Applied Statistics with Single-Valued Neutrosophic Fuzzy Soft Expert Sets for Market Trend Forecasting Model

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Abstract

Applied statistics has been instrumental in predicting behaviours and future market trends. In the field of financial time series analysis, the incorporation of deep learning (DL) methods and applied statistics has made a significant contribution to the prediction model. Practitioners and researchers can extract complex features and dependencies from past financial data by leveraging neural network structures like long short-term memory (LSTM) and recurrent neural networks (RNNs). These DL approaches advance the development of predictive models prone to forecasting different financial metrics, such as asset returns, stock prices, and market volatility, with outstanding accuracy. With the combination of statistical approaches with DL techniques, researchers can leverage the power of both worlds to make more informed investment decisions and improve forecasting capabilities in volatile and dynamic financial markets. This study develops a new Applied Statistics with Single Valued Neutrosophic Fuzzy Soft Expert Sets (AS-SVNFSES) technique for Financial Time Series Forecasting. The presented AS-SVNFSES technique aims to forecast the input financial time series data. The AS-SVNFSES technique primarily applies data preprocessing using a Z-score normalization approach. For the forecasting of financial data, the AS-SVNFSES technique makes use of the SVNFSES technique. Finally, the parameter tuning of the SVNFSES technique is performed using the chimp optimization algorithm's (ChOA) design. A series of experimentations have illustrated the amended performance of the AS-SVNFSES model. The experimental value inferred that the AS-SVNFSES technique gains improved performance over other models.

Keywords: Neutrosophic Set; Financial Time Series; Chimp Optimization Algorithm; Data Preprocessing; Neutrosophic Soft Sets

1. Introduction

The finance business was involved in successfully forecasting economic time series data. Many studies have been published on ML methods, which perform moderately well compared to traditional time series predicting methods [1]. In the meantime, the extensive use of automatic electronic trading models attached to enlarging demand for advanced yields retains compelling researchers and specialists to endure functioning on executing better techniques [2]. Financial market predicting has long been a complex but fundamental task. The possibility of economic improvement over effective prediction has driven many specialists to contribute to this action. Between the numerous kinds of predicting functions in the monetary part, a vital and essential task is price forecasting the future value of an economic time series [3]. As financial markets always develop and adjust, the necessity for strong and dependable price estimates has become gradually evident. If exact, price-predicting outcomes benefit

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traders, investors, and economic organizations in building learned decisions, handling risks, and enhancing investment plans [4]. However, precisely forecasting the prices of financial time series is very challenging because of its uncertain and intricate data. The efficient market hypothesis (EMH) suggests quality prices by considering every reachable data, suggesting that the velocity at which profitable trading plans are proposed repeatedly remains consistent with price variations due to price alterations before the plan is employed [5]. At the same time, price behaviour in a productive market is like a random walk, leaving invisible patterns in the historical data [6].

The price of financial outcomes in numerous economic markets, frequently in the method of financial time-series, are general topics to difficult and dangerous factors from usual macroeconomic features to currently growing climate variations [7]. As shown by many instances of experiential study, they reveal dissimilar data features like seasonal fluctuation, long-term dependence, and cyclical variation. Furthermore, financial market modelling over equilibrium models and studies and economic market forecasts over data analysis and moulding are famous research regions [8]. Dissimilar methods like econometric, linear and non-linear time series, and artificial intelligence (AI) have been discovered over the past few periods. All techniques have exclusive expectations and are intended to take exact data features regarding data modelling viewpoints. AI techniques like support vector regression (SVR) and neural network (NN) techniques demonstrate that non-linearity in data is highly significant to the predicting and modelling of economic time series [9]. The hybrid model has been exposed to unite diverse approaches, prime to enhanced model fit and predicting accuracy [10].

This study develops a new Applied Statistics with Single Valued Neutrosophic Fuzzy Soft Expert Sets (AS-SVNFSES) technique for Financial Time Series Forecasting. The presented AS-SVNFSES technique aims to forecast the input financial time series data. The AS-SVNFSES technique primarily applies data preprocessing using a Z-score normalization approach. For the forecasting of economic data, the AS-SVNFSES technique uses the SVNFSES technique. Finally, the parameter tuning of the SVNFSES technique is performed using the Chimp optimization algorithm's (ChOA) design. The experimental values inferred that the AS-SVNFSES technique gains improved performance over other models.

2. Literature Review

Kuo and Chiu [11] developed a new forecast method using a hybrid of jellyfish and particle swarm optimizer (HJPSO) systems. This technique was planned to efficiently handle the overcoming capacity of data like financial news and official indicators while simultaneously enhancing the restrictions of the SVM. Similarly, the study integrates a rule extractor model, discarding light on the verdict guidelines characteristic in the SVM post-forecast. In [12], a stock market forecast method is offered that removes the stock drive with the COVID range. In this work, the developed model used SA to stock news headings to forecast the everyday prospect trend of stock during COVID-19. Furthermore, the model employed ML classifiers to predict the last effect of COVID-19 on a few stocks. Thakkar and Chaudhari [13] developed a data fusion-based GA model with inter-intra crossover and adaptive mutation (ICAN) for the price of stock and tendency forecast. The main goal of this method is to improve the parameters of an LSTM prediction method and pick a group of features to discover these issues of attention.

