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Research Article

Risk Parity And Dynamic Portfolio Allocation-Integrated Personalized Financial Advice Provider Model Using RL-GPLinQ-GRU and IGP-Fuzzy

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ABSTRACT

Nowadays, individuals are increasingly seeking accessible and intelligent tools to help and manage their finances for better financial decision-making. However, traditional works failed to consider severe traditional assets, spending priority, real-time financial data, and market feedback to perform risk parity and dynamic allocation, leading to ineffective portfolio adjustment. Therefore, an efficient risk parity and dynamic portfolio allocation-integrated personalized financial advice provider framework is proposed using RL-GPLinQ-GRU and IGP-Fuzzy. Initially, financial data undergoes preprocessing, augmentation, bubble plot generation, and feature extraction. Meanwhile, the MT-DBSCAN is used to analyze behavioral patterns of preprocessed financial data, followed by portfolio extraction and portfolio optimization using PS-MPA. Now, RL-GPLinQ-GRU identifies financial scores from the extracted features and optimized portfolio via enhancing model integrity using VLIME. In the meantime, the sentiment classification model is trained using the stock market sentiment data through preprocessing, keyword extraction, word embedding, and sentiment analysis. Simultaneously, RL-GPLinQ-GRU predicts stock market status using the historical stock market data via preprocessing, technical indicator extraction, and feature extraction. Finally, based on the identified financial score with explanation, classified sentiments, and predicted stock market status, IGP-Fuzzy performs risk parity and dynamic portfolio allocation. Thus, the proposed framework outperforms the other prevailing techniques by attaining higher accuracy (99.21%).

Keywords: Personalized Financial Advisory, Dynamic Portfolio Allocation, Artificial Intelligence (AI), Reinforcement Learning-based Gradient Penalty Linear Quadratic Gated Recurrent Units (RL-GPLinQ-GRU), Inverse Gaussian Peaked-Fuzzy (IGP-Fuzzy), Powell Sum-Marine Predators Algorithm (PS-MPA), Viennet Local Interpretable Model-agnostic Explanation (VLIME), and Morra Tversky-based Spatial Clustering of Applications with Noise (MT-DBSCAN).

1. Introduction

In today's rapidly evolving financial landscapes, effective personal financial management requires more than simple budgeting and saving (Pahsa, 2024). Individuals face a wide range of financial decisions, ranging from debt management, investment planning, and retirement saving to tax optimization (Linnainmaa et al., 2018) (Garad et al., 2024). These decisions are often influenced by

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dynamic market conditions, changing regulations, and evolving personal circumstances, making financial planning more accessible to the average person (Mazzoli et al., 2024) (Vecchi et al., 2023).

Hence, personalized financial advisors have emerged as an important solution to deliver tailored financial guidance. A personalized financial advisor is a professional who provides customized financial guidance tailored to an individual's unique financial situation, goals, risk tolerance, and life circumstances (Kim et al., 2021) (H. Zhu et al., 2023). Unlike generic financial advisory models, personalized financial advising considers a person's income, assets, liabilities, family needs, and future aspirations to create a comprehensive and adaptive financial plan (Fong et al., 2021) (Hagen & Malisa, 2022). However, they may be resource-intensive and have limited scalability, particularly for a large and diverse user base (Yeo et al., 2024).

Therefore, various Artificial Intelligence (AI)-based methodologies have been implemented to provide efficient personalized financial advice to individuals. These methodologies offer the ability to analyze the vast amount of financial, behavioral, and market data in real-time, enabling more accurate and timely decision-making (L. Wu & Yu, 2024) (Fan, 2020). However, most of the work failed to ensure the reasons behind the financial decisions, consider ethical concerns, and identify unknown financial goals or life events, affecting the decision-making process (Li et al., 2024). Additionally, some conventional approaches struggled to identify the exact meaning of the corresponding stock market review data, decreasing training performance. Further, none of the prevailing works included risk parity and dynamic allocation by considering traditional assets, spending priority, real-time financial data, and market feedback. Therefore, defining and prioritizing financial goals for clients becomes challenging. Thus, an efficient risk parity and dynamic portfolio allocation-based personalized financial advice provider framework is proposed using RL-GPLinQ-GRU and IGP-Fuzzy.

1.1 Problem Statement

The limitations of several traditional works are depicted as follows,

- None of the existing approaches performed risk parity and dynamic portfolio allocation by considering the traditional assets, spending priority, real-time financial data, and market feedback, leading to suboptimal investment strategies.
- (Kou et al., 2021) failed to ensure that clients understand the reasoning behind recommendations, leading to inefficient financial decisions.
- (Hsu et al., 2023) failed to focus on ethical concerns of personalized financial advice, particularly demographic data, qualitative data, and socio-economic status, leading to potential biases in recommendations.
- (Rjoub et al., 2023) failed to identify new, previously unknown financial goals, income, life events, etc., affecting overall performance.
- Due to the utilization of the standard word embedding process, most of the traditional approaches failed to identify the exact meaning of the corresponding stock market review data.
- Some prevailing works failed to analyze the relationships between the portfolios, increasing the false alarm rate.

1.2 Objectives

The major objectives to overcome the above-mentioned limitations are illustrated as follows,

- To perform risk parity and dynamic portfolio allocation based on traditional assets, spending priority, real-time financial data, and market feedback, IGP-Fuzzy is applied.
- To understand the reason behind personalized financial recommendations, VLIME is utilized.
- MT-DBSCAN is used to identify user segments while minimizing bias related to ethical concerns of personalized financial advice.
- To enhance overall performance by identifying new, unknown financial goals, and so on, Reinforcement learning is applied.

- To identify the exact meaning of the stock market review data, EPD-FinBERT is utilized.
- To analyze the relationships between the portfolios or financial data, a Bubble plot is constructed.

The construction of this paper is described as follows: Section 2 illustrates the literature survey, Section 3 explains the proposed methodology, Section 4 demonstrates the results and discussion, and Section 5 concludes the proposed framework with future recommendations.

2. Literature Survey

(Kou et al., 2021) implemented a decision-making approach based on Interval Type-2 (IT2) fuzzy sets to evaluate FinTech-based investments in European banking services. This framework integrated IT2 fuzzy with DEcision-MAking Trial and Evaluation Laboratory (DEMATEL) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) for weighting and ranking investment. Additionally, the multi-criteria optimization and compromise solution were applied to validate the ranking. As per the results, this framework optimized receivable collection and reduced operational costs. Yet, it made ineffective financial decisions due to the lack of providing the reasons behind recommendations.

(Hsu et al., 2023) introduced a Deep Learning (DL)-based Financial Graph Attention Network (FinGAT) for recommending top-k profitable stocks. Here, the hierarchical learning was applied to capture long and short-term sequential patterns from stock time series. Then, the latent interactions were learned using fully connected graphs. Then, stock market prediction was done via learning the latent interactions using fully connected graphs, attaining 98% precision. However, this model failed to consider ethical concerns, leading to potential biases in recommendations.

(Rjoub et al., 2023) demonstrated a methodology based on blockchain for the banking sector using Adaptive Neuro-Fuzzy-based K-Nearest Neighbors (ANF-KNN). Here, the input data were preprocessed. Then, the chaotic-improved foraging optimization was incorporated in ANF-KNN to enhance efficiency. Also, the rolling window auto-regression lag modeling was applied to analyze FinTech growth, followed by storing it in a blockchain. As per the result, this model attained 91% accuracy. But, this model was not suitable for real-world application, owing to the lack of identifying previously unknown financial goals, income, and so on.

Then, three RL-based approaches were utilized to optimize portfolio management by defining the state representations. Finally, the model was trained using a Markov Decision Process (MDP) to maximize cumulative rewards, attaining a 0.66 Sharpe ratio. However, the state representation of this model was hindered owing to the limited number of factors.

(Huot et al., 2024) demonstrated a financial portfolio optimization model using a knapsack-based technique. Here, historical data were collected, followed by expected return estimation using the Markowitz model. Then, the Quantum Walk Mixer (QWM) within Quantum Approximate Optimization Algorithm (QAOA) was applied to refine portfolio selection. Finally, weight constraints were encoded using the Quantum Fourier Transform (QFT), attaining ~0.99 approximation ratio. Yet, the applicability of this approach was affected due to the limited qubit availability.

(Walczak et al., 2021) described the framework for examining the influence of environmental protection on financial decisions. This model incorporated statistical analyses, including nonparametric tests and Pearson's contingency coefficient for evaluating correlations between respondents' demographic characteristics. Additionally, to enhance sustainable financial practices, the policy measures were introduced, increasing public awareness. Due to the limited number of samples, this model was not generalized.

(Hao & Ma, 2024) introduced the Picture Fuzzy Measurement Alternatives and Ranking according to the Compromise Solution (PF-MARCOS)-based Multi-Criteria Group Decision-Making (MCGDM) to

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optimize managerial decision-making in financial accounting. Here, PF-MARCOS optimized financial decision-making, followed by alternative evaluation using fuzzy logic. As per the result, this model showed high flexibility and sensitivity. Yet, this model led to potential bias in parameter weighting, affecting robustness.

(Lim et al., 2022) implemented an approach for financial investment optimization using RL. By applying portfolio management strategies, this model balanced risks and returns. To detect trend reversals and adjust asset compositions, the RL agent was trained using market trend indicators. Finally, Long Short-Term Memory (LSTM) was used for price prediction, increasing the gradual rebalance by 46.7%. However, this model consumed more time due to the presence of a larger number of traders.

Here, the spherical fuzzy DEMATEL was applied to evaluate factors influencing carbon capture investments. Then, the financial features were ranked using spherical fuzzy Additive Ratio ASSessment (ARASS), followed by sensitivity analysis. As per the results, this model determined the most critical financial features. Owing to the reliance on specific ranking approaches, this model exhibited limited adaptability.

