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Stock Price Predictions with LSTM-ARIMA Hybrid Model under Neutrosophic Treesoft sets with MCDM interaction

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Abstract The stock market is regarded as volatile, complex, tumultuous, and dynamic. Forecasting stock performance has proven to be a challenging endeavour due to its increasing need for investment and growth prospects. At the forefront of machine learning, deep learning models facilitate the straightforward and efficient exploration and identification of optimal stocks, the hybrid forecasting models (LSTM and ARIMA) are used in the prediction of stock increase. This paper incorporated the MCDM technique to determine the optimal stocks for investment. The Analytic Hierarchy Process (AHP) is used to assign weights to various financial factors. These weights are then used by the Technique for Order Preference by Similarity to Ideal solution (TOPSIS) technique, which is a component Multi Criteria Decision Making method (MCDM), to compute and rank the optimal stocks for investment. Stock analysis involves considering numerous criteria and sub-criteria, which might lead to an unsuitable answer. To address this uncertainty, we utilize Neutrosophic Treesoft sets, which primarily handle numerous criteria, sub-criteria, and an increased number of sub-sub-criteria. Given a larger number of criteria, we will be capable of providing a precise solution to the problem. Furthermore, the definitions of fuzzy treesoft sets and neutrosophic treesoft sets have been presented for the first time. A plotly graph is generated to compare the real and projected stock prices for all the equities. All these are implemented using the program language python, which seems to be simple and easily understandable when compared to the other programming languages like Julia, MATLAB and so on. This hybrid methodology facilitates the forecast of stock prices, the ranking of stocks based on several financial and non-financial factors using AHP and TOPSIS, and the visualization of the outcomes.

Keywords: MCDM, TOPSIS, AHP, Treesoft sets, deep learning, LSTM, ARIMA, Stocks, equities

Abbreviations:

MCDM- Multi Criteria Decision Making

TOPSIS- Technique for Order Preference by Similarity to Ideal Solution

AHP- Analytic Hierarchy process

LSTM- Long Short Term Memory

ARIMA- Autoregressive Integrated Moving Average

1. Introduction: Ownership in a business is represented by stocks, which are often called shares or equity. Investors get a stake in a company when they buy stock; their ownership stake grows in direct proportion to their shareholdings. To finance operations, growth, and expansion, businesses issue stocks to the public. Investment and economic progress on a global scale are propelled by stocks, which play a pivotal role in the financial markets. An equity exchange is a platform where investors participate in the trading of equities. As an intermediary, it facilitates the transfer of capital from investors to enterprises. Among the most prominent stock exchanges are: New York Stock Exchange (NYSE), NASDAQ, Tokyo Stock Exchange Corporation, London Stock Exchange. The purpose of these exchanges is to facilitate stock trading and guarantee that transactions are carried out in a transparent and regulated setting [13].

For a comprehensive understanding of the stock market, it is crucial to grasp the many elements that influence stock prices and investor choices. The aforementioned include: Supply and demand, Earnings Reports, Market Sentiment, Interest rates and inflation, Company news and industry trends. Equity instruments are essential in the financial markets, providing investors with chances to amass money and experience capital appreciation. A comprehensive grasp of the intricacies of stock markets, encompassing valuation techniques, market dynamics, and risk elements, is crucial for making sound investing choices [15].

Given the on-going evolution of stock markets due to the incorporation of new technology and worldwide trends, investors need to stay well-informed and flexible in order to successfully navigate this extremely volatile environment. The Python programming language is an accessible instrument for software development that has experienced significant growth in recent years. This is widely used in artificial intelligence, deep learning, neural networks, and machine learning technologies. [21]

Deep learning is a comprehensive designation for machine learning methodologies that incorporate deep neural networks consisting of several layers. Deep learning is one of the new technologies which give the investors a clear idea about investing in the best stocks to avail large profit. It also provides the investors with a precise understanding of how to invest in the most profitable equities for significant financial gains. [23]

Deep learning model particularly Long Short-Term Memory (LSTM) models are components of deep learning architectures that excel in capturing intricate patterns in extensive dataset, often surpassing conventional models in situations when the data is abundant and intricate. It is form of recurrent neural network (RNN) often employed to forecast future values using past data. A linear statistical model known as ARIMA is commonly employed to analyse and predict stationary time series data. The temporal correlation (linear dependencies) is captured by employing autoregressive (AR), differencing (I), and moving average (MA) components. The ARIMA model is valuable for making short-term forecasts when the data demonstrates consistency or can be rendered stationary by differencing. Frequently, the combination of ARIMA with LSTM results in hybrid models that harness the individual strengths of both approaches. Due to the strong efficacy of ARIMA in capturing linear trends and the competence of LSTMs in detecting non-linear correlations, the combination of these two approaches leads to more precise predictions. Linear trends and non-linear fluctuations are frequently seen features in the prediction of stock market dynamics. The integration of both forms of interdependence in hybrid models has the potential to enhance the precision of stock price prediction [12].

Multi-criteria Decision Making (MCDM) refers to a set of strategies and methodologies used to evaluate, prioritize, and select from different alternatives based on many conflicting criteria. This methodology is widely employed in various fields including business, engineering, environmental management, and finance, where key decision-makers must meticulously evaluate several factors before arriving at a decision [11]. TOPSIS is a sophisticated Multi Criteria Decision Making (MCDM) technique that assists decision-makers in selecting the most optimal solution across several domains. The TOPSIS algorithm arranges choices based on their approximate distance to an optimum solution (the most desirable outcome) and a negative ideal solution (the least desirable outcome). The superiority of an alternative is established by its closeness to the optimal solution and its separation from the negative ideal [8].

To efficiently handle and address uncertainty and imprecision, the mathematical framework known as Treesoft sets is extensively used in the fields of multi-criteria decision making (MCDM) and fuzzy logic. Although traditional crisp sets are characterised by binary membership, where an element is either included in a set or not, treesoft sets provide a method to handle data with partial or uncertain membership. Treesoft sets use a tree-like structure to represent different degrees of membership or preferences, therefore facilitating a more complex assessment. In complicated procedures for decision-making including the evaluation of several factors with varying degrees of importance, this structure is particularly well-suited.

Treesoft sets are a versatile and effective tool for managing uncertainty by expanding the conventional set theory to suit complex decision-making dilemmas. They are especially advantageous when there are contradictory criteria, since they can help in effectively representing both qualitative and quantitative aspects. Here we implement a parallel hybridization strategy, in which the LSTM and ARIMA models independently generate forecasts based on historical stock price data. The final prediction for the stocks is obtained by aggregating the predicted values from both models. LSTM is employed to learn intricate patterns and long-term dependencies, while ARIMA is employed to capture linear trends. This method capitalizes on the strengths of both models. The output acquired from the hybrid LSTM-ARIMA model with MCDM techniques applied to Treesoft sets using TOPSIS provides a precise answer for the most prominent real-world problem, which is the stock increase prediction, when all of these factors are combined.

Motivation and Novelty: The need for a more thorough and accurate framework for evaluating stocks that incorporates sustainability considerations, market sentiment, and financial measures in order to make well-informed investment decisions is what motivates our effort. The intricacy of real-world uncertainty is frequently overlooked by traditional approaches, where Neutrosophic Treesoft sets can be useful. This method seeks to more accurately model both quantitative and qualitative characteristics by fusing the flexibility of Neutrosophic Treesoft set theory with a variety of financial metrics. The integration of environmental and sentiment data is further motivated by the increased emphasis on sustainable and responsible investing, which gives it relevance to contemporary decision-making scenarios. This work's key innovation is the application of Neutrosophic Treesoft sets in stock appraisal, a currently unexamined area. This method facilitates the sophisticated management of unclear, imprecise, and inconsistent information that conventional models find challenging. The integration of LSTM and ARIMA models for forecasting stock price fluctuations, coupled with an extensive AHP and TOPSIS assessment technique, signifies a notable advancement. This complex model is both theoretically distinctive and practically beneficial due to its improved accuracy and relevance in financial analysis.