Liao et al. [14] presented a dynamic hypergraph spatio-temporal networks (DHSTN) method. This approach uses GRU to acquire the successive embedding of stock, and a dynamic hypergraph network (DHN) was projected. In DHN, initially, a new dynamic hypergraph construction unit dependent upon a graph attention network (GAN) is planned. Next, an industry association's aggregator dependent upon hypergraph is reflected in convolutional. Lastly, a multi-relation fusion unit was planned. In [15], a stock forecast technique uniting multi-view stock data features with a dynamic market correlation information (MDF-DMC) approach has been developed. The method removes the stock trend feature by joining multi-view raw data of a solitary stock with an MLP-Mixer. The enhanced transformer encoding acquires the association among the stock to be forecasted, and every nominated stock in the stock market vigorously removes the feature of the market association.

Ari and Alagoz [16] project a hyperparameter optimum genetic programming-based prediction method generation algorithm. Here, a differential evolution (DE) technique has been utilized to enhance the hyperparameter of the GpOls system. This evolution hyperparameter optimizer model will improve the data-driven forming performance of the GpOls method and permit the optimum auto-tuning of user-defined parameters. Likewise, the projected DE-based hyper-GpOls (DEHypGpOls) technique has been utilized. In [17], an adaptive experimental method decomposition on the primary data to improve method accuracy is first used. Then, the indicator of technical data is nominated over the Boruta model, improving nominated functionalities through an adaptive noise reduction method. Then, the approach utilizes SVR combined with a brainstorm optimizer algorithm (BSO) for effectual data management and predicting objective variables.

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3. The Proposed Method

In this paper, we have developed a new AS-SVNFSES model for predicting financial time series. The presented AS-SVNFSES technique aims to forecast the input financial time series data. Fig. 1 demonstrates the entire flow of the AS-SVNFSES technique.

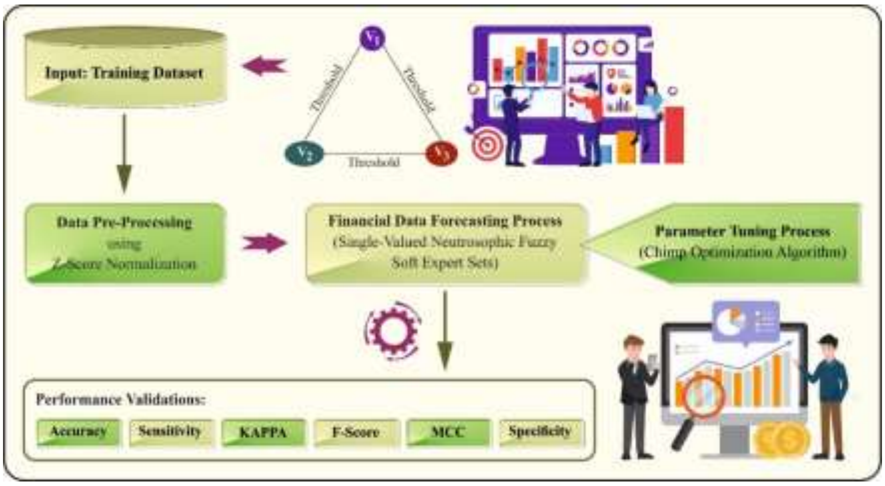

Figure 1: The overall flow of the AS-SVNFSES technique

A. Z-score Normalization

Primarily, the AS-SVNFSES technique applies data preprocessing using a Z-score normalization approach. Z-score normalization is a technique of normalization that is dependent upon the standard deviation (standard deviation) and mean (mean value) of the data [18]. This approach is precious, but the actual maximum and minimum data values will not be identified. The mathematical form will be represented below.

$$X_{new} = \frac{X - u}{o} = \frac{X - Meon(X)}{StdDev(X)} \quad (1)$$

Here, μ signifies the population's mean, σ represents the standard deviation value, X_{new} describes the novel values in the normalized outcomes, and X means the prior value.

B. Financial Data Forecasting AS-SVNFSES Model

For the forecasting of financial data, the AS-SVNFSES technique uses the SVNFSES technique. The idea of SNFSESS defines some properties, including the absolute, subset, equality, and null of SVNFES, which are discussed in this section [19].

Definition3.1. The ordered pair (H, O) indicates SNFSESS on U. When

1. The mapping H: $O \to SVNFN^U$ whereas $O \subseteq Z = M{\times}N{\times}Y$, so that for each $z \in Z$ then $z = (m{\times}n{\times}y = 0$ or $1)$

2. Now $U = \{u_1, u_2, u_3, \dots, u_s\}$, $M = \{m_1, m_2, m_3, \dots, m_s\}$, $N = \{n_1, n_2, n_3, \dots, n_s\}$ are the sets of reference, attribute, and experts correspondingly and $Y = \{0 \; and \; 1\}$.

3. A single set of neutrosophic (PIVNSS) $\mathcal{H}$ on $\widehat{U}$ is given below:

$$\mathcal{H}^{svnfses} = \{(u, \langle \ddot{\partial}^t_{\mathcal{H}}(z_i)(u_j), \ddot{\partial}^i_{\mathcal{H}}(z_i)(u_j), \ddot{\partial}^f_{\mathcal{H}}(z_i)(u_j)\rangle | u \in \widehat{U}, z \in \widehat{\mathbb{Z}}\}$$

Here $\ddot{\partial}^t_{\mathcal{H}}(z_i)(u_j), \ddot{\partial}^i_{\mathcal{H}}(z_i)(u_j),$ $an\ddot{d}$ $\partial^f_{\mathcal{H}}(z_i)(u_j)$ are the 3 SVNFSES membership functions as a solitary real amount, and $\mathcal{P}^{ivnss}$ indicates the SVNSESN degree of element $u_i \in \widehat{U}$ to $\mathcal{H}^{svnses}$ which is represented as $\mathcal{H}_O = (\mathcal{H}, O \subseteq \mathcal{Z})$