(Wu et al., 2021) demonstrated a Portfolio management system using RL. Initially, the stock price data were preprocessed and transformed into input tensors. Then, the RL framework was implemented using a Convolutional Neural Network (CNN) and a Recurrent Neural Network (RNN) to learn trading patterns and portfolio allocation. Finally, the Equity Market Neutral (EMN) strategy enhanced risk management, decreasing drawdown risk by 13.7%. Yet, this model showed limited performance due to its inability to capture temporal dependencies.

3. Proposed Methodology

In this section, the proposed methodology for the construction of a risk parity and dynamic portfolio allocation-based personalized financial advice provider framework using GPLinQ-GRU and IPG-Fuzzy is depicted. The main aim of this framework is to assist individuals in making real-time, accurate, and personalized financial decisions by performing four phases like financial-score identification, sentiment classification, stock market status prediction, and risk parity along with dynamic allocation. The block diagram for the proposed framework is depicted in Figure 1.

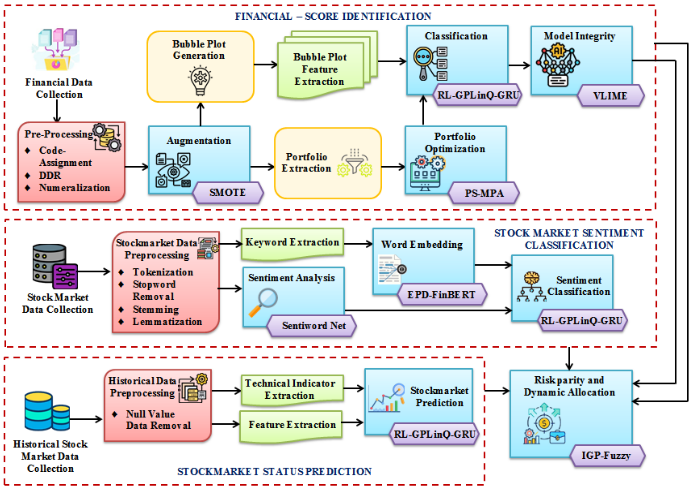

Figure 1: Block diagram for the proposed framework

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3.1 Financial-Score Identification

In this phase, users' financial scores are identified to recognize the user's financial condition, income level, and future financial goals.

3.1.1 Financial Data Collection

Initially, the users' financial data (F_a) is collected from publicly available sources. This data includes age, gender, job, household income, and other democratic and economic parameters.

$$F_a = \{F_1, F_2, F_3, \cdots, F_{\vec{a}}\} \qquad ;a = 1 \rightarrow \vec{a} \tag{1}$$

Where, $\vec{a}$ illustrates the maximum number of F_a.

3.1.2 Financial Data Preprocessing

Now, F_a often struggle with inconsistencies, format variation, and incompleteness, affecting financial score identification accuracy. So, the preprocessing is carried out to enhance the quality of F_a.

- **Code Assignment:** Initially, code assignment, which is the process of converting raw financial data into standardized categorical or numerical codes (C), is applied to each F_a, ensuring uniform representation.
- **Duplicate Data Removal (DDR):** Now, to ensure data uniqueness and integrity, duplicates are removed from C, attaining duplicate-removed codes $(\hat{C})$.
- **Numeralization**: Finally, $\hat{C}$ are transformed into numeric values to produce the preprocessed financial data (P_F^b), ensuring consistent scaling.

$$P_F^b = \{P_F^1, P_F^2, P_F^3, \cdots, P_F^{\vec{b}}\} \qquad ;b = 1 \rightarrow \vec{b} \tag{2}$$

Where, $\vec{b}$ demonstrates the maximum number of P_F^b.

3.1.3 Augmentation

Then, data augmentation is performed using the Synthetic Minority Oversampling Technique (SMOTE) to expand the size of the minority class set in P_F^b. The SMOTE helps to enhance financial score classification performance, offering augmented data, addressing data scarcity, and reducing class imbalance and the overfitting problem. Here, by calculating the sampling rate for the minority class set of P_F^b and by generating synthetic instances, the SMOTE provides augmented financial datasets (M^{aug}).

3.1.4 Bubble Plot Generation

Next, the relationships between each data in M^{aug} are analyzed by generating bubble plots, which are a type of scatter plot, where the x-axis, y-axis, and the size of the dots represent each M^{aug}. Thus, this visualization helps to identify patterns, clusters, and outliers in user financial behavior, thereby providing valuable insights for accurate financial-score identification. Then, the generated bubble plot is depicted as (B_{gen}).

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3.1.5 Bubble Plot Feature Extraction

Now, the features responsible for the acute financial score identification are extracted from B_{gen}. Here, position, size, color, density distribution, outliers, temporal changes, density, and so on are the extracted features $\left(\mathrm{F}_F^c\right)$.

$$\mathrm{F}_F^c = \left\{\mathrm{F}_F^1, \mathrm{F}_F^2, \mathrm{F}_F^3, \cdots, \mathrm{F}_F^{\ddot{c}}\right\} \qquad ;c = 1 \rightarrow \vec{c} \tag{3}$$

Where, $\vec{c}$ indicates the maximum number of F_F^c.

3.1.6 Behavioral Pattern Analysis

In the meantime, the behavioral patterns of users are analyzed from M^{aug} using MT-DBSCAN for accurate financial score identification. The Density-Based Spatial Clustering of Applications with Noise (DBSCAN) can effectively analyze complex, unstructured, or labeled behavioral data. However, it struggles with clusters having varying densities due to the same epsilon and minPts-eps. Therefore, to choose the minPts-eps combination effectively for various densities, the Morra-Tversky Index (MTI) is applied, which computes the minPts-eps points effectively based on the Average between-within data points.

Initially, epsilon points $\left(\kappa_{epi}\right)$ are selected randomly from M^{aug} while selecting minPts-eps points $\left(\kappa_{\min}\right)$ using MTI.

$$\kappa_{\min} = \frac{\left|\mathrm{M}_x^{aug} \cap \mathrm{M}_y^{aug}\right|}{\left|\mathrm{M}_x^{aug} \cap \mathrm{M}_y^{aug}\right| + \omega_{par}\left|\mathrm{M}_x^{aug} - \mathrm{M}_y^{aug}\right| + \omega_{par}\left|\mathrm{M}_y^{aug} - \mathrm{M}_x^{aug}\right|} \tag{4}$$

Here, $\left(\mathrm{M}_x^{aug}, \mathrm{M}_y^{aug}\right)$ and ω_{par} indicate x_{th} and y_{th} data in M^{aug} and the weighting parameters, respectively. Now, the core points $\left(\kappa_{core}\right)$ are computed if κ_{epi} exists within the neighborhood of $\kappa_{\min}$.

$$\kappa_{core} = \left\{\mathrm{M}_x^{aug}, \mathrm{M}_y^{aug} \in \mathrm{M}^{aug} \middle| \partial^{dis}\left(\mathrm{M}_x^{aug}, \mathrm{M}_y^{aug}\right) \leq \kappa_{epi}\right\} \tag{5}$$

$$\partial^{dis}\left(\mathrm{M}_x^{aug}, \mathrm{M}_y^{aug}\right) = \sqrt{\sum\left[\mathrm{M}_x^{aug} - \mathrm{M}_y^{aug}\right]^2} \tag{6}$$

Where, ∂^{dis} indicates the distance function. Next, for each κ_{core}, the clusters $\left(\mathrm{A}^{Clu}\right)$ are formed, and density reachable points $\left(\kappa_{den}\right)$ are iteratively added to A^{Clu} until convergence, attaining behavioral pattern analyzed data $\left(\Xi^{\mathrm{beh}}\right)$. Thus, MT-DBSCAN accurately analyzes the behavioral pattern of the financial data.

3.1.7 Portfolio Extraction

In the meantime, the portfolios $\left(\dddot{\mathrm{P}}\right)$, which represent the collection of financial assets held by the user, are extracted from Ξ^{beh} to identify the types and distribution of assets associated with users. $\dddot{\mathrm{P}}$ includes investments like stocks, bonds, mutual funds, and other financial instruments.

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3.1.8 Portfolio Optimization

Now, the portfolio optimization is held for each $\dddot{\mathrm{P}}$ to ensure the performance of financial score identification using PS-MPA. The conventional Marine Predators Algorithm (MPA) explores a large search space effectively using Brownian and Levy flight approaches. Also, it has the ability to adjust path decisions dynamically in real-time, particularly for a changing environment. However, it leads to slower convergence or a suboptimal path due to the poor agent or the solution space initialization. Therefore, the Powell Sum (PS) initialization is used to unitize solution space, helping to improve convergence speed by providing a near-optimal initial solution.