Research gap: The inability of current stock evaluation techniques to handle uncertainties in financial and qualitative data, such as sentiment and environmental factors, highlights the need for strategies like Neutrosophic Treesoft sets that efficiently handle ambiguous and inconsistent data. When paired with sophisticated uncertainty models, Multi-criteria Decision-making (MCDM) techniques, such as AHP and TOPSIS, are also underutilized, which restricts their capacity to handle both quantitative and qualitative criteria.

2. Preliminaries:

2.1 Linguistic Variables [1]: If the universe of discourse X is a continuous space (the real line R or its subset), we typically divide it into multiple fuzzy sets whose membership function's cover X in a more or less uniform manner. Linguistic values or linguistic labels are the terms used to describe these imprecise sets, which are typically named after adjectives that are commonly used in our daily language, such as "large," "medium," or "small". Consequently, the linguistic variable is frequently used to refer to the universe of discourse X.

Table 1 Linguistic variable

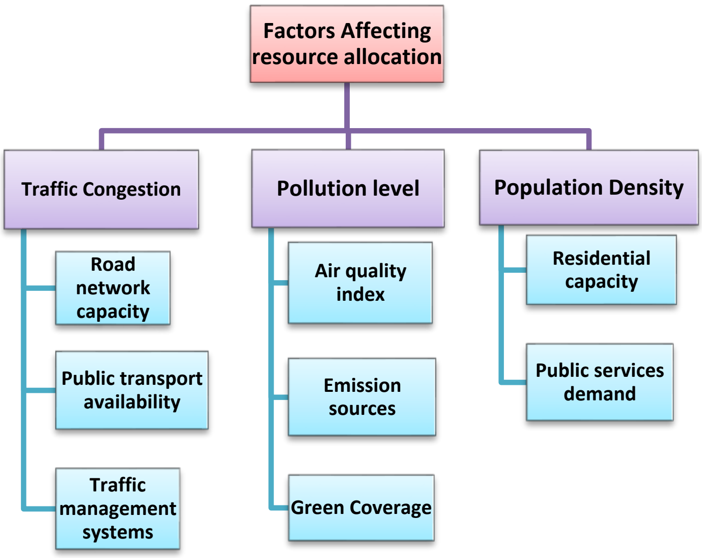
Linguistic Terms	Numerical range
Very Small	[0.0-0.225]
Small	[0.225-0.415]
Medium	[0.415-0.635]
Large	[0.635-0.825]
Very Large	[0.825-1.0]

2.2 Fuzzy set [24]: Denote the generic element of the universe Q as q. A fuzzy set ϑ defined on the universe Q can be characterized as a function $\vartheta: Q \to [0,1]$. The notation μ_ϑ is commonly employed to denote the membership function associated with the fuzzy set ϑ. This function maps elements from the universe of discourse Q to the interval $[0,1]$, assigning to each element q in Q a corresponding real number $\mu_{\vartheta(q)}$ that lies within this range.

2.3 Soft sets [2, 14]: Soft sets on Q are characterized by a pair (ω, Y), where Y comprises all the properties that define the members of the universe of discourse, and ω represents a function $\omega: Y \to P(Q)$. According to the findings presented by (Molodstov), a soft set on Q can be characterized as a parameterized collection of subsets of Q, with the set of parameters denoted as Y.

2.4 Hypersoft sets [4, 16, and 19]: The distinct attributes $g_1, g_2, g_3, \dots, g_n$ for $n \geq 1$ be n well defined attributes whose attribute values are contained in the sets $\mathcal{G}_1, \mathcal{G}_2, \mathcal{G}_3, \dots, \mathcal{G}_n$ here $\mathcal{G}_i \cap \mathcal{G}_j = \emptyset$ for $i \neq j$. A hypersoft set over the universal set Q is a pair $(\omega, \mathcal{G}_1 \times \mathcal{G}_2 \times \mathcal{G}_3 \times \dots \times \mathcal{G}_n)$, where ω is the mapping expressed as, $\omega: \mathcal{G}_1 \times \mathcal{G}_2 \times \mathcal{G}_3 \times \dots \times \mathcal{G}_n \to P(Q)$.

Example 1: Following the efficient allocation of resources in a smart city by tackling the obstacles presented by various parameters and sub-parameters across distinct zones where, $\mathcal{Z} = \{z_1, z_2, z_3, z_4, z_5\}$ represents the designated zones for consideration, the optimal zone is identified within this smart city.



Let $\breve{\mathcal{A}} = \{\mathcal{G}_1 \times \mathcal{G}_2 \times \mathcal{G}_3\}$ be a set of parameters

$$\breve{\mathcal{A}} = \{\mathcal{G}_1 \times \mathcal{G}_2 \times \mathcal{G}_3\} = \{a_{11}, a_{12}, a_{13}\} \times \{a_{21}, a_{22}, a_{23}\} \times \{a_{31}, a_{32}\}$$

Where, $\breve{\mathcal{A}} = \{\widetilde{a_1}, \widetilde{a_2}, \widetilde{a_3}, \widetilde{a_4}, \widetilde{a_5}, \widetilde{a_6}, \widetilde{a_7}, \widetilde{a_8}, \widetilde{a_9}, \widetilde{a_{10}}, \widetilde{a_{11}}, \widetilde{a_{12}}, \widetilde{a_{13}}, \widetilde{a_{14}}, \widetilde{a_{15}}, \widetilde{a_{16}}, \widetilde{a_{17}}, \widetilde{a_{18}}\}$ then the Hypersoft sets is given by:

$$(\omega, \breve{\mathcal{A}}) = \left\{ \begin{array}{c} (\widetilde{a_1}(z_1, z_2)), (\widetilde{a_2}(z_3, z_5)), (\widetilde{a_3}(z_4, z_3)), (\widetilde{a_4}(z_1)), (\widetilde{a_5}(z_2, z_4, z_5)), (\widetilde{a_6}(z_3)), \\ (\widetilde{a_7}(z_1, z_3)), (\widetilde{a_8}(z_1, z_3, z_5)), (\widetilde{a_9}(z_2, z_4)), (\widetilde{a_{10}}(z_1)), (\widetilde{a_{11}}(z_3)), (\widetilde{a_{12}}(z_1, z_2)), \\ (\widetilde{a_{13}}(z_1, z_4, z_5)), (\widetilde{a_{14}}(z_2, z_3, z_4)), \left(\widetilde{a_{16}}(z_1, z_3, z_4, z_5)\right), (\widetilde{a_{17}}(z_1, z_2, z_3, z_4, z_5)), \\ (\widetilde{a_{18}}(z_1, z_2, z_3)) \end{array} \right\}$$

2.5 Treesoft sets [18]: Let Q be the universal set and M a non-empty subset of Q, with $P(M)$ the power set of M. Let $\mathcal{G}$ be the set of attributes $\{\mathcal{G}_1, \mathcal{G}_2, \mathcal{G}_3, \dots, \mathcal{G}_n\}$, for integer $n \geq 1$, where $\mathcal{G}_1, \mathcal{G}_2, \dots, \mathcal{G}_n$ are attributes of first level (since they have one-digit indexes). Each attribute $\mathcal{G}_i$, $1 \leq i \leq n$, is formed by sub-attributes:

$$\mathcal{G}_1 = \{\mathcal{G}_{1,1}, \mathcal{G}_{1,2}, \dots\}$$

$$\mathcal{G}_2 = \{\mathcal{G}_{2,1}, \mathcal{G}_{2,2}, \dots\}$$

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$$\mathcal{G}_n = \{\mathcal{G}_{n,1}, \mathcal{G}_{n,2}, \dots\}$$

where $\mathcal{G}_{i,j}$ are sub-attributes (or attributes of second level) (since they have two-digit indexes). Again, each sub-attribute $\mathcal{G}_{i,j}$ is formed by sub-sub-attributes(or attributes of third level): $\mathcal{G}_{i,j,k}$ and so on, as much refinement as needed into each application, up to sub-sub-…-sub-attributes or attributes of $m - level$ (or having m digits into indexes):$\mathcal{G}_{i_1, i_2, \dots, i_m}$. Therefore, a graph is formed, that we denote as Tree$(\mathcal{G})$, whose root is $\mathcal{G}$ (considered as level zero), then nodes of $level 1, level 2, \dots, level m$, we call it as leaves of the graph-tree, all terminal nodes (nodes that have no descendants). Then the treesoft set is:

$$\mathcal{F}: P(Tree(\mathcal{G})) \rightarrow P(M)$$

Tree$(\mathcal{G})$ is the set of all nodes and leaves $(from\ level\ 1\ to\ level m\ )$ of the graph-tree, and $P(Tree(\mathcal{G}))$ is the power set of the Tree$(\mathcal{G})$. All node sets of the Treesoft set of $level\ m$ are:

$$Tree(\mathcal{G}) = \{\mathcal{G}_{i_1} | i_1 = 1,2, \dots\} \cup \{\mathcal{G}_{i_1, i_2} | i_1, i_2 = 1,2, ..\} \cup \dots \cup$$

$\{\mathcal{G}_{i_1, i_2, \dots, i_m} | i_1, i_2, \dots, i_m = 1,2, \dots\}$.The first set is formed by the nodes of $level\ 1$, second set by the nodes of $level\ 2$, third set by the nodes of $level\ 3$, and so on; the last set is formed by the nodes of $level\ m$.