Example3.2. Please assume that the tourism corporation evaluates the collection of hotels it retains to see who is better. Now U contains three hotels, and the objects are assessed by the two experts $N = \{n_1, n_2\}$, and $M = \{m_1, m_2, m_3\}$ where $m_1 = Food\ services$ $m_2 = Staff$, $m_3 = Number\ of\ rooms$.

$$\mathcal{H}(z_1 = (m_1, n_1, 1)) = \left\{\left(\frac{u_1}{\langle 0.2, 0.5, 0.3\rangle}\right), \left(\frac{u_2}{\langle 0.3, 0.6, 0.7\rangle}\right), \left(\frac{u_3}{\langle 0.8, 0.1, 0.6\rangle}\right)\right\}.$$

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$$\mathcal{H}(z_2=(m_1,n_2,1))=\left\{\left(\frac{u_1}{\langle 0.5,0.4,0.2\rangle}\right),\left(\frac{u_2}{\langle 0.1,0.5,0.7\rangle}\right),\left(\frac{u_3}{\langle 0.2,0,0.8\rangle}\right)\right\}.$$

$$\mathcal{H}(z_3=(m_2,n_1,1))=\left\{\left(\frac{u_1}{\langle 0.7,0.6,0.2\rangle}\right),\left(\frac{u_2}{\langle 0.6,0.3,0.1\rangle}\right),\left(\frac{u_3}{\langle 0.2,0.3,0.5\rangle}\right)\right\}.$$

$$\mathcal{H}(z_4=(m_2,n_2,1))=\left\{\left(\frac{u_1}{\langle 0.5,0.3,0.2\rangle}\right),\left(\frac{u_2}{\langle 0.6,0.4,0.7\rangle}\right),\left(\frac{u_3}{\langle 0.5,0.4,0.3\rangle}\right)\right\}.$$

$$\mathcal{H}(z_5=(m_3,n_1,1))=\left\{\left(\frac{u_1}{\langle 0.7,0.5,0.9\rangle}\right),\left(\frac{u_2}{\langle 0.2,0.6,0.7\rangle}\right),\left(\frac{u_3}{\langle 0.3,0.4,0.6\rangle}\right)\right\}.$$

$$\mathcal{H}(z_6=(m_3,n_2,1))=\left\{\left(\frac{u_1}{\langle 0.2,0.5,0.3\rangle}\right),\left(\frac{u_2}{\langle 0.3,0.6,0.7\rangle}\right),\left(\frac{u_3}{\langle 0.8,0.1,0.6\rangle}\right)\right\}.$$

$$\mathcal{H}(z_7=(m_1,n_1,0))=\left\{\left(\frac{u_1}{\langle 0.2,0.5,0.3\rangle}\right),\left(\frac{u_2}{\langle 0.3,0.6,0.7\rangle}\right),\left(\frac{u_3}{\langle 0.8,0.1,0.6\rangle}\right)\right\}.$$

$$\mathcal{H}(z_8=(m_1,n_2,0))=\left\{\left(\frac{u_1}{\langle 0.4,0.6,0.2\rangle}\right),\left(\frac{u_2}{\langle 0.7,0.2,0.5\rangle}\right),\left(\frac{u_3}{\langle 0.1,0.1,0.3\rangle}\right)\right\}.$$

$$\mathcal{H}(z_9=(m_2,n_1,0))=\left\{\left(\frac{u_1}{\langle 0.4,0.5,0.8\rangle}\right),\left(\frac{u_2}{\langle 0.9,0.8,0.7\rangle}\right),\left(\frac{u_3}{\langle 0.1,0.6,0.9\rangle}\right)\right\}.$$

$$\mathcal{H}(z_{10}=(m_2,n_2,0))=\left\{\left(\frac{u_1}{\langle 0.3,0.4,0.7\rangle}\right),\left(\frac{u_2}{\langle 0.3,0.4,0.2\rangle}\right),\left(\frac{u_3}{\langle 0.6,0.6,0.2\rangle}\right)\right\}.$$

$$\mathcal{H}(z_{11}=(m_3,n_1,0))=\left\{\left(\frac{u_1}{\langle 0.4,0.5,0.6\rangle}\right),\left(\frac{u_2}{\langle 0.1,0.2,0.8\rangle}\right),\left(\frac{u_3}{\langle 0.2,0.4,0.7\rangle}\right)\right\}.$$

$$\mathcal{H}(z_{12}=(m_3,n_2,0))=\left\{\left(\frac{u_1}{\langle 0.6,0.8,0.6\rangle}\right),\left(\frac{u_2}{\langle 0.2,0.5,0.6\rangle}\right),\left(\frac{u_3}{\langle 0.4,0.9,0.9\rangle}\right)\right\}.$$

$$\mathcal{H}(z_i)=\begin{pmatrix}
((0.2,0.5,0.3)) & ((0.3,0.6,0.7)) & ((0.8,0.1,0.6))\\
((0.5,0.4,0.2)) & ((0.1,0.5,0.7)) & ((0.2,0.0,0.8))\\
((0.7,0.6,0.2)) & ((0.6,0.3,0.1)) & ((0.2,0.3,0.5))\\
((0.5,0.3,0.2)) & ((0.6,0.4,0.7)) & ((0.5,0.4,0.3))\\
((0.7,0.5,0.9)) & ((0.2,0.6,0.7)) & ((0.3,0.4,0.6))\\
((0.2,0.5,0.3)) & ((0.3,0.6,0.7)) & ((0.8,0.1,0.6))\\
((0.4,0.6,0.2)) & ((0.7,0.2,0.5)) & ((0.1,0.1,0.3))\\
((0.4,0.5,0.8)) & ((0.9,0.8,0.7)) & ((0.1,0.6,0.9))\\
((0.3,0.4,0.7)) & ((0.3,0.4,0.2)) & ((0.6,0.6,0.2))\\
((0.4,0.5,0.6)) & ((0.1,0.2,0.8)) & ((0.2,0.4,0.7))\\
((0.6,0.8,0.6)) & ((0.2,0.5,0.6)) & ((0.4,0.9,0.9))
\end{pmatrix}$$