- Primarily, the prey or solution space $\left(\dddot{\mathrm{P}}\right)$ is initialized using the PS approach, followed by elite or predator position $\left(\mathrm{M}_{\dddot{\mathrm{P}}}\right)$ computation, which encompasses the best portfolio $\left(\mathrm{I}_{e,d}^{bst}\right)$.

$$\mathrm{I}^{\dddot{\mathrm{P}}} = \sum_{\ddot{e}=1}^{e} \left(\dddot{\mathrm{P}}\right)_{0,\ddot{e}} \tag{7}$$

$$\mathrm{I}^{\dddot{\mathrm{P}}} = \begin{bmatrix} \mathrm{I}_{1,1}^{\dddot{\mathrm{P}}} & \mathrm{I}_{1,2}^{\dddot{\mathrm{P}}} & \cdots & \mathrm{I}_{1,d}^{\dddot{\mathrm{P}}} \\ \mathrm{I}_{2,1}^{\dddot{\mathrm{P}}} & \mathrm{I}_{2,2}^{\dddot{\mathrm{P}}} & \cdots & \mathrm{I}_{2,d}^{\dddot{\mathrm{P}}} \\ \vdots & \vdots & \ddots & \vdots \\ \mathrm{I}_{e,1}^{\dddot{\mathrm{P}}} & \mathrm{I}_{e,2}^{\dddot{\mathrm{P}}} & \cdots & \mathrm{I}_{e,d}^{\dddot{\mathrm{P}}} \end{bmatrix} \tag{8}$$

$$\mathrm{M}_{\dddot{\mathrm{P}}} = \begin{bmatrix} \mathrm{I}_{1,1}^{bst} & \mathrm{I}_{1,2}^{bst} & \cdots & \mathrm{I}_{1,d}^{bst} \\ \mathrm{I}_{2,1}^{bst} & \mathrm{I}_{2,2}^{bst} & \cdots & \mathrm{I}_{2,d}^{bst} \\ \vdots & \vdots & \ddots & \vdots \\ \mathrm{I}_{e,1}^{bst} & \mathrm{I}_{e,2}^{bst} & \cdots & \mathrm{I}_{e,d}^{bst} \end{bmatrix}^{e\times d} \tag{9}$$

Here, $\mathrm{I}^{\dddot{\mathrm{P}}}$, e, and d indicate the initialized $\dddot{\mathrm{P}}$, number of $\dddot{\mathrm{P}}$, and number of dimensions, respectively.

- Now, the objective function is calculated by considering the maximum classification accuracy $\left(\partial_{CA}\right)$ as fitness $\left(\lambda_{fit}\right)$ for each $\mathrm{I}^{\dddot{\mathrm{P}}}$.

$$\lambda_{fit}\left(\dddot{\mathrm{P}}\right) = \max\left(\partial_{CA}\right) \tag{10}$$

- In the exploration phase, the position of $\mathrm{I}^{\dddot{\mathrm{P}}}$ is updated based on the high-velocity ratio concept, where $\mathrm{I}^{\dddot{\mathrm{P}}}$ moves faster than $\mathrm{M}_{\dddot{\mathrm{P}}}$.

$$\mathrm{I}_{new}^{\dddot{\mathrm{P}}} = \mathrm{I}^{\dddot{\mathrm{P}}} + N_{con} \cdot ran \otimes \partial_{ss} \tag{11}$$

$$\partial_{ss} = m_B^{ran} \otimes \left[\mathrm{M}_{\dddot{\mathrm{P}}} - m_B^{ran} \otimes \mathrm{I}^{\dddot{\mathrm{P}}}\right] \tag{12}$$

Where, $\mathrm{I}^{\dddot{\mathrm{P}}}_{new}$, $N_{con}, \partial_{ss}, m_B^{ran}$, and $\otimes$ depict the new position of $\mathrm{I}^{\dddot{\mathrm{P}}}$, constant number, step size, vector of uniform random numbers (ran) that refers to the Brownian motion, and element-wise multiplication, correspondingly.

- Now, based on the unit-velocity ratio concept, the position of $\mathrm{I}^{\dddot{\mathrm{P}}}$ is upgraded $\left(\mathrm{I}^{\dddot{\mathrm{P}}}_{new+1}\right)$ when $\mathrm{I}^{\dddot{\mathrm{P}}}$ and $\mathrm{M}_{\dddot{\mathrm{P}}}$ move towards the same area.

$$\mathrm{I}^{\dddot{\mathrm{P}}}_{new+1} = \mathrm{I}^{\dddot{\mathrm{P}}} + N_{con} \cdot \varsigma_{\mathrm{con}} \otimes \partial_{ss} \tag{13}$$

$$\partial_{ss} = m_B^{ran} \otimes \left[m_B^{ran} \otimes \mathrm{M}_{\dddot{\mathrm{P}}} - \mathrm{I}^{\dddot{\mathrm{P}}} \right] \tag{14}$$

$$\varsigma_{\mathrm{con}} = \left[\frac{\forall_{\max} - \forall}{\forall_{\max}} \right]^{\frac{2}{\forall_{\max}}} \tag{15}$$

Here, ς_{con} and $\forall_{\max}$ depict the step-size control parameter and the maximum number of iterations $(\forall)$, correspondingly.

- Then, if the movement of $\mathrm{M}_{\dddot{\mathrm{P}}}$ is faster than $\mathrm{I}^{\dddot{\mathrm{P}}}$, then the low-velocity ratio concept is applied, attaining a new position for $\mathrm{I}^{\dddot{\mathrm{P}}}$ $\left(\mathrm{I}^{\dddot{\mathrm{P}}}_{new+2}\right)$.

$$\mathrm{I}^{\dddot{\mathrm{P}}}_{new+2} = \mathrm{I}^{\dddot{\mathrm{P}}} + N_{con} \cdot \varsigma_{\mathrm{con}} \otimes \partial_{ss} \tag{16}$$

$$\partial_{ss} = m_L^{ran} \otimes \left[m_L^{ran} \otimes \mathrm{M}_{\dddot{\mathrm{P}}} - \mathrm{I}^{\dddot{\mathrm{P}}} \right] \tag{17}$$

Where, m_L^{ran} depicts the vector of numbers randomly generated based on the Levy distribution.

- Finally, the new position of $\mathrm{I}^{\dddot{\mathrm{P}}}$ $\left(\mathrm{I}^{\dddot{\mathrm{P}}}_{new+3}\right)$ is found via formulating the effect of Fish Aggregating Devices (FAD) to attain the best solutions, followed by memory retention and $\mathrm{M}_{\dddot{\mathrm{P}}}$ updation.

$$\mathrm{I}^{\dddot{\mathrm{P}}}_{new+3} = \begin{cases} \mathrm{I}^{\dddot{\mathrm{P}}} + \varsigma_{con} \left[\dddot{\mathrm{P}}_{low} + ran \otimes \left(\dddot{\mathrm{P}}_{upp} - \dddot{\mathrm{P}}_{low} \right) \otimes s^{bin} \right] & ; if\,(ran < \mathrm{FAD}) \\ \mathrm{I}^{\dddot{\mathrm{P}}} + \left[\mathrm{FAD}(1 - ran) + ran \right] \left[\mathrm{I}^{\dddot{\mathrm{P}}}_{ran1} - \mathrm{I}^{\dddot{\mathrm{P}}}_{ran2} \right] & ; if\,(ran > \mathrm{FAD}) \end{cases} \tag{18}$$

Here, $\left(\dddot{\mathrm{P}}_{upp}, \dddot{\mathrm{P}}_{low}\right)$ illustrate the upper and lower bounds of the variables in $\mathrm{I}^{\dddot{\mathrm{P}}}$, respectively, s^{bin} depicts the binary vector, and $\left(\mathrm{I}^{\dddot{\mathrm{P}}}_{ran1}, \mathrm{I}^{\dddot{\mathrm{P}}}_{ran2}\right)$ demonstrates the random $\mathrm{I}^{\dddot{\mathrm{P}}}$. Now, based on $\mathrm{I}^{\dddot{\mathrm{P}}}_{new+3}$, the position of $\mathrm{M}_{\dddot{\mathrm{P}}}$ is updated to provide optimized portfolios $\left(\mathrm{O}^{\dddot{\mathrm{P}}}\right)$.

The pseudo-code for PS-MPA is depicted as follows,

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Pseudo-code for PS-MPA

Input: Portfolios $\dddot{\mathrm{P}}$

Output: Optimized Portfolios $\mathrm{O}^{\dddot{\mathrm{P}}}$

Begin

Initialize $\mathrm{M}_{\dddot{\mathrm{P}}}, d, \lambda_{fit}, \partial_{ss}$, movement (mv), iteration $(\forall)$, and maximum iteration $(\forall_{\max})$

Set $(\forall = 1)$

While $(\forall \leq \forall_{\max})$

For each $\dddot{\mathrm{P}}$ do

Initialize $\mathrm{I}^{\dddot{\mathrm{P}}} = \sum_{\ddot{e}=1}^{e} \left(\dddot{\mathrm{P}}\right)_{0,\ddot{e}}$ **#PS**

Compute $\mathrm{M}_{\dddot{\mathrm{P}}}$

Calculate $\lambda_{fit}\left(\dddot{\mathrm{P}}\right) = \max\left(\partial_{CA}\right)$

If $\left(mv\left[\mathrm{I}^{\dddot{\mathrm{P}}}\right] > mv\left[\mathrm{M}_{\dddot{\mathrm{P}}}\right]\right)$

{

Update position

$\mathrm{I}_{new}^{\dddot{\mathrm{P}}} = \mathrm{I}^{\dddot{\mathrm{P}}} + N_{con} \cdot ran \otimes \partial_{ss}$

}

Else If $\left(mv\left[\mathrm{M}_{\dddot{\mathrm{P}}}\right] \& \, mv\left[\mathrm{I}^{\dddot{\mathrm{P}}}\right] \Rightarrow \text{same area}\right)$

{

Update position

$\mathrm{I}_{new+1}^{\dddot{\mathrm{P}}} = \mathrm{I}^{\dddot{\mathrm{P}}} + N_{con} \cdot \varsigma_{\mathrm{con}} \otimes \partial_{ss}$

}

Else If $\left(mv\left[\mathrm{M}_{\dddot{\mathrm{P}}}\right] > mv\left[\mathrm{I}^{\dddot{\mathrm{P}}}\right]\right)$

{

Update Position

$\mathrm{I}_{new+2}^{\dddot{\mathrm{P}}} = \mathrm{I}^{\dddot{\mathrm{P}}} + N_{con} \cdot \varsigma_{\mathrm{con}} \otimes \partial_{ss}$

}

Else

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{

Return $\mathrm{I}^{\dddot{\mathrm{P}}}$

}

End If

Formulate FAD

End For

End While

Return: $\mathrm{O}^{\dddot{\mathrm{P}}}$

End

Thus, PS-MPA effectively optimizes $\dddot{\mathrm{P}}$ by simulating the natural hunting behavior of marine predators.