Remark 1: Consider

$$Tree(\mathcal{G}) = \mathcal{D}$$
$$\mathcal{D} = \{\mathcal{G}_{i_1} | i_1 = 1,2, \dots\} \cup \{\mathcal{G}_{i_1, i_2} | i_1, i_2 = 1,2, \dots\} \cup \dots \cup \{\mathcal{G}_{i_1, i_2, \dots, i_m} | i_1, i_2, \dots, i_m = 1,2, \dots\}$$

Where $\mathcal{K}_1 = \{\mathcal{G}_{i_1} | i_1 = 1,2,\dots\}$,$\mathcal{K}_2 = \{\mathcal{G}_{i_1,i_2} | i_1, i_2 = 1,2,\dots\}$… $\mathcal{K}_m = \{\mathcal{G}_{i_1,i_2,\dots,i_m} | i_1, i_2, \dots, i_m\}$

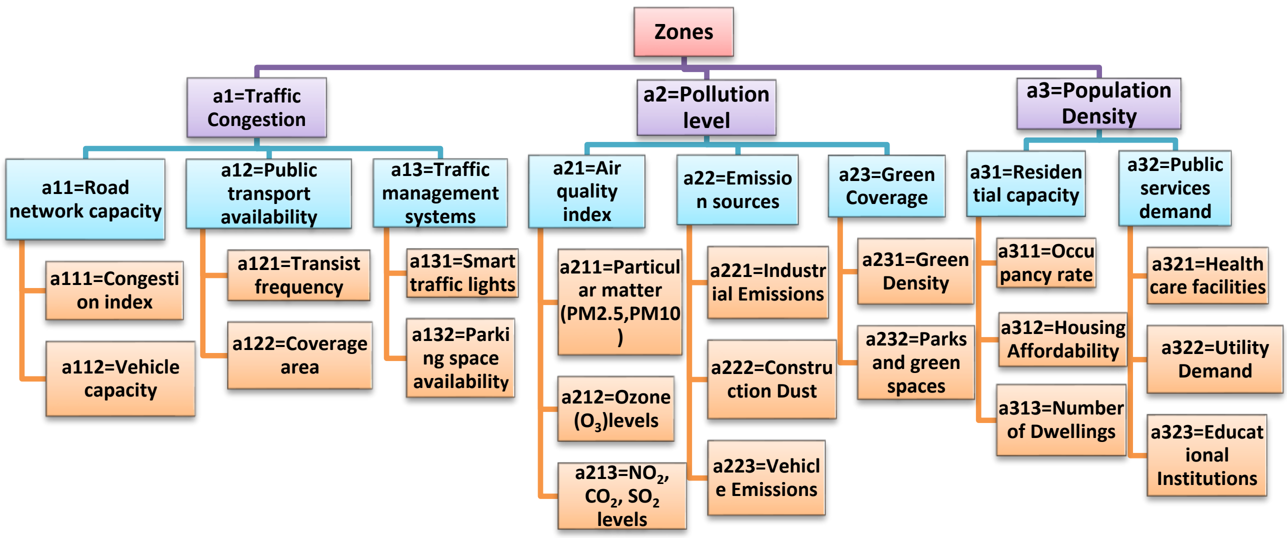
Therefore $Tree(\mathcal{G})$ can also be written as follows:

$$Tree(\mathcal{G}) = \mathcal{K}_1 \cup \mathcal{K}_2 \cup, \dots, \cup \mathcal{K}_m$$

2.6 Fuzzy Treesoft sets: Q the universal set and $FP(Q)$ the be a family of all fuzzy power set Q. $\mathcal{G}$ set of attributes, $\mathcal{G} = \{\mathcal{G}_1, \mathcal{G}_2, \mathcal{G}_3, \dots, \mathcal{G}_n\}$, for integer $n \geq 1$, where $\mathcal{G}_1, \mathcal{G}_2, \dots, \mathcal{G}_n$ are attributes of first level. Each attribute $\mathcal{G}_i, 1 \leq i \leq n$, is formed by the sub-attributes $\mathcal{G}_{i,j}$ attributes of second level. Again, each sub-attribute $\mathcal{G}_{i,j}$ is formed by sub-sub-attributes of third level $\mathcal{G}_{i,j,k}$ and so on, as much refinement needed into each application, upto sub-sub-…-sub-attributes or attributes of m level. A fuzzy treesoft set defined as the pair $(\mathcal{F}, P(Tree(\mathcal{G}))$ where $\mathcal{F}: P(Tree(\mathcal{G})) \to FP(Q)$

Here $Tree(\mathcal{G})$ is the set of all nodes from level 1 to level m. $P(Tree(\mathcal{G}))$ is the powerset of $Tree(\mathcal{G})$, therefore we have $\mathcal{F}: P(\mathcal{K}_1 \cup \mathcal{K}_2 \cup \dots \cup \mathcal{K}_m) \to FP(Q)$ (from the above Remark 1)

Example 2 [6]: Consider the set $\mathcal{Z} = \{z_1, z_2, z_3, z_4, z_5\}$ are the different zones in a smart city, and $\mathcal{P}(\mathcal{Z})$ the power set $\mathcal{Z}$ with the equivalent attributes $\mathcal{T} = \{t_1, t_2, t_3\}$



$$a_1 = \mathcal{Z}_1 = \{a_{11} = Road\ capacity, a_{12} = Public\ transport\ availablity, a_{13} = Traffic\ management\ systems\};$$

$$a_2 = \mathcal{Z}_2 = \{a_{21} = Air\ quality\ index, a_{22} = Emission\ sources, a_{23} = Green\ coverage\};$$

$$a_3 = \mathcal{Z}_3 = \{a_{31} = Residential\ capacity, a_{32} = Public\ services\ demand\}$$

Below is the example of Treesoft sets, the function $\mathcal{F}$ takes the values:

$$\mathcal{F}(Road\ capacity, air\ quality\ index, construction\ dust) = \{z_1, z_2, z_3\}$$

$$\mathcal{F}(Road\ capacity, air\ quality\ index, utility\ demand) = \{z_2, z_4\}$$

$$\mathcal{F}(Road\ capacity, air\ quality\ index, construction\ dust) \cup \mathcal{F}(Traffic\ congestion, air\ quality\ index, utility\ demand) = \{z_1, z_2, z_3, z_4\}$$

Fuzzy treesoft sets is given by:

Consider the function $\mathcal{F}: \mathcal{Z}_1 \cup \mathcal{Z}_2 \cup \mathcal{Z}_3 \to \mathcal{P}(\mathcal{Z})$

Assume the relation

$$\mathcal{F}(\mathcal{Z}_1 \cup \mathcal{Z}_2 \cup \mathcal{Z}_3) = \mathcal{F}\big(Road\ capacity(a_{11}), construction\ dust(a_{222}), utility\ demand(a_{322})\big)$$

$$= \mathcal{F}\left(\frac{z_1}{a_{11}(0.7), a_{222}(0.8), a_{322}(0.6)}, \frac{z_2}{a_{11}(0.5), a_{222}(0.2), a_{322}(0.7)}, \frac{z_3}{a_{11}(0.4), a_{222}(0.7), a_{322}(0.6)}, \frac{z_4}{a_{11}(0.8), a_{222}(0.4), a_{322}(0.7)}, \frac{z_5}{a_{11}(0.5), a_{222}(0.6), a_{322}(0.7)}\right)$$