Definition3.3. (Agree to SVNFSES): Agree SVNFSES $\mathcal{H}_1$ signifies the agreement with the specialist's opinion, which is shown below:

$$\mathcal{H}_O=\{H_O(z_i): z_i\in M\times N\times\{1\}\}$$

$$\mathcal{K}(z_1=(m_1,n_1,1))=\left\{\left(\frac{u_1}{\langle 0.2,0.5,0.3\rangle}\right),\left(\frac{u_2}{\langle 0.3,0.6,0.7\rangle}\right),\left(\frac{u_3}{\langle 0.8,0.1,0.6\rangle}\right)\right\}.$$

Definition3.5. (Disagree SVNFSES): disagree SVNFSES $\mathcal{H}_0$ signifies the disagreement of specialist's views and is shown below:

$$\mathcal{H}_O=\{H_O(z_i): z_i\in M\times N\times\{0\}\}$$

$$\mathcal{K}(z_9=(m_2,n_1,0))=\left\{\left(\frac{u_1}{\langle 0.4,0.5,0.8\rangle}\right),\left(\frac{u_2}{\langle 0.9,0.8,0.7\rangle}\right),\left(\frac{u_3}{\langle 0.1,0.6,0.9\rangle}\right)\right\}.$$

Definition3.7. (subset of SVNFSE): Consider $\mathcal{H}_O=(\mathcal{H},\mathcal{O}\subseteq\mathcal{Z})$ and $\mathcal{K}_P=(\mathcal{H},\mathcal{O}\subseteq\mathcal{Z})$ as dual SVNFSE set of reference $\widehat{U}$. $\mathcal{H}_O$ denotes the subset of SVNFSE $\mathcal{K}_P$ which can be represented as $\mathcal{H}_O\subseteq\mathcal{K}_P$ when:

1. $\mathcal{H}_O(u)$ is SVNFSE-subset of $\mathcal{K}_P(u_i)$, $\forall u_i\in\widehat{U}$.

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2. $O \subseteq P$.

$$\mathcal{K}(z_1 = (m_1, n_1, 1)) = \left\{\left(\frac{u_1}{\langle 0.2,0.5,0.3\rangle}\right), \left(\frac{u_2}{\langle 0.3,0.6,0.7\rangle}\right), \left(\frac{u_3}{\langle 0.8,0.1,0.6\rangle}\right)\right\}.$$

$$\mathcal{K}(z_9 = (m_2, n_1, 0)) = \left\{\left(\frac{u_1}{\langle 0.4,0.5,0.8\rangle}\right), \left(\frac{u_2}{\langle 0.9,0.8,0.7\rangle}\right), \left(\frac{u_3}{\langle 0.1,0.6,0.9\rangle}\right)\right\}.$$

Now, the two terms are subsets of $\mathcal{H}_O$.

Definition3.9. (Equality of SVNFSE set): Consider $\mathcal{H}_O = (\mathcal{H}, \mathcal{O} \subseteq \mathcal{Z})$ and $\mathcal{K}_P = (\mathcal{H}, \mathcal{O} \subseteq \mathcal{Z})$ as binary SVNFSE sets on a reference $\widehat{U}$. Next, $\mathcal{H}_O = (\mathcal{H}, \mathcal{O} \subseteq \mathcal{Z})$ is equivalent to $\mathcal{K}_P = (\mathcal{H}, \mathcal{O} \subseteq \mathcal{Z})$ which represented as $\mathcal{H}_O = \mathcal{K}_P$ if:

1. $\mathcal{H}(u_i)$ represents the SVNFSE subset of $\mathcal{K}(u_i)$ and $\mathcal{K}(u_i)$ represents the SVNFSE subset of $\mathcal{H}(u_i)$, $\forall u_i \in \widehat{U}$.

2. $\mathcal{O}$ represents the subset of $\mathcal{P}$, and $\mathcal{P}$ represents the subset of $\mathcal{O}$, $\forall u_i \in \widehat{U}$.

$$\mathcal{H}_O = \begin{pmatrix} (0.2,0503) & (0.3,0.6,0.8) & (0.8,0.1,0.6) \\ (0.5,0802) & (0.2,0.4,0.8) & (0.8,0,0.2) \\ (0.4,0.50.3) & (0.9,0.6,0.8) & (0.8,0.7,0.7) \end{pmatrix}$$

$$\mathcal{G}c = \begin{pmatrix} (0.1,0.30.3) & (0.6,0.8,0.8) & (0.8,0.1,0.1) \\ (0.5,0.80.2) & (0.2,0.4,0.8) & (0.8,0,0.2) \\ (0.4,0.7,0.8) & (0.4,0.6,0.8) & (0.8,0.5,0.4) \end{pmatrix}$$

$$\mathcal{K}_P = \begin{pmatrix} (0.2,0503) & (0.3,0.6,0.8) & (0.8,0.1,0.6) \\ (0.5,0802) & (0.2,0.4,0.8) & (0.8,0,0.2) \\ (0.4,0.50.3) & (0.9,0.6,0.8) & (0.8,0.7,0.7) \end{pmatrix}$$

Then, $\mathcal{H}_O = \mathcal{K}_P$ and $\mathcal{H}_O \neq \mathcal{G}c$.