3.1.9 Classification

Finally, the classification model is trained using the RL-GPLinQ-GRU to identify the user's financial score based on $\mathrm{O}^{\dddot{\mathrm{P}}}$ and F_F^c. The Gated Recurrent Unit (GRU) captures the temporal dependencies and identifies patterns effectively, helping to identify users' financial scores accurately. However, it is prone to overfitting when applied to small data or a lack of sufficient variance. Hence, the Gradient Penalty (GP) regularization is applied, which eliminates the overfitting issue by promoting sparsity and simplifying the model. Likewise, the sigmoid activation function in GRU is saturating, limiting the model's output to values between 0 and 1. Also, it leads to a vanishing gradient issue as it uses very large and very small inputs. Therefore, the Linear Quadratic (LQ) activation function is applied, which enables more efficient and deeper learning and eliminates the vanishing gradient issue by maintaining a non-saturating response and stable gradient. Moreover, to enhance financial score identification, Reinforcement Learning (RL) is incorporated, which has the ability to adapt the model to real-world applications by continuously learning from user interactions. The classifier diagram for RL-GPLinQ-GRU is depicted in Figure 2.

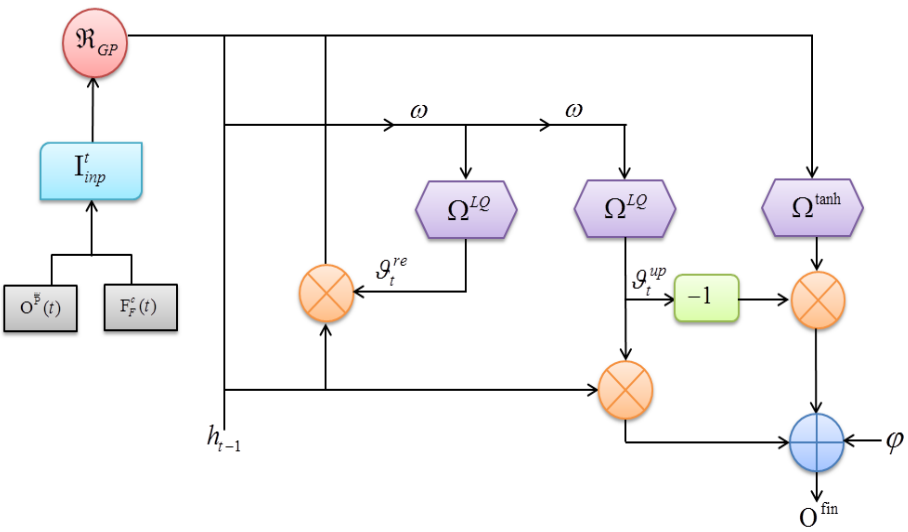

Figure 2: Classifier Diagram for RL-GPLinQ-GRU

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Primarily, the previous hidden state (h_{t-1}) is represented for each $\mathrm{O}^{\ddot{\overline{\mathrm{P}}}}$ and F_F^c with time step (t). Then, the GP regularization $(\Re_{GP})$ is applied for each I_{inp}^t to enhance the model's performance in financial score identification.

$$\mathrm{I}_{inp}^t = \begin{cases} \mathrm{O}^{\ddot{\overline{\mathrm{P}}}}(t) \\ \mathrm{F}_F^c(t) \end{cases} \tag{19}$$

$$\Re_{GP}\left(\mathrm{I}_{inp}^t\right) = \begin{cases} \hat{c}_p \mathrm{I}_{inp}^t + \left(1 - 2\mathrm{I}_{inp}^t + \left(\mathrm{I}_{inp}^t\right)^2\right) & ; \mathrm{I}_{inp}^t \geq 2 - 2\hat{c}_p \\ \dfrac{1}{4}\mathrm{I}_{inp}^t\left(4 - \left|\mathrm{I}_{inp}^t\right|\right) & ; -2 + 2\hat{c}_p < \mathrm{I}_{inp}^t < 2 - 2\hat{c}_p \\ \hat{c}_p \mathrm{I}_{inp}^t - \left(1 - 2\mathrm{I}_{inp}^t + \left(\mathrm{I}_{inp}^t\right)^2\right) & ; \mathrm{I}_{inp}^t \leq -2 + 2\hat{c}_p \end{cases} \tag{20}$$

Where, I_{inp}^t illustrates the input of RL-GPLinQ-GRU and $\hat{c}_p$ depicts the control parameter. Now, from $\Re_{GP}$, the amount of past information to remove and allow through the gates is determined by computing the update gate (ϑ_t^{up}) and reset gate (ϑ_t^{re}) with the LQ activation function (Ω^{LQ}).

$$\vartheta_t^{re} = \left(\omega\left[h_{t-1} \cdot \Re_{GP}\right] + \varphi\right) * \Omega^{LQ} \tag{21}$$

$$\vartheta_t^{up} = \left(1 - \left[\omega\left[h_{t-1} \cdot \Re_{GP}\right] + \varphi\right]\right) * \Omega^{LQ} \tag{22}$$

$$\Omega^{LQ}(\Re_{GP}) = \tau^{reg} \cdot \gamma_{\exp}(\Re_{GP})\left[\left(\left\|\Delta^{gra}(\Re_{GP})\right\|_2 - 1\right)^2\right] \tag{23}$$

Here, ω , φ , τ^{reg}, $\gamma_{\exp}$, and Δ^{gra} depict the weight, bias, regularization coefficient, expectation over distribution function, and gradient values of $\Re_{GP}$, respectively. Then, the learning efficiency is improved by calculating the output of the hidden state (h_t) and candidate hidden state (h_t^{can}) using the tanh activation function $(\Omega^{\tanh})$.

$$h_t^{can} = \Omega^{\tanh}\left[\omega\left(\vartheta_t^{re} * h_{t-1}; \Re_{GP}\right) + \varphi\right] \tag{24}$$

$$h_t = h_{t-1} - \vartheta_t^{up} \cdot h_{t-1} + \vartheta_t^{up} h_t^{can} \tag{25}$$

$$\Omega^{\tanh}(\Re_{GP}) = \frac{e^{\Re_{GP}} - e^{-\Re_{GP}}}{e^{\Re_{GP}} + e^{-\Re_{GP}}} \tag{26}$$

Finally, based on RL, h_t identify the user's financial scores by adapting the model for real-time applications. Here, RL computes the maximum expected reward (ℓ_{rew}) for the randomly selected actions (ac) of the agents based on h_t.

$$\mathrm{O}^{\mathrm{fin}} = \arg\max\left[\sum \xi^{dis} \ell_{rew}(ac, h_t)\right] \tag{27}$$

Where, $\mathrm{O}^{\mathrm{fin}}$ depicts the output of RL-GPLinQ-GRU and ξ^{dis} depicts the discount factor. The pseudo-code for RL-GPLinQ-GRU is demonstrated as follows,

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Pseudo-code for RL-GPLinQ-GRU

Input: Optimized Portfolios $\mathrm{O}^{\ddot{\mathrm{P}}}$ and Extracted Bubble plot features F_F^c

Output: Financial Score $\mathrm{O}^{\mathrm{fin}}$

Begin

Initialize $\mathrm{I}_{inp}^t, \hat{c}_p, \omega, \varphi$, iteration $(\forall)$, and maximum iteration $(\forall_{\max})$

Set $(\forall = 1)$

While $(\forall \le \forall_{\max})$

For each I_{inp}^t do

Represent h_{t-1}

Regularize I_{inp}^t **#GP**

$$\Re_{GP}\left(\mathrm{I}_{inp}^t\right) = \begin{cases} \hat{c}_p \mathrm{I}_{inp}^t + \left(1 - 2\mathrm{I}_{inp}^t + \left(\mathrm{I}_{inp}^t\right)^2\right) & ; \mathrm{I}_{inp}^t \ge 2 - 2\hat{c}_p \\ \frac{1}{4}\mathrm{I}_{inp}^t\left(4 - \left|\mathrm{I}_{inp}^t\right|\right) & ; -2 + 2\hat{c}_p < \mathrm{I}_{inp}^t < 2 - 2\hat{c}_p \\ \hat{c}_p \mathrm{I}_{inp}^t - \left(1 - 2\mathrm{I}_{inp}^t + \left(\mathrm{I}_{inp}^t\right)^2\right) & ; \mathrm{I}_{inp}^t \le -2 + 2\hat{c}_p \end{cases}$$

Use

$$\Omega^{LQ}\left(\Re_{GP}\right) = \tau^{reg} \cdot \gamma_{\exp}\left(\Re_{GP}\right)\left[\left(\left\|\Delta^{gra}\left(\Re_{GP}\right)\right\|_2 - 1\right)^2\right]$$

Compute ϑ_t^{up} and ϑ_t^{re}

Find h_t and h_t^{can}

Use RL

$$\mathrm{O}^{\mathrm{fin}} = \arg\max\left[\sum \xi^{dis} \ell_{rew}\left(ac, h_t\right)\right]$$

End For

End While

Return: $\mathrm{O}^{\mathrm{fin}}$

End

Thus, RL-GPLinQ-GRU accurately identifies the user's financial score, thereby ensuring model generalizability and interpretability in personalized financial advice.