2.7 Neutrosophic sets [10, 20]: A neutrosophic set $\mathcal{N}$ on the universe Q is defined as

$$\mathcal{N} = \{\langle q, \mathcal{T}_{\mathcal{N}}(q), \mathcal{I}_{\mathcal{N}}(q), \mathcal{F}_{\mathcal{N}}(q)\rangle : q \in Q\}$$

where $\mathcal{T}_{\mathcal{N}}, \mathcal{I}_{\mathcal{N}}, \mathcal{F}_{\mathcal{N}}: Q \to]0^-, 1^+[$ and $0^- \leq \mathcal{T}_{\mathcal{N}} + \mathcal{I}_{\mathcal{N}} + \mathcal{F}_{\mathcal{N}} \leq 3^+$.The neutrosophic set derives its value from genuine standard or non-standard subsets of $]0^-, 1^+[$ from an intellectual point of view. However, it is challenging to employ a neutrosophic set with a value from an actual standard or non-standard subset of $]0^-, 1^+[$ in real-world scientific and engineering applications. Therefore, we examine the neutrosophic set, which derives its value from the subset of [0,1].

2.8 Neutrosophic Hypersoft sets [17, 18, and 20]: Take Q to be the universal set, and $P(Q)$ be the power set of Q. Considering the well-defined attributes $g_1, g_2, \dots, g_n$and the associated attribute values are the sets $\mathcal{G}_1, \mathcal{G}_2, \mathcal{G}_3, \dots, \mathcal{G}_n$.Suppose that $\mathcal{G}_i \cap \mathcal{G}_j = \emptyset$ for $i \neq j$ and $i, j \in \{1,2,3, \dots, n\}$, the relation $\mathcal{G}_1 \times \mathcal{G}_2 \times \mathcal{G}_3 \times \dots \times \mathcal{G}_n = \mathcal{S}$ then the pair $(\omega, \mathcal{S})$ is referred to as neutrosophic hypersoft set over Q, where $\omega: \mathcal{G}_1 \times \mathcal{G}_2 \times \mathcal{G}_3 \times \dots \times \mathcal{G}_n \to P(Q)$,

$\omega(\mathcal{G}_1 \times \mathcal{G}_2 \times \mathcal{G}_3 \times \dots \times \mathcal{G}_3) = \{\langle q, \mathcal{T}(\omega(\mathcal{S})), \mathcal{I}(\omega(\mathcal{S})), \mathcal{F}(\omega(\mathcal{S}))\rangle\}$, where $\mathcal{T}$ the membership value of truth, $\mathcal{I}$ the membership value of indeterminacy and $\mathcal{F}$ the membership value of falsity. These values are defined as $\mathcal{T}, \mathcal{I}, \mathcal{F}: Q \to [0,1]$. In addition

$$0 \leq \mathcal{T}(\omega(\mathcal{S})) + \mathcal{I}(\omega(\mathcal{S})) + \mathcal{F}(\omega(\mathcal{S})) \leq 3$$

2.9 Neutrosophic Treesoft sets: Q the universal set and $P(Q)$ be the power set of Q. $\mathcal{G}$ a set of attributes, $\mathcal{G} = \{\mathcal{G}_1, \mathcal{G}_2, \mathcal{G}_3, \dots, \mathcal{G}_n\}$, for integer $n \geq 1$, where $\mathcal{G}_1, \mathcal{G}_2, \dots, \mathcal{G}_n$ are attributes of first level. Each attribute $\mathcal{G}_i$, $1 \leq i \leq n$, is formed by the sub-attributes $\mathcal{G}_{i,j}$ attributes of second level. Again, each sub-attribute $\mathcal{G}_{i,j}$ is formed by sub-sub-attributes of third level $\mathcal{G}_{i,j,k}$ and so on, as much refinement needed into each application, upto sub-sub-,…-sub-attributes or attributes of m level.The relation $P(\mathcal{K}_1 \cup \mathcal{K}_2 \cup \dots \cup \mathcal{K}_m) = \mathcal{D}$ then the neutrosophic treesoft set defined as the pair $(\omega, \mathcal{D})$ where $\omega: P(\mathcal{K}_1 \cup \mathcal{K}_2 \cup \dots \cup \mathcal{K}_m) \to P(Q)$ (using Remark 1),

$\omega\big(P(\mathcal{K}_1 \cup \mathcal{K}_2 \cup \dots \cup \mathcal{K}_m)\big) = \{\langle q, \mathcal{T}(\omega(\mathcal{D})), \mathcal{I}(\omega(\mathcal{D})), \mathcal{F}(\omega(\mathcal{D}))\rangle\}$, where $\mathcal{T}, \mathcal{I}, \mathcal{F} \to [0,1]$. Additionally $0 \leq \mathcal{T}(\omega(\mathcal{D})) + \mathcal{I}(\omega(\mathcal{D})) + \mathcal{F}(\omega(\mathcal{D})) \leq 3$

Example 3: Considering the same example used for Hypersoft sets and, by applying the conditions of neutrosophic hypersoft sets we get the following:

$$
(\omega, \check{\mathcal{A}}) = \left\{ \begin{array}{l}
\left(\breve{a}_1\left(\frac{z_1}{(0.2,0.4,0.6)}, \frac{z_2}{(0.3,0.5,0.7)}, \frac{z_3}{(0.8,0.5,0.8)}, \frac{z_4}{(0.1,0.8,0.4)}, \frac{z_5}{(0.4,0.1,0.7)}\right)\right), \\
\left(\breve{a}_2\left(\frac{z_1}{(0.5,0.6,0.7)}, \frac{z_2}{(0.2,0.3,0.7)}, \frac{z_3}{(0.7,0.4,0.5)}, \frac{z_4}{(0.2,0.4,0.6)}, \frac{z_5}{(0.1,0.7,0.1)}\right)\right), \\
\left(\breve{a}_3\left(\frac{z_1}{(0.4,0.5,0.6,)}, \frac{z_2}{(0.1,0.2,0.3)}, \frac{z_3}{(0.8,0.5,0.2)}, \frac{z_4}{(0.5,0.2,0.6)}, \frac{z_5}{(0.8,0.2,0.5)}\right)\right), \\
\left(\breve{a}_4\left(\frac{z_1}{(0.8,0.2,0.3)}, \frac{z_2}{(0.5,0.2,0.4)}, \frac{z_3}{(0.8,0.5,0.6)}, \frac{z_4}{(0.4,0.1,0.6)}, \frac{z_5}{(0.8,0.5,0.3)}\right)\right), \\
\left(\breve{a}_5\left(\frac{z_1}{(0.6,0.2,0.3)}, \frac{z_2}{(0.5,0.4,0.6)}, \frac{z_3}{(0.4,0.2,0.6)}, \frac{z_4}{(0.7,0.9,0.1)}, \frac{z_5}{(0.8,0.5,0.7)}\right)\right), \\
\left(\breve{a}_6\left(\frac{z_1}{(0.2,0.5,0.8)}, \frac{z_2}{(0.3,0.6,0.9)}, \frac{z_3}{(0.1,0.4,0.7)}, \frac{z_4}{(0.1,0.5,0.9)}, \frac{z_5}{(0.3,0.5,0.7)}\right)\right), \\
\left(\breve{a}_7\left(\frac{z_1}{(0.2,0.4,0.7)}, \frac{z_2}{(0.4,0.9,0.3)}, \frac{z_3}{(0.7,0.9,0.2)}, \frac{z_4}{(0.1,0.6,0.7)}, \frac{z_5}{(0.8,0.4,0.6)}\right)\right), \\
\left(\breve{a}_8\left(\frac{z_1}{(0.4,0.2,0.1)}, \frac{z_2}{(0.8,0.3,0.1)}, \frac{z_3}{(0.4,0.5,0.1)}, \frac{z_4}{(0.3,0.5,0.7)}, \frac{z_5}{(0.1,0.5,0.2)}\right)\right), \\
\left(\breve{a}_9\left(\frac{z_1}{(0.4,0.2,0.8)}, \frac{z_2}{(0.7,0.1,0.3)}, \frac{z_3}{(0.4,0.3,0.9)}, \frac{z_4}{(0.1,0.2,0.3)}, \frac{z_5}{(0.3,0.5,0.7)}\right)\right), \\
\left(\breve{a}_{10}\left(\frac{z_1}{(0.3,0.4,0.9)}, \frac{z_2}{(0.2,0.5,0.7)}, \frac{z_3}{(0.9,0.2,0.4)}, \frac{z_4}{(0.4,0.7,0.3)}, \frac{z_5}{(0.7,0.8,0.3)}\right)\right), \\
\left(\breve{a}_{11}\left(\frac{z_1}{(0.4,0.8,0.3)}, \frac{z_2}{(0.4,0.8,0.1)}, \frac{z_3}{(0.7,0.3,0.4)}, \frac{z_4}{(0.1,0.5,0.3)}, \frac{z_5}{(0.7.0.5,0.9)}\right)\right), \\
\left(\breve{a}_{12}\left(\frac{z_1}{(0.1,0.5,0.7)}, \frac{z_2}{(0.3,0.5,0.9)}, \frac{z_3}{(0.7,0.5,0.9)}, \frac{z_4}{(0.2,0.4,0.6)}, \frac{z_5}{(0.8,0.6,0.2)}\right)\right), \\
\left(\breve{a}_{13}\left(\frac{z_1}{(0.5,0.8,0.2)}, \frac{z_2}{(0.5,0.2,0.3)}, \frac{z_3}{(0.9,0.2,0.4)}, \frac{z_4}{(0.3,0.4,0.1)}, \frac{z_5}{(0.7,0.2,0.1)}\right)\right), \\
\left(\breve{a}_{14}\left(\frac{z_1}{(0.6,0.7,0.2)}, \frac{z_2}{(0.4,0.8,0.2)}, \frac{z_3}{(0.3,0.4,0.9)}, \frac{z_4}{(0.2,0.5,0.4)}, \frac{z_5}{(0.3,0.6,0.9)}\right)\right), \\
\left(\breve{a}_{15}\left(\frac{z_1}{(0.2,0.5,0.8)}, \frac{z_2}{(0.7,0.4,0.1)}, \frac{z_3}{(0.1,0.5,0.9)}, \frac{z_4}{(0.7,0.3,0.5)}, \frac{z_5}{(0.2,0.5,0.3)}\right)\right), \\
\left(\breve{a}_{16}\left(\frac{z_1}{(0.6,0.5,0.4)}, \frac{z_2}{(0.8,0.9,0.7)}, \frac{z_3}{(0.7,0.5,0.3)}, \frac{z_4}{(0.4,0.9,0.2)}, \frac{z_5}{(0.3,0.1,0.2)}\right)\right), \\
\left(\breve{a}_{17}\left(\frac{z_1}{(0.7,0.6,0.4)}, \frac{z_2}{(0.4,0.6,0.5)}, \frac{z_3}{(0.3,0.5,0.9)}, \frac{z_4}{(0.4,0.2,0.1)}, \frac{z_5}{(0.2,0.4,0.5)}\right)\right), \\
\left(\breve{a}_{18}\left(\frac{z_1}{(0.4,0.5,0.6)}, \frac{z_2}{(0.7,0.8,0.9)}, \frac{z_3}{(0.5,0.8,0.4)}, \frac{z_4}{(0.8,0.2,0.4)}, \frac{z_{50}}{(0.6,0.4,0.1)}\right)\right)
\end{array} \right\}
$$

Example 4: Take the example utilized for treesoft sets and by implementing the specifications of neutrosophic treesoft sets, we derive the outcome:

Neutrosophic treesoft sets is given by

$$\mathcal{F}(\mathcal{Z}_1 \cup \mathcal{Z}_2 \cup \mathcal{Z}_3) = \mathcal{F}\big(Road\ capacity(a_{11}), Construction\ dust(a_{222}), Utility\ demand(a_{322})\big)$$

$$= \left\{ \begin{array}{l} \left(\frac{z_1}{a_{11}(0.25,0.71,0.63), a_{222}(0.68,0.47,0.31), a_{322}(0.47,0.51,0.28)}\right); \\ \left(\frac{z_2}{a_{11}(0.52,0.84,0.61), a_{222}(0.82,0.56,0.71), a_{322}(0.59,0.62,0.48)}\right); \\ \left(\frac{z_3}{a_{11}(0.84,0.67,0.45), a_{222}(0.74,0.73,0.75), a_{322}(0.74,0.61,0.81)}\right); \\ \left(\frac{z_4}{a_{11}(0.94,0.21,0.52), a_{222}(0.24,0.84,0.86), a_{322}(0.75,0.84,0.56)}\right); \\ \left(\frac{z_5}{a_{11}(0.24,0.45,0.55), a_{222}(0.91,0.54,0.64), a_{322}(0.72,0.61,0.53)}\right) \end{array} \right\}$$

3. Multi Criteria Decision Making Technique (MCDM):

3.1 Analytical Hierarchy Process (AHP) [5]: This is the simplest weight calculation method, here is the algorithm for the method:

Step 1: Define the Decision Problem

Step 2: Identify the criteria and sub-criteria

Step 3: Establish the pairwise comparison matrix

Step 4: Normalize pairwise comparison matrix

Step 5: Calculate criteria weights

Step 6: Check consistency of pairwise matrix

Step 7: Calculate final scores and make the decisions

3.2 Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [3]:

Step 1: Create an evaluation matrix

Step 2: The evaluation matrix is normalized using the below formula

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k-1}^{m} x_{kj}^2}}, i = 1,2,\ldots,m; j = 1,2,\ldots,n$$

Step 3: Calculate the weighted normalized decision matrix

$$t_{ij} = r_{ij}.\mathcal{W}_j, i = 1,2,\ldots,m; j = 1,2,\ldots,n$$

where $\mathcal{W}_j = \frac{w_j}{\sum_{k=1}^{n} w_k}, j = 1,2,\ldots,n$

Step 4: Establish the worst alternative ($\mathcal{A}_{w}$) and best alternative ($\mathcal{A}_{b}$);

$$\mathcal{A}_{w} = \{\langle max(t_{ij}|i = 1,2,\dots,m)|j \in \mathcal{J}_{-}\rangle, \langle min(t_{ij}|i = 1,2,\dots,m)|j \in \mathcal{J}_{+}\rangle\} \equiv \{t_{wj}|j = 1,2,\dots,n\}$$

$\mathcal{A}_{b} = \{\langle min(t_{ij}|i = 1,2,\dots,m)j \in \mathcal{J}_{-}\rangle, \langle max(t_{ij}|i = 1,2,\dots,m)|j \in \mathcal{J}_{+}\rangle\} \equiv \{t_{bj}|j = 1,2,\dots,n\}$

Step 5: Compute the $\mathcal{L}^2$ the distance among the target alternative i & worst condition $\mathcal{A}_{w}$

$$d_{iw} = \sqrt{\sum_{j=1}^{n}\left(t_{ij} - t_{wj}\right)^2}, i = 1,2,\dots,m$$

and distance among the alternative i & best condition $\mathcal{A}_{b}$

$$d_{ib} = \sqrt{\sum_{j=1}^{n}\left(t_{ij} - t_{bj}\right)^2}, i = 1,2,\dots,m$$

where d_{iw} & d_{ib} are $\mathcal{L}^2$- norm distances from a target alternative to the worst & best conditions, correspondingly.

Step 6: Determine how similar it is to the worst situation.