Definition3.11. (null set of SVNFSE): Consider $\mathcal{H}_O = (\mathcal{H}, \mathcal{O} \subseteq \mathcal{Z})$ as a set of SVNFSE on position $\widehat{U}$. $\mathcal{H}_O$ denotes the null set of SVNFSE that is represented as $\widehat{\Phi}_{(0)}$ when $\mathcal{H}(u_i) = (0,1,1)$ and $\Theta(z_i) = 0, \forall u_i \in \widehat{U}$.

$$\widehat{\Phi}_{(0)} = \begin{pmatrix} ((0,1,1)) & ((0,1,1)) & ((0,1,1)) \\ ((0,1,1)) & ((0,1,1)) & ((0,1,1)) \\ ((0,1,1)) & ((0,1,1)) & ((0,1,1)) \end{pmatrix}$$

Definition3.13. (absolute set of SVNFES): Consider $\mathcal{H}_O = (\mathcal{H}, \mathcal{O} \subseteq \mathcal{Z})$ as SVNFSE on a reference set $\widehat{U}$. $\mathcal{H}_O$ signifies the entire set of SVNFES, which is represented as $\widehat{\Omega}_{(1)}$ if $\mathcal{H}(u_i) = (1,0,0)$ and $\Theta(z_i) = 1, \forall u_i \in \widehat{U}$.

$$\widehat{\Phi}_{(0)} = \begin{pmatrix} ((1,0,0)) & ((1,0,0)) & ((1,0,0)) \\ ((1,0,0)) & ((1,0,0)) & ((1,0,0)) \\ ((1,0,0)) & ((1,0,0)) & ((1,0,0)) \end{pmatrix}$$

Definition3.15. (Complement act of SVNFSE set): Consider $\mathcal{H}_O = (\mathcal{H}, \mathcal{O} \subseteq \mathcal{Z})$ as SVNFSE set on a reference set $\widehat{U}$

$$\mathcal{H}_O = \{(u, \langle \ddot{\partial}^t_{\mathcal{H}}(z_i)(u_j), \ddot{\partial}^i_{\mathcal{H}}(z_i)(u_j), \ddot{\partial}^f_{\mathcal{H}}(z_i)(u_j)\rangle | u \in \widehat{U}, z \in \widehat{\mathbb{Z}}\}$$

$$\mathcal{H}^c_O = \{(u, \langle \ddot{\partial}^f_{\mathcal{H}}(z_i)(u_j), 1 - \ddot{\partial}^i_{\mathcal{H}}(z_i)(u_j), \ddot{\partial}^t_{\mathcal{H}}(z_i)(u_j)\rangle | u \in \widehat{U}, z \in \widehat{\mathbb{Z}}\}$$

$$\mathcal{H}(z_1 = (m_1, n_1, 1)) = \left\{\left(\frac{u_1}{\langle 0.2,0.5,0.3\rangle}\right), \left(\frac{u_2}{\langle 0.3,0.6,0.7\rangle}\right), \left(\frac{u_3}{\langle 0.8,0.1,0.6\rangle}\right)\right\}.$$

$$\mathcal{H}(z_9 = (m_2, n_1, 0)) = \left\{\left(\frac{u_1}{\langle 0.4,0.5,0.8\rangle}\right), \left(\frac{u_2}{\langle 0.9,0.8,0.7\rangle}\right), \left(\frac{u_3}{\langle 0.1,0.6,0.9\rangle}\right)\right\}.$$

$$\mathcal{H}^c(z_1 = (m_1, n_1, 1)) = \left\{\left(\frac{u_1}{\langle 0.3,0.5,0.2\rangle}\right), \left(\frac{u_2}{\langle 0.7,0.4,0.3\rangle}\right), \left(\frac{u_3}{\langle 0.6,0.9,0.8\rangle}\right)\right\}.$$

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$$\mathcal{H}^c(z_9 = (m_2, n_1, 0)) = \left\{\left(\frac{u_1}{\langle 0.8,0.5,0.4\rangle}\right), \left(\frac{u_2}{\langle 0.7,0.2,0.9\rangle}\right), \left(\frac{u_3}{\langle 0.9,0.4,0.1\rangle}\right)\right\}.$$

C. Hyperparameter Tuning using ChOA

Finally, the parameter tuning of the SVNFSES technique is performed using ChOA's design. ChOA is stimulated by the alterations in the intellect and capability of entities in the chimpanzee population and their hunting actions [20]. Generally, chimpanzees were separated into barriers, drivers, attackers, and chasers dependent upon separate intellect and capability to complete the four core stages of the preying procedure, such as barring, driving, attacking, and chasing the victim. The accurate formulation for chimpanzees to prevent victims is exposed in Eq. (2), and the formulation for hunting targets is in Eq. (3).

$$D = |cX_P(t) - mX_c(t)| \tag{2}$$

$$X_c(t+1) = X_P(t) - A \cdot D \tag{3}$$

Here: XP denotes the vector of prey location, t signifies the existing iteration count, XC represents the existing location vector, c, and m refers to the co-efficient values, and the computations for resolving every parameter have been exposed in Eqs. (4), (5) and (6).

$$A = 2f \cdot r_1 - f \tag{4}$$

$$c = 2 \cdot r_2 \tag{5}$$

$$m = chaotic\_value \tag{6}$$

Meanwhile, f denotes a direct convergence feature that reduces from 2.5 to 0 as the iteration gains. r_1 and r_2 are randomly generated vectors among $[0\ and\ 1]$. m represents the vector of the chaotic map; A signifies the randomly generated variable where separate chimpanzees tactic their victim if $A < 1$ and vice versa. c refers to the prey location on chimp expulsion and prey chasing that is arbitrarily produced among $[0\ and\ 2]$. Fig. 2 depicts the flowchart of ChoA.