3.1.10 Model Integrity

Now, based on $\mathrm{O}^{\mathrm{fin}}$, the VLIME is used to explain how the financial score is identified, ensuring the financial score identification model's integrity. The conventional Local Interpretable Model-agnostic Explanation (LIME) provides an explanation and valuable insights for each individual prediction made by the personalized financial advice model. Based on the inappropriate kernel function, LIME

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assigns a weight to each instance. However, LIME fails to capture the underlying structure of the data. Hence, the Viennet function is introduced to assign weight values, thereby capturing the underlying structure of the data, eliminating overfitting issues, and producing optimal results.

⇔ Initially, based on $\mathrm{O}^{\mathrm{fin}}$, the specific instances $\left(\rho^{spc}\right)$ are chosen to generate an explanation, followed by a set of perturbed instance $\left(\hat{\bar{\rho}}^{spc}\right)$ creations. Then, the prediction model (PM) is applied to make predictions $\left(\delta_{pre}\right)$from $\hat{\bar{\rho}}^{spc}$.

$$\delta_{pre} = PM\left[\hat{\bar{\rho}}^{spc}\right] \tag{28}$$

⇔ Now, ω for each δ_{pre} is assigned using the Vinnet function.

$$\delta_{pre}^{\omega} = \begin{cases} 0.5\left(\left(\delta_{pre}^{p}\right)^2 + \left(\delta_{pre}^{q}\right)^2\right) + \sin\left(\left(\delta_{pre}^{p}\right)^2 + \left(\delta_{pre}^{q}\right)^2\right) \\ \dfrac{\left(3\delta_{pre}^{p} - 2\delta_{pre}^{q} + 4\right)^2}{8} + \dfrac{\left(\delta_{pre}^{p} - \delta_{pre}^{q} - 1\right)^2}{27} + 15 \\ \dfrac{1}{\left(\delta_{pre}^{p}\right)^2 + \left(\delta_{pre}^{q}\right)^2 + 1} - 1.1\exp\left(-\left(\left(\delta_{pre}^{p}\right)^2 + \left(\delta_{pre}^{q}\right)^2\right)\right) \end{cases} \tag{29}$$

Where, δ_{pre}^{ω} indicates ω assigned δ_{pre}, and $\left(\delta_{pre}^{p}, \delta_{pre}^{q}\right)$ depict p_{th} and q_{th} terms in δ_{pre}, respectively.

⇔ Finally, δ_{pre}^{ω} is trained on δ_{pre} to obtain a surrogate model Y^{sur}, which provides the explanation of $\mathrm{O}^{\mathrm{fin}}$.

$$\mathrm{Y}^{sur} = \ell_{\mathrm{int}} + \sum \delta_{pre} \cdot \delta_{pre}^{\omega} \tag{30}$$

Here, ℓ_{int} demonstrates the intercept term.

Thus, VLIME ensures the model's transparency and integrity by providing an efficient explanation of the identified financial score.

3.2 Stock Market Sentiment Classification

After finding the financial score, the stock market sentiments classification phase begins to access public opinion regarding the stock market.

3.2.1 Stock Market Data Collection

Initially, stock market data $\left(S_f\right)$, including positive, negative, and neutral sentiments, are collected from publicly available sources.

$$S_f = \left\{S_1, S_2, S_3, \cdots, S_{\vec{f}}\right\} \qquad ; f = 1 \rightarrow \vec{f} \tag{31}$$

Here, $\vec{f}$ illustrates the maximum number of S_f.

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3.2.2 Stock Market Data Preprocessing

Now, preprocessing is applied to each S_f as they often contain unstructured, noisy, and irrelevant content, influencing sentiment classification accuracy. So, the quality of S_f is enhanced by performing preprocessing.

- **Tokenization:** Primarily, S_f is decomposed into the $\vec{g}$ number of tokens (τ_g) for word-level analysis.
- **Stop Word Removal:** Then, stop words (i.e., less or non-meaningful words) are removed from τ_g, reducing text dimensionality.
- **Stemming:** Now, to reduce complexity, the words in τ_g are reduced to their root form.
- **Lemmatization:** Finally, the preprocessed stock market data $\left(P_h^{S_f}\right)$ are obtained by converting τ_g into their dictionary-based form.

$$P_h^{S_f} = \left\{P_1^{S_f}, P_2^{S_f}, P_3^{S_f}, \cdots, P_{\vec{h}}^{S_f}\right\} \qquad ; h = 1 \to \vec{h} \tag{32}$$

Where, $\vec{h}$ indicates the maximum number of $P_h^{S_f}$.

3.2.3 Keyword Extractions

In this phase, keywords that are responsible for the classification of stock market sentiments are extracted from $P_h^{S_f}$. These keywords help to highlight the most informative and sentiment-rich words from $P_h^{S_f}$, contributing to the underlying sentiment polarity. Then, the extracted keywords are indicated as K^{S_f}, which include stock, share, equity, volume, spread, and so on.

3.2.4 Word Embedding

Now, K^{S_f} are transformed into dense and rich contextual vector representations using the Exponential Polynomial Decay-based Financial Bidirectional Encoder Representation from Transformers (EPD-FinBERT) to preserve both semantic and sentiment-related context. The traditional Financial Bidirectional Encoder Representations from Transformers effectively find the polarity of the text based on the context. However, this model performs ineffectively in domain-specific tasks due to improper fine-tuning. Therefore, the Exponential Polynomial Decay (EPD) is applied to perform fine-tuning by effectively categorizing the various parts of the parameter space.

Initially, the dimensional vector $(v_{\dim})$ is estimated for each K^{S_f} using token embedding $(\in_{tok})$, position embedding $(\in_{pos})$, and segment type embedding $(\in_{seg})$.

$$v_{\dim}\left(K^{S_f}\right) = \in_{tok}\left(K^{S_f}\right) + \in_{pos}\left(K^{S_f}\right) + \in_{seg}\left(K^{S_f}\right) \tag{33}$$

Then, the multiple transformer encoder blocks learn the contextualized representation (Cr) of K^{S_f}.

$$Cr = \sum \omega \cdot \exists^{val}(v_{\dim}) \tag{34}$$

Here, $\exists^{val}$ illustrates the values computed for each $v_{\dim}$. Finally, EPD is applied to generate high-quality, rich vector values $\left(\mathrm{V}^{sen}\right)$ by updating K^{S_f} based on Cr.

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$$\hat{\hat{K}}^{S_f} = \sum Cr(v_{\dim}) \tag{35}$$

$$\mathrm{V}^{sen} = e^{\left(\hat{\hat{K}}^{S_f} \cdot \left[1 - \frac{\forall}{\forall_{\max}}\right]\right)} \tag{36}$$

Where, $\hat{\hat{K}}^{S_f}$ indicates the updated K^{S_f}. Thus, EPD-FinBER ensures rich, contextual embedding for accurate stock market sentiment analysis.

3.2.5 Sentiment Analysis

Meanwhile, sentiment analysis is carried out for each $P_h^{S_f}$ to analyze the sentiment score value of the stock market using SentiWordNet. The SentiWordNet is a lexical resource that assigns sentiment scores to synsets in WordNet, indicating their positivity, negativity, and neutrality. Here, Parts-Of-Speech (POS) tags in $P_h^{S_f}$ are initially identified, followed by the mapping of Senti-wordNet-compatible tags. Also, the sentiment scores (Z^{SS}) are extracted by retrieving synsets corresponding to each word in $P_h^{S_f}$ and its POS.

3.2.6 Sentiment Classification

Finally, the stock market sentiment is classified based on Z^{SS} and V^{sen} to provide efficient financial advice using the RL-GPLinQ-GRU. The working of RL-GPLinQ-GRU is elaborated in Section 3.1.10. Thus, by using RL-GPLinQ-GRU, the proposed framework classifies the stock market sentiments as positive (K^{P}), negative (K^{N}), or neutral (K^{Neu}).

$$\mathrm{O}^{stock} = \begin{cases} \mathrm{K}^{P} \\ \mathrm{K}^{N} \\ \mathrm{K}^{Neu} \end{cases} \tag{37}$$

Where, O^{stock} illustrates the output of RL-GPLinQ-GRU in sentiment classification.

3.3 Stock Market Status Prediction

Afterward, the status of the stock market is predicted to anticipate the market movement and assist users in making informed financial decisions.

3.3.1 Historical Stock Market Data Collection

For this purpose, the proposed framework gathers historical stock market data (H_i) from publicly available sources.

$$H_i = \{H_1, H_2, H_3, \cdots, H_{\ddot{i}}\} \qquad ; i = 1 \rightarrow \ddot{i} \tag{38}$$

Here, $\ddot{i}$ illustrates the maximum number of H_i.

3.3.2 Historical Data Preprocessing

Now, H_i often contains missing entries and inconsistencies, influencing prediction accuracy. So, H_i are preprocessed.

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- **Null value data removal:** Here, fields in H_i containing null or missing values (∂_{null}) are identified and removed, ensuring data completeness and quality in predicting stock market status.

$$P_{H_i}^{j} = H_i - \partial_{null} \tag{39}$$

Where, $P_{H_i}^{j}$ indicates the null value removed or preprocessed data.

3.3.3 Technical Indicator Extraction

Next, for accurate stock market prediction, technical indicators $(\mathrm{T}_{\mathrm{ind}})$, which learn both short-term and long-term trends, are extracted from $P_{H_i}^{j}$ to capture the underlying market patterns, volatility, and momentum. Here, $\mathrm{T}_{\mathrm{ind}}$ includes moving average convergences, relative strength, momentum indicators, standard deviation, average directional index, stochastic oscillator, and so on.

