processed utilizing various reprocessing levels such as removal of stop words, tokenization, stemming, spelling correction, and lemmatization to make it suited for additional processing. In addition, the word embedding procedure is mainly implemented by the TF-IDF method to convert economic text into an important vector representation. For classification purposes, the presented SOIFET-IVQNSM approach designs an IV-Q-NSM technique. The performance assessment of the SOIFET-IVQNSM technique is verified on the benchmark database, and the results are estimated under varied conditions. The experimental outcome emphasized the development of the SOIFET-IVQNSM technique in semantic orientation identification.

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