After the population was initialized, the locations of barrier, attacker, chaser, and driver were nominated as optimum solutions, and the locations of the other chimpanzees in the populace were upgraded around these four chimp locations.

$$X_1 = X_{attacker} - A_1 * |C_1 * X_{attacker} - m_1 * X| \tag{7}$$

$$X_2 = X_{barrier} - A_2 * |C_2 * X_{barrier} - m_2 * X| \tag{8}$$

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Figure 2: Flowchart of ChoA

$$X_3 = X_{chaser} - A_3 * |C_3 * X_{chaser} - m_3 * X| \quad (9)$$

$$X_4 = X_{driver} - A_4 * |C_4 * X_{driver} - m_4 * X| \quad (10)$$

$$x_{t+1} = \frac{(X_1 + X_2 + X_3 + X_4)}{4} \quad (11)$$

Here, $X(t+1)$ refers to the location vector of the existing chimp afterwards the upgrade, $X_{attacker}$ signifies the location vector of the optimum solution, $X_{barrier}, X_{chaser}$, and X_{driver} embody the location vector of the 2nd, 3rd and 4th best solution, respectively.

The ChoA derives a fitness function (FF) to complete the amended classification performance. It defines an optimistic number to imply the superior solution of the candidate. In this paper, the minimizer of the classifier error rate has been measured as FF was assumed in Eq. (12).

$$fitness(x_i) = ClassifierErrorRate(x_i)$$
$$= \frac{number\ of\ misclassified\ samples}{Total\ number\ of\ samples} * 100 \quad (12)$$

4. Result Analysis and Discussion

The experimental results of the AS-SVNFSES technique are studied on dual datasets: German Credit (GC) [21] and Australian Credit (AC) datasets [22]. Table 1 represents the FS outcomes of the AS-SVNFSES technique on both datasets. On German Credit, the AS-SVNFSES model has chosen ten features. Besides, on Australian Credit, the AS-SVNFSES model has eight preferred features.

Table 1: FS analysis of AS-SVNFSES technique on both datasets

Dataset	Selected features
German Credit	1,2,5,10,15,17,19,20,21,24

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Australian Credit	1,4,7,9,10,13,14,15

Table 2 lists the overall results of the AS-SVNFSES technique on the GC dataset [23].

Fig. 3 inspects the outcomes of the AS-SVNFSES technique in terms of $sens_y$, $spec_y$, and kappa on the GC dataset. Based on $sens_y$, the AS-SVNFSES technique offers higher $sens_y$ of 92.39% while the ODL-FCP, QABOLSTM, LSTM-RNN, ACO, MLP, SVM, and AdaBoost models obtain lower $sens_y$ of 89.11%, 86.06%, 80.77%, 78.09%, 72.60%, 71.54%, and 70.62%, correspondingly. Also, based on $spec_y$, the AS-SVNFSES system provides larger $spec_y$ of 96.69% whereas the ODL-FCP, QABOLSTM, LSTM-RNN, ACO, MLP, SVM, and AdaBoost techniques attain lesser $spec_y$ of 95.03%, 92.81%, 87.59%, 70.14%, 66.10%, 64.98%, and 62.90%, respectively. Meanwhile, the AS-SVNFSES model provides a greater kappa of 95.38% depending upon kappa. In contrast, the ODL-FCP, QABOLSTM, LSTM-RNN, ACO, MLP, SVM, and AdaBoost approach attain lesser kappa of 93.67%, 88.57%, 72.76%, 36.29%, 30.70%, 28.57%, and 37.16%, correspondingly.

Table 2: Comparative analysis of AS-SVNFSES technique with other models on the GC dataset

German Credit Dataset						
Classifiers	Sensitivity	Specificity	Accuracy	F-score	MCC	KAPPA
AS-SVNFSES	92.39	96.69	95.13	93.51	93.42	95.38
ODL-FCP	89.11	95.03	93.45	91.72	91.80	93.67
QABOLSTM	86.06	92.81	90.93	89.24	88.79	88.57
LSTM-RNN	80.77	87.59	84.84	87.10	76.39	72.76
ACO Model	78.09	70.04	76.78	84.89	38.17	36.29
MLP Model	72.60	66.10	70.46	73.56	32.66	30.70
SVM Model	71.54	64.98	69.59	71.61	30.72	28.57
AdaBoost Model	70.62	62.90	66.70	69.60	39.67	37.16