3.3.4 Feature Extraction

In the meantime, feature extraction is carried out for each $P_{H_i}^{j}$ to extract the important features that are responsible for the accurate stock market status prediction. These features $\left(F_{H_i}^{k}\right)$include date, symbol, series, open, high, low, last, etc.

$$F_{H_i}^{k} = \left\{F_{H_i}^{1}, F_{H_i}^{2}, F_{H_i}^{3}, \cdots, F_{H_i}^{\vec{k}}\right\} \qquad ;k = 1 \rightarrow \vec{k} \tag{40}$$

Here, $\vec{k}$ demonstrates the maximum number of $F_{H_i}^{k}$.

3.3.5 Prediction

Now, the stock market prediction model is trained based on $F_{H_i}^{k}$ and $\mathrm{T}_{\mathrm{ind}}$ using the RL-GPLinQ-GRU to predict the stock market status for providing efficient personalized financial advice. The explanation of the RL-GPLinQ-GRU is described in Section 3.1.10. As per the explanation, the proposed framework predicts whether the stock market status is high $\left(\mathrm{M}^{H}\right)$, medium $\left(\mathrm{M}^{M}\right)$, or low $\left(\mathrm{M}^{L}\right)$.

$$\mathrm{O}_{SMP} = \begin{cases} \mathrm{M}^{H} \\ \mathrm{M}^{M} \\ \mathrm{M}^{L} \end{cases} \tag{41}$$

Where, O_{SMP} illustrates the output of RL-GPLinQ-GRU in stock market status prediction.

3.4 Risk Parity and Dynamic Allocation

Finally, personalized financial advice is provided to the users by performing risk parity and dynamic portfolio allocation. For this purpose, the IGP-Fuzzy is used based on O_{SMP}, O^{stock}, $\mathrm{O}^{\mathrm{fin}}$, and Y^{sur}. The traditional Fuzzy provides a flexible framework for labeling data, which can be useful in complex or nuanced scenarios. However, it has the tuning difficulty of the membership function, degrading the performance. Hence, the Inverse Gaussian Peaked (IGP) membership function is included with the Fuzzy, providing sharper transitions and a better fit for risk parity and dynamic portfolio allocation. This also aids in enhancing both interpretability and performance in personalized financial advice.

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- Primarily, $\mathrm{N}^{\mathrm{inp}}$ are converted into fuzzy sets $\left(\Psi_{\mathrm{fuzz}}\right)$ using the IGP membership function.

$$\mathrm{N}^{\mathrm{inp}} \in \begin{Bmatrix} \mathrm{O}_{SMP} \\ \mathrm{O}^{stock} \\ \mathrm{O}^{\mathrm{fin}} \\ \mathrm{Y}^{sur} \end{Bmatrix} \tag{42}$$

$$\Psi_{\mathrm{fuzz}}\left(\mathrm{N}^{\mathrm{inp}}\right) = 1 - \exp\left[-\left(\frac{\mathrm{N}^{\mathrm{inp}} - \wp_{cen}}{\sigma^{sd}}\right)\right] \tag{43}$$

Here, $\mathrm{N}^{\mathrm{inp}}$, $\wp_{cen}$, and σ^{sd} illustrate the input of IGP-Fuzzy, center value of membership function, and standard deviation, respectively.

- Now, to determine the risk parity, the fuzzy rules are generated based on Ψ_{fuzz}.

$$\aleph_{RP}^{rule} = \begin{cases} if\left(\left(\mathrm{O}^{\mathrm{fin}} = 700 - 850\right) \& \&\left(\mathrm{O}^{stock} > 0.5\right) \& \&\left(\mathrm{O}_{SMP} > 75\%\right)\right) & ;\mathrm{Low\text{-}risk} \\ if\left(\left(\mathrm{O}^{\mathrm{fin}} = 500 - 699\right) \& \&\left(-0.3 < \mathrm{O}^{stock} \le 0.5\right) \& \&\left(\mathrm{O}_{SMP} = 50 - 75\%\right)\right) & ;\mathrm{Medium\text{-}risk} \\ if\left(\left(\mathrm{O}^{\mathrm{fin}} < 500\right) \& \&\left(\mathrm{O}^{stock} \le -0.3\right) \& \&\left(\mathrm{O}_{SMP} < 50\%\right)\right) & ;\mathrm{High\text{-}risk} \end{cases} \tag{44}$$

Where, $\aleph_{RP}^{rule}$ depicts the rules for risk parity analysis. Here, low-risk, medium-risk, and high-risk indicate stable financial behavior, moderate, and poor financial indicators as well as low confidence in investment performance, respectively.

- Next, the portfolios are allocated dynamically, which is an adaptive method to assign investments according to $\aleph_{RP}^{rule}$ to provide personalized financial advice using the fuzzy rule.

$$\aleph_{DPA}^{rule} = \begin{cases} if\left(\left(\mathrm{O}^{\mathrm{fin}} = \mathrm{M}^{H}\right) \& \&\left(\mathrm{O}^{stock} = \mathrm{K}^{P}\right) \& \&\left(\mathrm{O}_{SMP} = \mathrm{M}^{H}\right)\right) & ;\Phi^{R1} \\ if\left(\left(\mathrm{O}^{\mathrm{fin}} = \mathrm{M}^{H}\right) \& \&\left(\mathrm{O}^{stock} = \mathrm{K}^{N}\right) \& \&\left(\mathrm{O}_{SMP} = \mathrm{M}^{M}\right)\right) & ;\Phi^{R2} \\ if\left(\left(\mathrm{O}^{\mathrm{fin}} = \mathrm{M}^{M}\right) \& \&\left(\mathrm{O}^{stock} = \mathrm{K}^{Neu}\right) \& \&\left(\mathrm{O}_{SMP} = \mathrm{M}^{M}\right)\right) & ;\Phi^{R3} \\ if\left(\left(\mathrm{O}^{\mathrm{fin}} = \mathrm{M}^{L}\right) \& \&\left(\mathrm{O}^{stock} = \mathrm{K}^{N}\right) \& \&\left(\mathrm{O}_{SMP} = \mathrm{M}^{L}\right)\right) & ;\Phi^{R4} \\ if\left(\left(\mathrm{O}^{\mathrm{fin}} = \mathrm{M}^{M}\right) \& \&\left(\mathrm{O}^{stock} = \mathrm{K}^{P}\right) \& \&\left(\mathrm{O}_{SMP} = \mathrm{M}^{H}\right)\right) & ;\Phi^{R5} \\ if\left(\left(\mathrm{O}^{\mathrm{fin}} = \mathrm{M}^{L}\right) \& \&\left(\mathrm{O}^{stock} = \mathrm{K}^{Neu}\right) \& \&\left(\mathrm{O}_{SMP} = \mathrm{M}^{M}\right)\right) & ;\Phi^{R6} \\ if\left(\left(\mathrm{O}^{\mathrm{fin}} = \mathrm{M}^{H}\right) \& \&\left(\mathrm{O}^{stock} = \mathrm{K}^{Neu}\right) \& \&\left(\mathrm{O}_{SMP} = \mathrm{M}^{H}\right)\right) & ;\Phi^{R7} \\ if\left(\left(\mathrm{O}^{\mathrm{fin}} = \mathrm{M}^{M}\right) \& \&\left(\mathrm{O}^{stock} = \mathrm{K}^{N}\right) \& \&\left(\mathrm{O}_{SMP} = \mathrm{M}^{L}\right)\right) & ;\Phi^{R8} \end{cases} \tag{45}$$

Here, $\aleph_{DPA}^{rule}$ represents the rules for portfolio allocation. Each rule in $\aleph_{DPA}^{rule}$ corresponds to a specific dynamic allocation strategy; Φ^{R1} suggests increasing equity and entering growth stocks, Φ^{R2} indicates hedge positions and shift to the defensive sector, Φ^{R3} refers to the diversifying portfolio, Φ^{R4} illustrates reducing debt and limiting investments, Φ^{R5} demonstrates moderate equity, Φ^{R6} indicates investing in low-risk bonds, Φ^{R7} describes the selective growth and stay cautious, and Φ^{R8} illustrates to preserve capital.

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- Then, the rule strength (ε_{rs}) is identified to determine the consequent fuzzy set $(\dddot{\Psi}_{\text{fuzz}})$ based on $\aleph_{RP}^{rule}$ and $\aleph_{DPA}^{rule}$.

$$\dddot{\Psi}_{\text{fuzz}} = \varepsilon_{rs} \cdot \left[\aleph_{RP}^{rule} \cdot \aleph_{DPA}^{rule}\right] \tag{46}$$

- Finally, to effectively perform risk parity and dynamic allocation, defuzzification is applied to generate crisp data (ϑ_{crisp}), providing efficient decision-making and personalized financial advice.

$$\vartheta_{crisp} = \frac{\sum \varepsilon_{rs} \cdot \wp_{cen}(\Psi_{\text{fuzz}})}{\sum \varepsilon_{rs}} \tag{47}$$

Thus, based on ϑ_{crisp}, the proposed framework determines the risk parity and allocates the portfolios dynamically for providing efficient personalized financial decisions to the users.

4. Result And Discussion

In this section, the proposed framework's performances in providing personalized financial advice are demonstrated by comparing it with conventional works. The implementation of the proposed framework is carried out on the working platform of PYTHON.

4.1 Dataset Description

In order to provide efficient financial advice, this model uses three benchmarking datasets, namely the Dataset on Self-Employed Youths' Financial and Retirement Literacy, the National Stock Exchange fIFTY (NIFTY)-50 Stock Market Dataset, and the Stock-Market Sentiment Dataset. Primarily, the proposed framework utilizes the Dataset on Self-Employed Youths' Financial and Retirement Literacy to train the financial-score identification model. This dataset captures youth's financial and retirement literacy levels, including their awareness, knowledge, and capability levels. Similarly, to train the sentiment classification model, data are collected from the Stock-Market Sentiment Dataset. It contains 5791 stock news, including 2106 negative and 3685 positive sentiments. Moreover, by using the NIFTY-50 stock market data, this framework trains the stock-market status prediction model.