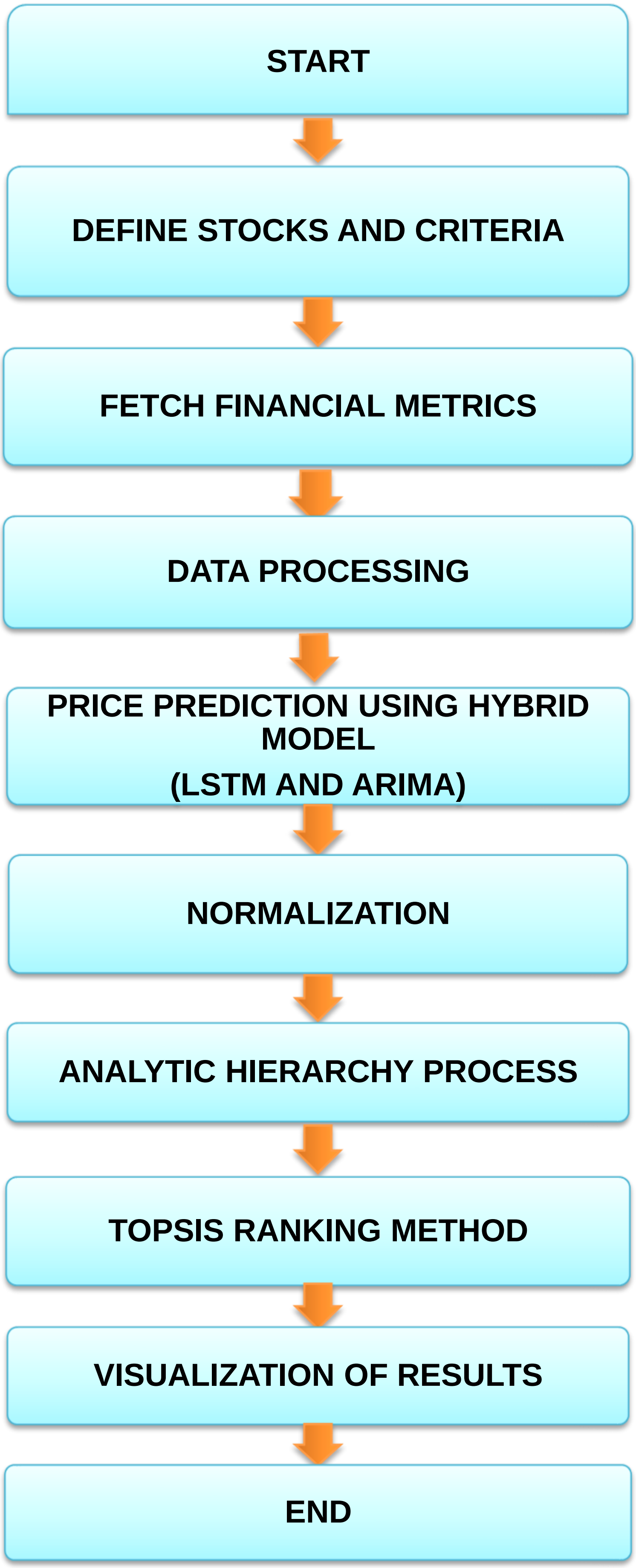
$$s_{iw} = \frac{d_{iw}}{(d_{iw} + d_{ib})}, 0 \leq s_{iw} \leq 1, i = 1,2,\dots,m.$$

$s_{iw} = 0$ if and only if the alternative solution has the worst condition and

$s_{iw} = 1$ if and only if the alternative solution has the best condition

Step 7: Rank the alternative using $s_{iw}(i = 1,2,\dots,m)$.

Flow Chart for Stock analysis and Prediction process: The below flowchart gives a brief outline of the working of the proposed model.


START
DEFINE STOCKS AND CRITERIA
FETCH FINANCIAL METRICS
DATA PROCESSING
PRICE PREDICTION USING HYBRID MODEL
(LSTM AND ARIMA)
NORMALIZATION
ANALYTIC HIERARCHY PROCESS
TOPSIS RANKING METHOD
VISUALIZATION OF RESULTS
END

Formulation of the problem: Investors are confronted with the challenge of selecting the most advantageous equities from a competitive and diverse market place in the contemporary financial landscape. Furthermore, the increasing significance of market sentiment, risk management, growth potential, and sustainability (ESG) considerations requires a more comprehensive evaluation approach. The objective of the decision-maker is to address the challenge of comprehensive stock evaluation by creating a multi-criteria decision-making (MCDM) framework that will evaluate seven influential stocks: Apple Inc. (AAPL), Microsoft Corp. (MSFT), Amazon. Com Inc. (AMZN), Alpabet Inc. (GOOGL), Tesla Inc. (TSLA), NVIDIA Corp. (NVDA), and Johnson & Johnson (JNJ). The assessment will be predicated on seven primary criteria, each of which is further divided into sub-criteria and sub-sub-criteria as listed below:

The criteria's include

$$d = Finanical\ Performance;\ e = Market\ Sentiment;\ f = Risk\ Profile;$$

$$g = Growth\ Potential;\ h = Valuation;\ i = Liquidity;$$

$$j = Sustainability\ and\ ESG\ factors$$

Each criteria is subdivided into sub-criteria's as

$$d_1 = revenue\ growth;\ d_2 = Profitability;\ d_3 = return\ on\ equity;$$

$$e_1 = social\ media\ sentiment;\ e_2 = news\ sentiment;\ e_3 = analyst\ recommendations;$$

$$f_1 = volatility;\ f_2 = financial\ leverage; f_3 = liquidity\ risk;$$

$$g_1 = predicted\ price\ increase; g_2 = market\ share\ growth; g_3 = innovation;$$

$$h_1 = price - to - eaarnings; h_2 = price - to - book\ ratio;\ h_3 = dividend\ yield;$$

$$i_1 = trading\ volume; i_2 = cash\ flow; i_3 = short - term\ solvency;$$

$$j_1 = environmental\ score; j_2 = social\ responsibility; j_3 = governance;$$

Following are the sub-sub-criteria's of each sub-criteria's

$$d_{11} = quarterly; d_{12} = annual\ ; d_{13} = 5 - year\ CAGR;$$

$$d_{21} = net\ profit\ margin; d_{22} = operating\ margin; d_{23} = gross\ margin;$$

$$d_{31} = TTM; d_{32} = 3 - year\ average; d_{33} = 5 - year\ average;$$

$$e_{11} = twitter; e_{12} = reddit; e_{13} = stock\ twits;$$

$$e_{21} = positive\ ; e_{22} = negative\ ; e_{23} = neutral\ news\ ratio;$$

$$e_{31} = buy; e_{32} = hold; e_{33} = sell\ ratings;$$

$$f_{11} = 1 - year; f_{12} = 5 - year; f_{13} = beta;,$$

$$f_{21} = debt - to - equity; f_{22} = interest\ coverage;\ f_{31} = current\ ration;\ f_{32} = quick\ ratio; f_{33} = cash\ ratio;$$

$$g_{11} = 1 - month; g_{12} = 3 - month; g_{13} = 6 - month;$$

$$g_{21} = industry\ comparison;$$

$$g_{31} = R\&D\ investments; g_{32} = patents; g_{33} = new\ product\ launches;$$

$$h_{11} = forward\frac{P}{E}; h_{12} = trailing\frac{P}{E}; h_{13} = industry\ comparison;$$

$$h_{21} = book\ value\ per\ share; h_{22} = market\ price\ per\ share;$$

$$h_{31} = payout\ ratio; h_{32} = growth\ rate; h_{33} = historical\ yield;$$

$$i_{11} = average\ daily\ volume; i_{12} = relative\ volume;$$

$$i_{21} = operating\ cash\ flow; i_{22} = free\ cash\ flow, i_{31} = current\ ratio; i_{32} = quick\ ratio; i_{33} = cash\ ratio;$$

$$j_{11} = carbon\ footprint; j_{12} = energy\ efficiency; j_{13} = waste\ management;$$

$$j_{21} = employee\ diversity; j_{22} = community\ engagement;$$

$$j_{31} = board\ diversity; j_{32} = transparency; j_{33} = anti - corruption;$$

The below table shows the alternatives and criteria's taken from all the above mentioned criteria's sub-criteria's, sub-sub-criteria's

Table 2 Alternatives and criteria's

	Alternatives	Criteria's
1.	AAPL	Net profit margin
2.	MSFT	P\E ratio
3.	AMZN	Average daily trading volume
4.	GOOGL	Beta (stock availability)
5.	TSLA	Environmental score
6.	NVDA	Sentiment scores
7.	JNJ	Predicted 3-month increase

The following code illustrates a hybrid approach to stock analysis and prediction that employs financial metrics, sentiment scores, environment scores, and hybrid price forecasting models (LSTM and ARIMA). It incorporates the Analytic Hierarchy Process (AHP) for weight determination and TOPSIS for alternative ranking.