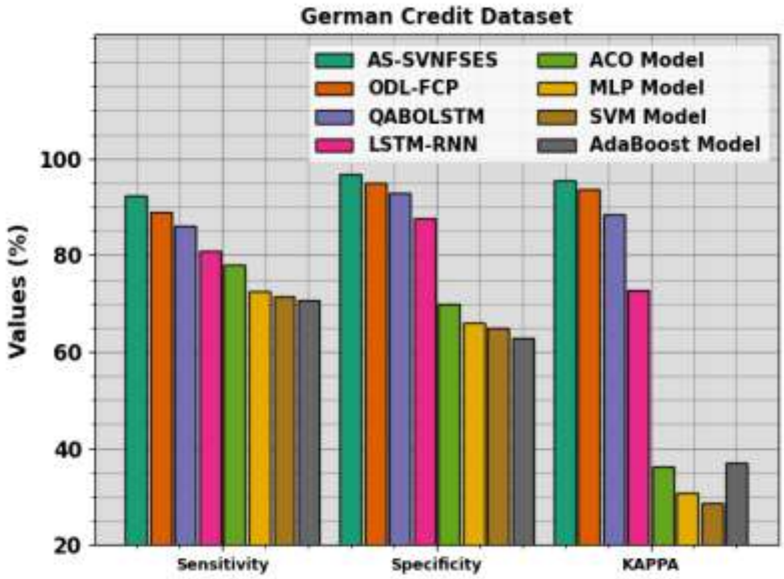

Figure 3: $Sens_y$, $spec_y$, and kappa of AS-SVNFSES technique on GC dataset

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Fig. 4 examines the outcomes of the AS-SVNFSES model in terms of $accu_y$, F_{score}, and MCC on the AC dataset. Based on $accu_y$, the AS-SVNFSES system provides an upper $accu_y$ of 95.13%, whereas the ODL-FCP, QABOLSTM, LSTM-RNN, ACO, MLP, SVM, and AdaBoost techniques attain lesser $accu_y$ of 93.45%, 90.93%, 84.84%, 76.78%, 70.46%, 69.59%, and 66.70%, respectively. Likewise, based on F_{score}, the AS-SVNFSES method offers greater F_{score} of 93.51% whereas the ODL-FCP, QABOLSTM, LSTM-RNN, ACO, MLP, SVM, and AdaBoost approaches get lower F_{score} of 91.72%, 89.24%, 87.10%, 84.89%, 73.56%, 71.61%, and 69.60%, respectively. Meanwhile, based on MCC, the AS-SVNFSES system provides higher MCC of 93.42% but the ODL-FCP, QABOLSTM, LSTM-RNN, ACO, MLP, SVM, and AdaBoost approaches get lowest MCC of 91.80%, 88.79%, 76.39%, 38.17%, 32.66%, 30.72%, and 39.67%, correspondingly.

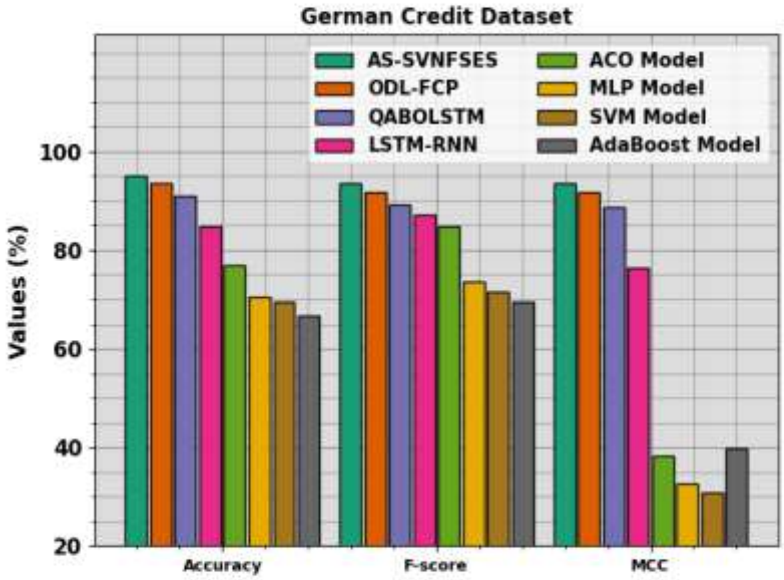

Figure 4: $Accu_y$, F_{score}, and MCC of AS-SVNFSES technique on GC dataset

Table 3 lists the general outcomes of the AS-SVNFSES system on the AC dataset. Fig. 5 examines the results of the AS-SVNFSES system in terms of $sens_y$, $spec_y$, and kappa on the AC dataset. Based on $sens_y$, the AS-SVNFSES model provides greater $sens_y$ of 95.57% but the ODL-FCP, QABOLSTM, LSTM-RNN, ACO, MLP, SVM, and AdaBoost methodologies got lesser $sens_y$ of 93.92%, 90.86%, 85.95%, 79.56%, 75.49%, 72.64%, and 70.60%, correspondingly. Also, based on $spec_y$, the AS-SVNFSES system delivers a higher $spec_y$ of 97.36%. In contrast, the ODL-FCP, QABOLSTM, LSTM-RNN, ACO, MLP, SVM, and AdaBoost approach attain lower $spec_y$ of 95.85%, 94.94%, 92.89%, 89.58%, 82.64%, 76.18%, and 68.64%, correspondingly.