Table 1: Dataset Details

Phases	Training	Testing	Total
Financial Score Identification	2680	670	**Before Augmentation:** 300 **After Augmentation:** 3350
Sentiment Classification	4633	1158	5791
Stock-market status Prediction	188154	47038	235192

Table 1 depicts the dataset details for the proposed framework. From these individual datasets, the proposed framework uses 80% data for training and 20% data for testing.

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4.2 Performance Analysis

Here, the proposed framework's performance is compared with traditional works regarding risk parity and dynamic allocation, stock market prediction, sentiment classification, financial score identification, behavioral pattern analysis, word embedding, and portfolio optimization.

4.2.1 Efficiency Analysis for IPG-Fuzzy

In this section, IPG-Fuzzy's efficiency is compared with traditional techniques like Triangular Fuzzy, Cubic Fuzzy, Sigmoid Fuzzy, and Gaussian Fuzzy.

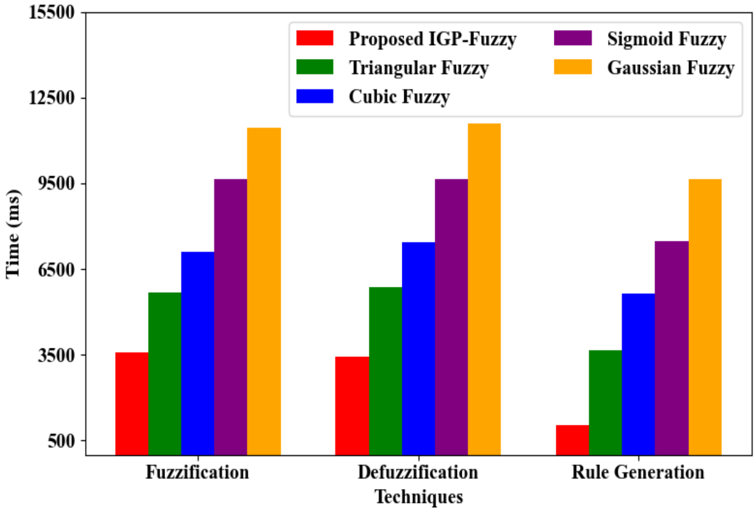

Figure 3: Time analysis for IPG-Fuzzy

Figure 3 indicates that the IPG-Fuzzy takes minimum time for performing both risk parity (i.e., 3568ms fuzzification time and 3418ms defuzzification time) and dynamic portfolio allocation (i.e., 1021ms rule generation time). This is because of the integration of IPG into Fuzzy to eliminate the tuning difficulty, leading to faster convergence. However, the conventional approaches take more time than IPG-Fuzzy due to the lack of capability for complex or nuanced scenarios.

4.2.2 Effectiveness Validation for RL-GPLinQ-GRU

The RL-GPLinQ-GRU's effectiveness is compared with prevailing techniques like GRU, Bidirectional Long-Short Term Memory (BiLSTM), LSTM, and Recurrent Neural Network (RNN).

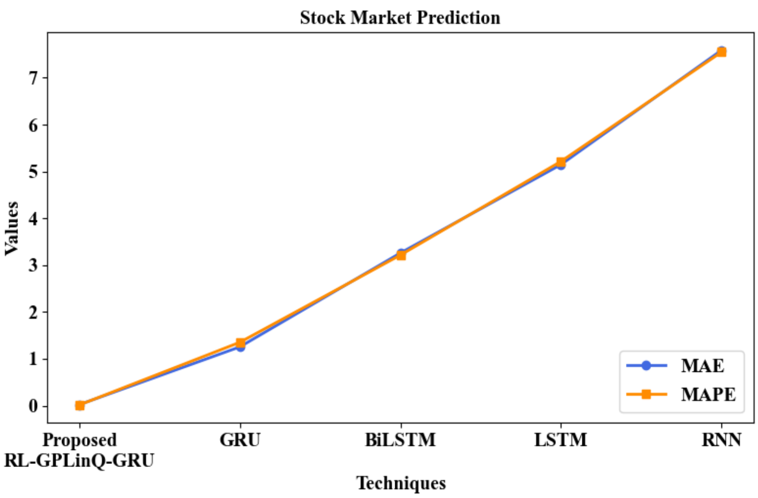

Figure 4: MAE and MAPE Analysis

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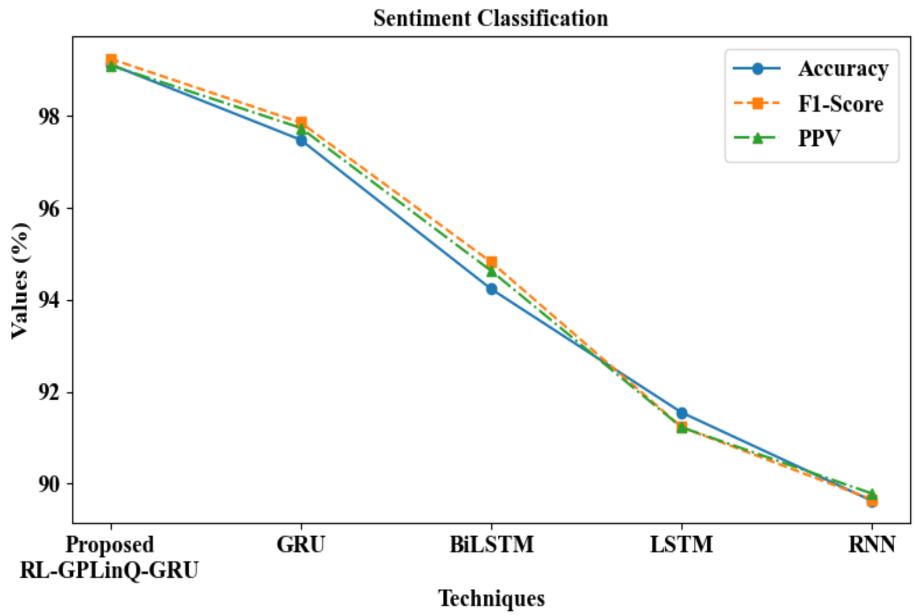

Figure 5: Accuracy, F1-score, and PPV Evaluation

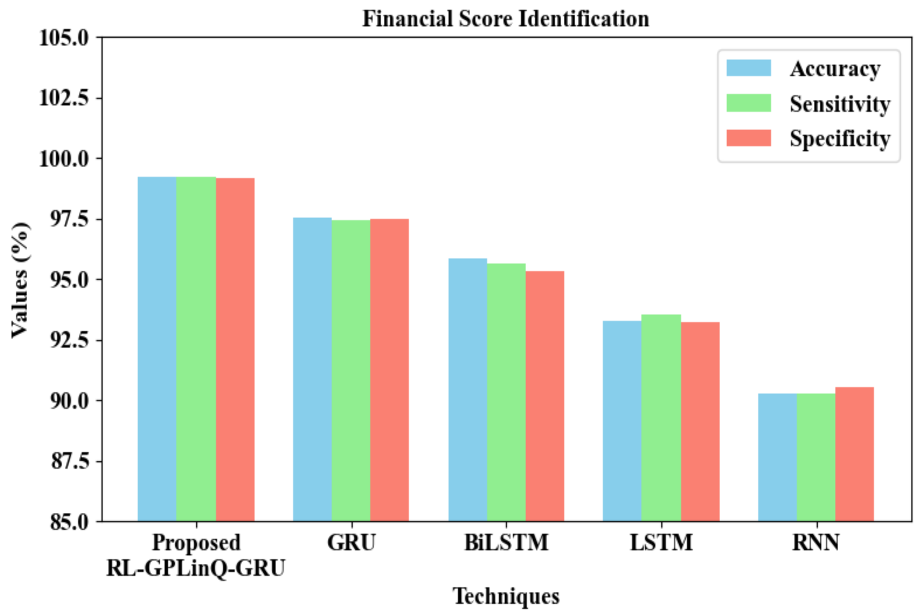

Figure 6: Accuracy, Sensitivity, and Specificity analysis

Figures 4, 5, and 6 illustrate RL-GPLinQ-GRU's effectiveness in stock market prediction, sentiment classification, and financial score identification, respectively. From these figures, it is proven that RL-GPLinQ-GRU outperforms the traditional methodologies by attaining lower Mean Absolute Error (MAE) (0.0214) and Mean Absolute Percentage Error (MAPE) (0.0145) for stock-market prediction. Moreover, RL-GPLinQ-GRU performs well by attaining higher accuracies for both sentiment classification (99.12%) and financial-score identification (99.21%). It also attains a higher F1-score (99.24%), Positive Predictive Value (PPV) (99.1%), Sensitivity (99.23%), and Specificity (99.18%). Thus, by using the RL, GP, and LQ approaches, the proposed framework enhances its ability in real-time applications to provide efficient personalized financial decisions. However, due to the vanishing gradient issues, higher computational cost, and poor adaptability, the conventional approaches fail to perform better in financial decision-making.

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4.2.3 Performance Evaluation for MT-DBSCAN

In this section, MT-DBSCAN's performance is compared with conventional methodologies like DBSCAN, K-Means, Balanced Iterative Reducing and Clustering using Hierarchies (BIRCH), and Fuzzy C-Means (FCM).