Step 1: Here the necessary libraries to be installed and imported in the code

Step 2: Defining stocks and simulated data.

```python
stocks = ['AAPL', 'MSFT', 'AMZN', 'GOOGL', 'TSLA', 'NVDA', 'JNJ']
```

The simulated data includes:

```python
sentiment_scores = {...}
environmental_scores = {...}
```

Step 3: Fetching financial metrics

```python
def fetch_financial_metrics(stocks):
```

The below mentioned are the financial metrics to be considered

- Net profit margin
- P\E ratio
- Average daily trading volume
- Beta
- Environmental score

Step 4: LSTM and ARIMA model prediction

LSTM uses past stock prices to predict future prices

```python
def get_hybrid_predicted_price_increase(ticker, start_date, end_date, sequence_length=60):
    stock_data = yf.download(ticker, start=start_date, end=end_date)
    stock_data = stock_data[['Close']]
```

LSTM works best with scaled data, hence MinMaxScaler is used to normalize the stock prices between 0 and 1.

```python
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_data = scaler.fit_transform(stock_data)
```

In order to train the LSTM model, the data is partitioned into sequences. The stock prices are sequence over a period of 60 days.

```python
def create_sequences(data, sequence_length):
```

The TensorFlow/Keras Sequential API is employed to construct a two-layer LSTM model. The Huber loss is employed to mitigate the effects of outliers. For a period of 20 epochs, the model is trained on 80% of the data.

```python
model = Sequential()
...
model.compile(optimizer='adam', loss=Huber())
model.fit(X_train, y_train, batch_size=32, epochs=20, verbose=1)
```

Upon completion of training, the LSTM model forecasts future prices by utilizing the most recent 60 days of stock price data.

```python
last_sequence = scaled_data[-sequence_length:]
predicted_price_scaled = model.predict(last_sequence)
predicted_price_lstm = scaler.inverse_transform(predicted_price_scaled)
```

The stock data is also fitted with an ARIMA (AutoRegressive Integrated Moving Average) model, which aids in the identification of linear trends. The stock price for the following day is predicted [7].

```python
model_arima = ARIMA(stock_data, order=(5, 1, 0))
model_fit = model_arima.fit()
predicted_price_arima = model_fit.forecast(steps=1)
```

The forecasts from LSTM and ARIMA are averaged to obtain a hybrid anticipated price. The percentage increase from the most recent price is calculated and provided [9].

```python
predicted_price = (predicted_price_lstm[0][0] + predicted_price_arima) / 2
```

Step 5: Financial Metrics and Predicted price increase

```python
predicted_increases = {}
for stock in stocks:
    predicted_increases[stock] = get_hybrid_predicted_price_increase(stock, '2023-01-01',
```

In the forthcoming period, the probable price increases for each stock are recorded in predicted_increases.

Step 6: Normalization of Financial Metrics:

Using MinMaxScaler the financial data, sentiment scores, and predicted price increases are normalized for comparison

```python
def normalize_data(data):
    scaler = MinMaxScaler()
    return pd.DataFrame(scaler.fit_transform(data), columns=data.columns, index=data.index
```

Step 7: AHP Method for Weight Calculation [22]

Based on user preferences (such as the significance of criteria such as Net Profit Margin and P\E ratio), a pairwise comparison matrix is generated. The final weights are determined by normalizing the matrix and computing the priority vector.

```python
def ahp_method():
```

Step 8: TOPSIS for Stock Ranking [24]

According to the criteria weights determined by AHP, the financial data is first normalized and subsequently weighted.

```python
evaluation_matrix = normalized_df.values
...
weighted_df = norm_matrix * weights.values
```

The best and worst alternatives are identified for each criterion. For certain criteria (e.g., Net Profit Margin), elevated values are advantageous, whilst for others (e.g., Beta), diminished values are preferred.

```python
def determine_best_worst(weighted_df, is_benefit):
```

The Euclidean distance of each stock from the ideal best and worst solutions is used to calculate the TOPSIS score. The stocks are arranged in accordance with their scores.

```python
d_best, d_worst = calculate_distances(weighted_df, best, worst)
topsis_score = d_worst / (d_best + d_worst)
```

Step 9: Visualization of Predicted prices:

This tool visualizes the actual against expected pricing utilizing plotly. It superimposes both LSTM and ARIMA forecasts onto the real stock price data.

```python
# Plot all stocks in a single graph and save as image and HTML
def plot_all_stocks_actual_vs_predicted_and_save(stocks, start_date, end_date, image_file_
```

Step 10: Final output

The table below displays the rating of seven stocks, the final output presents the model's projection based on the criteria; the predicted 3-month gain fluctuates according to the market's stock value changes.

Table 3 Final ranking

	Alternatives	TOPSIS scores	Ranking
1.	AAPL	0.135899	7
2.	MSFT	0.200582	5
3.	AMZN	0.595582	1

4.	GOOGL	0.219955	4
5.	TSLA	0.406424	3
6.	NVDA	0.558132	2
7.	JNJ	0.159474	6

Comparative study of the Model:

1. **Comparison of Prediction Models: Hybrid LSTM-ARIMA vs. Other Models**
    - **Hybrid Model (LSTM+ARIMA)**
      Advantages: Integrates the efficacy of LSTM, which excels in capturing sequential relationships in time-series data, with ARIMA, which is proficient in modelling trends and seasonality. It enables the application of linear elements using ARIMA and non-linear patterns using LSTM.
      Disadvantages: It requires significant computational resources, as it necessitates the training of both LSTM and ARIMA models. Neural Networks often lack interpretability due to their perceived "black box" nature. **Accuracy:** Hybrid models often surpass single models in analysing complex stock data, contingent upon the stock's volatility and historical trends.

    - **Alternative Models**
        - ♦ **Single ARIMA model:** This method is more straightforward and interpretable, as it relies solely on three factors (p,d,q). It works better for steady time series with strong seasonality, but it's less useful for extremely volatile stocks.
        - ♦ **Single LSTM Model:** This method proves to be effective in pinpointing non-linear correlations within time-series data. The system requires more data for the best training, and its performance could decline with fewer datasets.
        - ♦ **Prophet Model:** Facebook created this tool, which excels at handling time series data that includes distinct seasonal and trend elements. It is quick and relatively easy to modify, yet it might not adequately react to sudden changes in the market.

2. **Comparison of weighting and Ranking Techniques: AHP-TOPSIS vs. Alternative Decision-Making methods:**
    - **AHP-TOPSIS Approach:**
      Advantages: The Analytic Hierarchy Process (AHP) facilitates the integration of expert judgement and enables subjective weighting according to the significance of criteria. TOPSIS is simple to compute and yields a singular score that rates equities based on their closeness to an optimal solution**.**
      Disadvantages: AHP process may exhibit sensitivity to biases in judgment during weight assignment. TOPSIS ignores trade-offs among criteria and assumes that all criteria have equal significance after weighting.

Suitability: It is ideal for situations where expert preference is present and decision-making involves a well-defined set of criteria.

- **Alternative methods:**
  - **Simple Additive Weighting (SAW):** With direct weighting and summation of criteria, it is simpler to compute. The absence of TOPSIS's ideal-best/worst comparison could potentially impact the clarity of the displayed rankings.
  - **Analytic Network Process:** A modification of AHP that considers the interrelationships among criteria. Increased complexity enhances the representation of realistic relationships among decision factors.
  - **Machine Learning-**Based Ranking (e.g., Gradient Boosting): Models can acquire intricate non-linear associations between variables and results. The model demands labelled data, it presents interpretative challenges, and may be inappropriate for scenarios where interpretability is crucial.