Table 3: Comparative analysis of the AS-SVNFSES model with other models on the AC dataset

Australian Credit Dataset						
Classifiers	Sensitivity	Specificity	Accuracy	F-score	MCC	KAPPA
AS-SVNFSES	95.57	97.36	96.61	95.76	94.78	95.49
ODL-FCP	93.92	95.85	95.01	94.15	93.00	93.92
QABOLSTM	90.86	94.94	94.06	92.88	90.97	91.79
LSTM-RNN	85.95	92.89	91.84	89.84	85.57	87.24
ACO Model	79.56	89.58	89.65	83.62	69.18	69.10
MLP Model	75.49	82.64	83.22	79.68	64.74	64.05
SVM Model	72.64	76.18	76.46	76.00	63.29	69.64

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AdaBoost Model	70.60	68.64	69.06	67.59	60.84	68.03

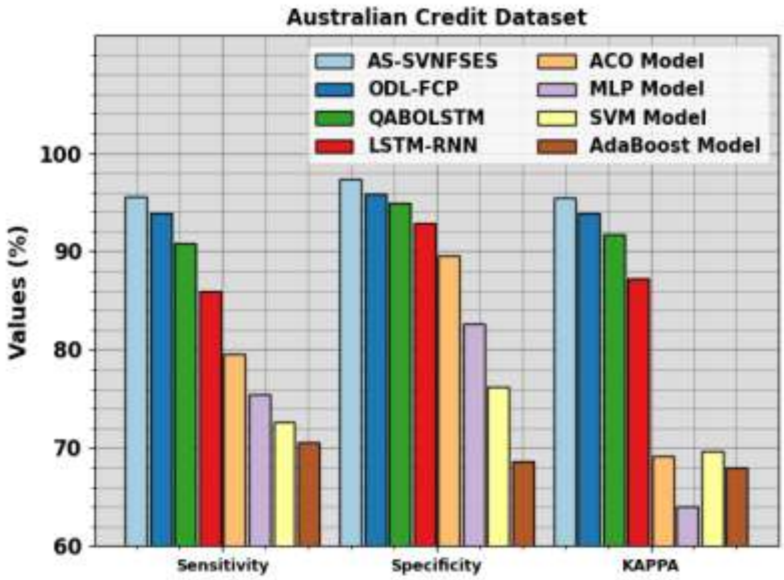

Figure 5: $Sens_y$, $spec_y$, and kappa of AS-SVNFSES technique on AC dataset

In the meantime, the AS-SVNFSES approach offers a greater kappa of 95.49% depending upon kappa. In contrast, the ODL-FCP, QABOLSTM, LSTM-RNN, ACO, MLP, SVM, and AdaBoost methods get lower kappa of 93.92%, 91.79%, 87.24%, 69.10%, 64.05%, 69.64%, and 68.03%, correspondingly.

Fig. 6 reviews the outcomes of the AS-SVNFSES system in terms of $accu_y$, F_{score}, and MCC on the AC dataset. Based on $accu_y$, the AS-SVNFSES model provides a larger $accu_y$ of 96.61%, but the ODL-FCP, QABOLSTM, LSTM-RNN, ACO, MLP, SVM, and AdaBoost techniques got lesser $accu_y$ of 95.01%, 94.06%, 91.84%, 89.65%, 83.22%, 76.46%, and 69.06%, respectively. Also, based on F_{score}, the AS-SVNFSES model provides upper F_{score} of 95.76% but the ODL-FCP, QABOLSTM, LSTM-RNN, ACO, MLP, SVM, and AdaBoost approaches obtain lower F_{score} of 94.15%, 92.88%, 89.84%, 83.62%, 79.68%, 76.00%, and 67.59%, correspondingly.

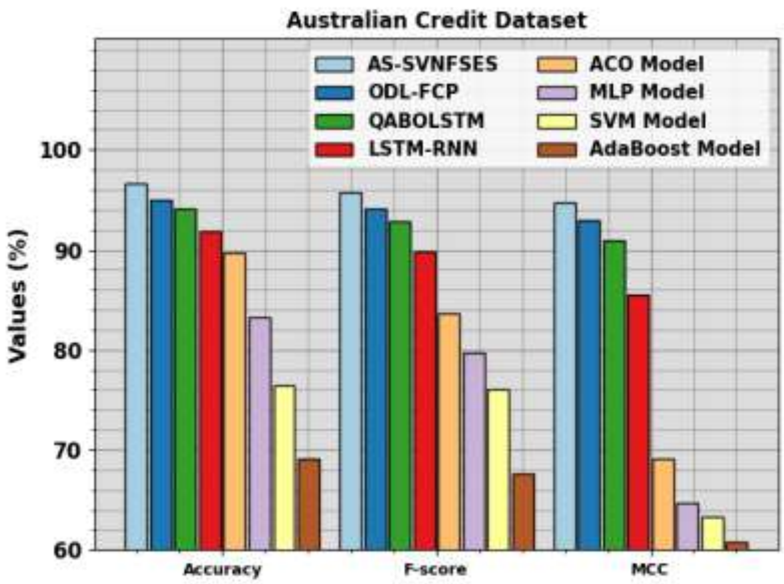

Figure 6: $Accu_y$, F_{score}, and MCC of AS-SVNFSES technique on AC dataset

Meanwhile, based on MCC, the AS-SVNFSES model offers advanced MCC of 94.78%, but the ODL-FCP, QABOLSTM, LSTM-RNN, ACO, MLP, SVM, and AdaBoost systems get lower MCC of 93.00%, 90.97%, 85.57%, 69.18%, 64.74%, 63.29%, and 60.84%, correspondingly.

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5. Conclusion

In this study, we have presented a unique AS-SVNFSES approach for financial time series forecasting. The presented AS-SVNFSES technique aims to forecast the input financial time series data. The AS-SVNFSES technique primarily applies data preprocessing using a Z-score normalization approach. For the forecasting of economic data, the AS-SVNFSES technique uses the SVNFSES technique. Finally, the parameter tuning of the SVNFSES technique is performed using ChOA's design. A sequence of experimentations was used to illustrate the enhanced performance of the AS-SVNFSES model. The experimental value inferred that the AS-SVNFSES technique gains improved performance over other models.

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