Table 2: Clustering Time Analysis

Methodologies	Clustering Time (ms)
Proposed MT-DBSCAN	27415
DBSCAN	33621
K-Means	37458
BIRCH	43265
FCM	47856

The clustering time for MT-DBSCAN in behavioral pattern analysis is demonstrated in Table 2. Here, the MTI is integrated into DBSCAN to select minPts-eps points with a minimum clustering time of 27415ms. However, in conventional works, all points are selected randomly or with the same values, leading to clusters with varying densities. Thus, MT-DBSCAN outperforms the other conventional methodologies like DBSCAN (33621ms), K-Means (37458ms), BIRCH (43265ms), and FCM (47856ms).

4.2.4 Efficacy Analysis for EPD-FinBERT

The EPD-FinBERT's effectiveness is compared with conventional methodologies like FinBERT, BERT, Global Vector for word representations (GLoVe), and Embeddings from Language Model (ELMo).

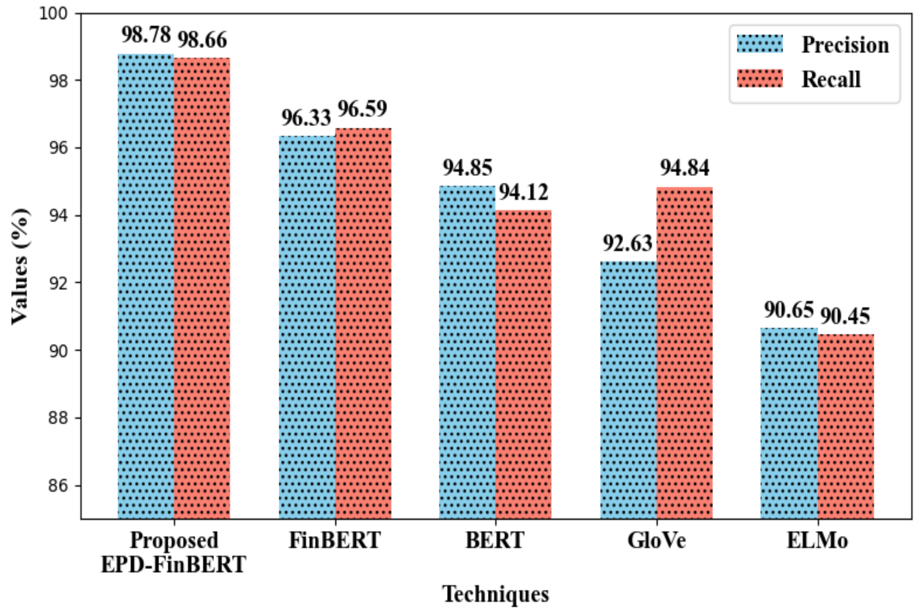

Figure 7: Precision and Recall Validation

As given in Figure 7, the precision and recall values of EPD-FinBERT in word embedding are 98.78% and 98.66%, respectively, which are very high when compared to the traditional methodologies. This is because of the utilization of EPD tuning, which helps to effectively categorize various parts of the parameter by efficiently performing domain-specific tasks. However, the conventional approaches attain an average precision and recall of 93.61% and 94%, respectively. Thus, EPD-FinBERT outperforms the other traditional approaches.

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4.2.5 Effectiveness Validation for PS-MPA

The proposed framework's effectiveness in portfolio optimization using PS-MPA is compared with existing approaches like MPA, Flower Pollination Algorithm (FPA), Squirrel Search Algorithm (SSA), and Black Hole Algorithm (BHA).

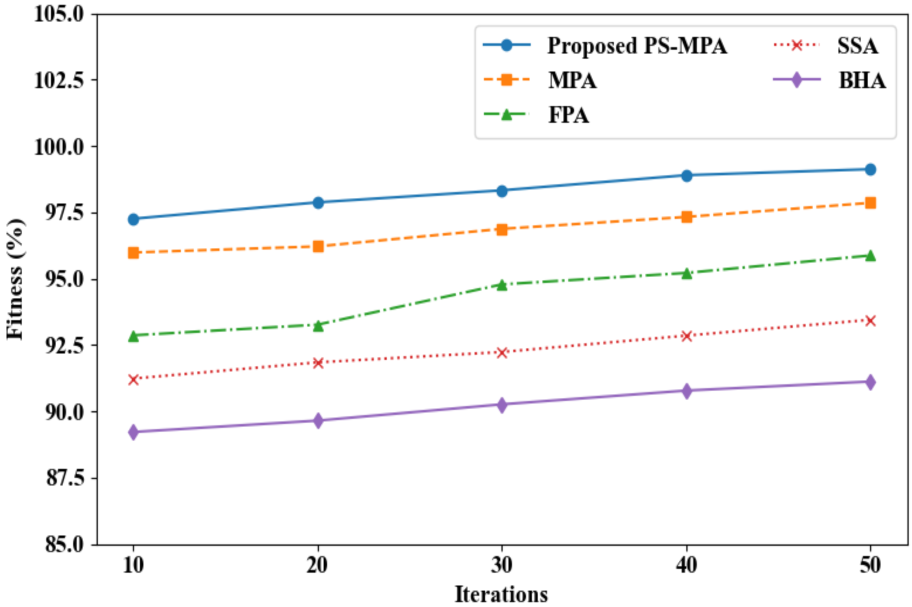

Figure 8: Fitness vs Iteration

Figure 8 illustrates the PS-MPA's efficiency in portfolio optimization. As per the figure, PS-MPA not only achieves high fitness for low iterations but also outperforms for a high number of iterations. Thus, by integrating PS with MPA, the portfolios are initialized, which leads the model to attain higher fitness of 97.25% and 99.12% for both the minimum (10) and maximum number of iterations (50), respectively. However, the conventional methodologies exhibit slower convergence and are more prone to local optima due to poor initialization, attaining lower fitness for both minimum and maximum iterations.

4.2.6 Performance Evaluation for VLIME

In this phase, the VLIME's performance is compared with prevailing techniques like LIME, SHapley Additive exPlantations (SHAP), Partial Dependence Plot (PDP), and Global Surrogate (GS).

Table 3: Fidelity analysis

Methods	Fidelity
Proposed VLIME	0.2056
LIME	2.2689
SHAP	4.2598
PDP	6.3217
GS	8.2659

The fidelity of VLIME in model integrity enhancement is depicted in Table 3. From this table, it is noted that the traditional methods attain higher fidelity than VLIME, leading to increased deviations from the original model's behavior during explanations. In contrast, VLIME achieves a significantly

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lower fidelity score of 0.2056, generating optimal and accurate explanations about how the financial score is identified. This is primarily due to the utilization of the Viennet function that improves explanation quality and reduces overfitting, outperforming the conventional approaches.

4.3 Comparative Evaluation

A comprehensive analysis of the proposed framework and traditional works is depicted in this section.

Table 4: Comparative Evaluation

Authors' Name	Objectives	Methods	Advantages	Limitations
Proposed Framework	Risk parity and dynamic portfolio allocation-based personalized financial advice provider	RL-GPLinQ-GRU and IGP-Fuzzy	Enhanced personalized financial advice by offering dynamic portfolio optimization	This model failed to improve processing speed, security, and transparency in personalized financial advice.
(Zhu, 2024)	Financial decision-making for emerging adults	Python-based Personalized Financial Projection (PFP)	Improved financial literacy	This model exhibited limited effectiveness for unfamiliar data.
(Abrishami et al., 2024)	Robust predictive model development for stock selection and asset allocation	End-to-end Decision Support System (DSS)	Enhanced investment decision-making	This approach failed to consider investor risk level, leading to potential bias.
(Xiong et al., 2024)	Financial investment decision-making based on DL	Type-2 Fuzzy Aczel-Alsina Weighed Power Averaging (T2FAAWPA)	Found the best optimal solutions	Due to the presence of a falsity grade, this model was not reliable.
(Ren, 2021)	AI-based decision-making for financial investment	Fuzzy Logic-based decision-making	Improved timeliness	This approach provided an inconsistent time discount rate due to the inconsistency of the expected rate.
(Shafiee et al., 2024)	Supporting framework for financial decisions	Personalized Financial Configurator (PFC)	Customized financial insights based on financial asset changes	Owing to the reliance on basic inputs, this model failed to provide automated financial management.

Table 4 illustrates the comparative analysis of the proposed framework against several traditional works. As per the table, the traditional approaches contribute to specific aspects like financial literacy,

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investment decision-making, and customization. However, they often suffer from limitations like unreliability, lack of risk consideration, limited adaptability to new data, and absence of automation. In contrast, the proposed framework addresses these limitations by offering dynamic portfolio optimization and personalized financial advice using RL-GPLinQ-GRU and IGP-Fuzzy, outperforming other conventional works.

5. Conclusion

In this paper, an efficient risk parity and dynamic portfolio allocation-integrated personalized financial advice provider model was implemented using RL-GPLinQ-GRU and IGP-Fuzzy. The proposed framework provided effective financial advice to the users by dynamically allocating the portfolios. In this model, MT-DBSCAN efficiently analyzed the behavioral patterns with less clustering time. Moreover, PS-MPA optimized portfolios with a high fitness of 99.12%. The EPD-FinBERT attained 98.78% precision for word embedding. Further, the VLIME provided the optimal and accurate explanation of the identified financial score. Also, Also, RL-GPLinQ-GRU accurately identified financial scores, classified sentiments, and predicted stock-market status with a maximum accuracy of 99.12%. Thus, this paper provided a real-time, applicable, reliable, and generalizable framework for generating personalized financial advice by integrating advanced approaches, thereby outperforming the other prevailing techniques.

Future Scope: Although the proposed framework focused on personalized financial recommendations, it lacked enhancements in speed, complexity, and security. Hence, in the future, quantum computing and blockchain will be integrated into wealth management to ensure robust security, transparency, and real-time adaptability in financial decision-making.

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Dataset:

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