Table 4 Comparative study table

Criteria	Hybrid LSTM-ARIMA	ARIMA	AHP-TOPSIS	SAW	ANP
Complexity	High	Medium	Medium	Low	High
Accuracy	High	Medium-High	High	Medium	High
Interpretability	Medium	High	High	High	Medium
Computational Requirements	High	Low	Medium	Low	High
Optimal Application	Volatile stocks	Stable stocks	Criteria ranking	Simple decision-making	Complex interdependencies

Sensitivity Analysis: Sensitivity analysis in this work entails how variations in the weights or significance of each criterion affect the final TOPSIS rankings for each stock. This assists in determining which criteria exert the most significant impact on the decision-making process and the resilience of the rankings to variations in these criteria.

Case 1: By adjusting the weights of the criterion by a small percentage of $\pm 10\%$

Table 5

Stocks	Baseline score	Baseline rank	Net profit +10%	Rank	Net profit -10%	Rank	Average +10%	Rank	Average -10%	Rank
AAPL	0.136	7	0.138	7	0.134	7	0.138	7	0.134	7
MSFT	0.201	5	0.204	5	0.197	5	0.195	5	0.206	5
AMZN	0.596	1	0.593	1	0.597	1	0.578	1	0.613	1
GOOGL	0.220	4	0.221	4	0.219	4	0.214	4	0.226	4

TSLA	0.406	3	0.405	3	0.407	3	0.400	3	0.412	3
NVDA	0.558	2	0.560	2	0.557	2	0.573	2	0.544	2
JNJ	0.159	6	0.166	6	0.153	6	0.155	6	0.164	6

In the aforementioned case, stocks that continuously get high rankings across diverse situations may be regarded as robust in their weight, exhibiting percentage fluctuations in their weights.

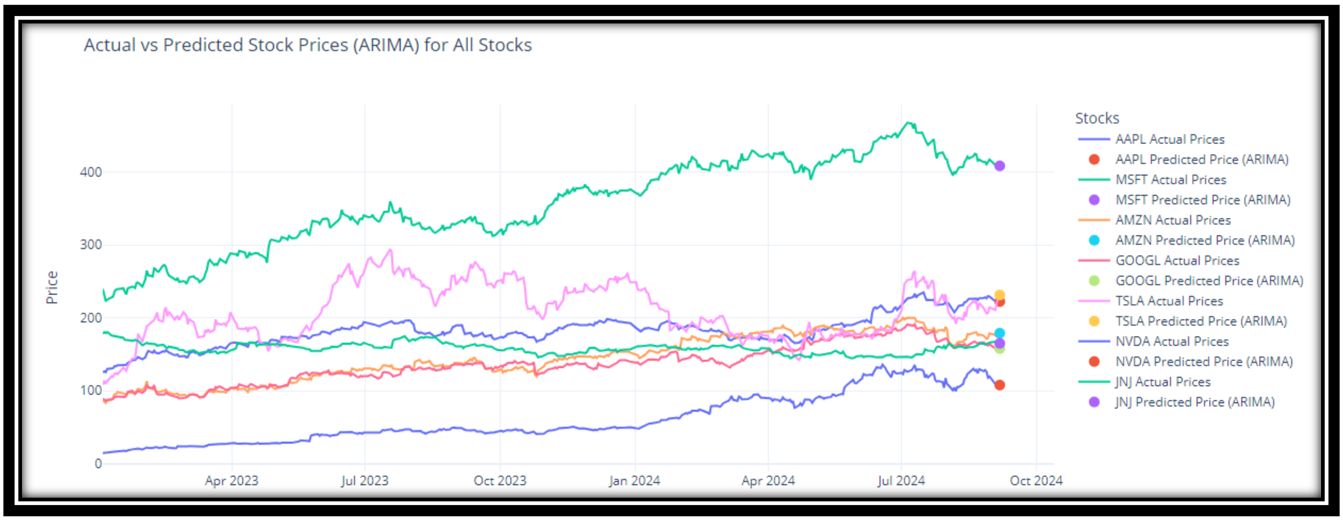
Case 2: Enhancing the weight of a beneficial criteria and lowering the weight of a non-beneficial criteria we get the below table

Table 6

Stocks	Baseline score	Baseline rank	Change in score	Rank
AAPL	0.136	7	0.431	6
MSFT	0.201	5	0.500	3
AMZN	0.596	1	0.445	5
GOOGL	0.220	4	0.478	4
TSLA	0.406	3	0.169	7
NVDA	0.558	2	0.588	1
JNJ	0.159	6	0.558	2

The most significant shifts in ranking occurred when the non-beneficial criterion Beta was elevated and the beneficial criterion environmental score was minimized. These criteria exert the most substantial impact on stock performance as per the model

Description of the graph performance: The graph illustrates a comparison between actual stock prices and forecasted prices for various equities (AAPL, MSFT, AMZN, GOOGL, TSLA, NVDA, JNJ) over a designated time period. Each stock possesses a solitary marker (point) that signifies the anticipated price for the subsequent day following the conclusion of the actual price data (September 7, 2024). The markers are positioned at the terminus of the actual price lines and are typically depicted as larger dots in an alternate colour (eg., red). The marker’s location indicates the projected price for the following day, derived from the ARIMA model



Below is the link for the working of a plotly graph based on python coding language

stocks-plot.html

Interpretation of the figure

- **Trend analysis:** The overall trend in the prices of each stock over the specified time frame can be analysed by examining the lines. For example, an upward-sloping price line of a stock suggests that its price is on the rise.
- **Forecasting Accuracy:** The predicted markers serve as a benchmark for comparison with the actual price lines. The forecasting model (ARIMA) has performed has performed well if the predicted price (marker) is in close proximity to the last point of the actual price line.
- **Volatility:** Additionally, it is possible to evaluate the volatility of each stock through assessing the degree of fluctuation in the actual price lines. Larger fluctuations may suggest that the stock in question is more volatile or prone to risk.
- **Investment Decisions:** This graphic aids investors in decision-making by utilizing trends and forecasts. A stock with a robust growth trajectory and an optimistic outlook may be regarded as a favourable investment prospect.

Overall this graphical representation is a potent instrument for the analysis of stock performance and the formulation of well-informed investment decisions based on historical data and predictions.

Limitations and impact: This approach is limited by the complexity arising from the use of Neutrosophic Treesoft sets, which although beneficial for managing uncertainty, may hinder understanding and practical use in real-time trading. The hybrid ARIMA-LSTM model, while excellent for forecasting, can be computationally intensive, presenting difficulties for high-frequency trading. Moreover, the precision depends on the quality of subjective inputs such as sentiment scores, which may be susceptible to bias. Considering these constraints, the significance of this research it considerable; it improves stock forecast precision by integrating both quantitative and qualitative indicators, facilitating more informed and balanced investment choices. The innovative use of Neutrosophic Treesoft sets may impact future research in uncertainty modelling in finance and other fields where decision-making under ambiguous settings is crucial.

Discussion: A robust methodology for assessing the performance of the selected stocks was established through the integration of MCDM techniques and LSTM/ARIMA predictive models. Although traditional financial metrics are still significant, a more comprehensive and forward-thinking evaluation was achieved by incorporating advanced price forecasting, sentiment analysis, and ESG factors. Stocks such as AAPL and JNJ may be preferred by investors who prioritize sustainable practices and long-term development. Conversely, investors who prioritize high-growth, innovation-driven investments may favour AMZN, NVDA or TSLA, although with a higher risk tolerance.

Conclusion: This paper defines neutrosophic treesoft sets and provides examples of both neutrosophic and fuzzy treesoft sets. Using Neutrosophic treesoft sets along with hybrid predictive models and AHP-TOPSIS ranking methods in this study shows that it is possible to make a flexible, accurate, and advanced framework for financial analysis. The hybrid model for predicting stock price increases combines the long-term dependencies and trend-capturing capabilities of LSTM with the precision of ARIMA in time-series modelling. The use of Neutrosophic treesoft sets allows the framework to systematically capture three essential aspects of information: truth, indeterminacy, and falsity. This structure demonstrates enhanced flexibility and responsiveness to real-world situations marked by ambiguous or conflicting data. Future research may focus on assessing this framework using larger datasets, integrating additional financial indicators, or applying real-time sentiment analysis via NLP to improve its accuracy and adaptability and extend this model to other environments like Intuitionistic, Pythagorean, Bipolar fuzzy sets.

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