A Gamified AI-Powered Investment Recommendation System for Novice Investors

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Abstract-*In the evolving landscape of retail investing, novice users often face challenges in understanding market dynamics and making informed decisions due to limited financial literacy. This paper presents an interactive, gamified investment recommendation system designed to guide beginner investors through real-time stock analysis, educational content, and personalized investment suggestions. The system integrates Alpha Vantage's financial API for live stock data, uses machine learning techniques for market trend prediction, and computes technical indicators such as the Relative Strength Index (RSI) to support decision-making. To enhance user engagement and learning, a gamification layer rewards users with points, badges, and educational progress tracking for activities such as watching tutorial videos, reading guides, and performing analyses. This combination of financial analytics and game-design principles offers an intuitive, educational, and motivational tool tailored to the needs of new investors. Experimental usage demonstrates the system's effectiveness in improving investment awareness, strategy formulation, and user retention.*

Keywords-Gamified Finance,StockMarket Education,Investment Recommendation System**,**BeginnerInvestors**,**FinancialLiteracy**,**Trend Prediction**,**RSIIndicator**,**Alpha Vantage API**,**BehavioralFinance**,**Python Financial Tools

I. INTRODUCTION

The accessibility of stock trading platforms and zero-commission brokers has attracted a growing number of novice investors. However, many of these individuals lack fundamental financial literacy, making them susceptible to poor decision-making and market volatility. Traditional investment platforms often cater to experienced users, leaving new investors overwhelmed by data and terminology. The integration of machine learning and real-time data processing in finance offers an opportunity to bridge this gap. Gamification—the application of game-design elements in non-game contexts—has proven effective in enhancing learning and engagement. In the context of investment education, gamified systems can incentivize users to explore financial concepts while building decision-making confidence. Our system seeks to marry analytical rigor with motivational design by providing users with immediate feedback, educational content, and performance-based rewards.

This paper presents the development and evaluation of a Python-based investment advisor that utilizes trend analysis, RSI indicators, stock comparison visuals, and gamified mechanics. The goal is to create a self-contained, educational tool that guides beginners toward better investment habits without the need for professional mentorship or expensive advisory services.

The design of the system emphasizes accessibility, interactivity, and educational value. By utilizing Python's extensive data visualization and API integration capabilities, the tool provides real-time feedback through intuitive plots, tabular summaries, and personalized investment suggestions. Users are not only shown predicted stock trends and risk-adjusted investment strategies but are also guided through the reasoning behind these outputs, helping to demystify key financial concepts. The incorporation of learning resources—such as embedded video tutorials and step-by-step investment guides—ensures that users are continuously building their financial knowledge base as they interact with the platform.

Additionally, the gamification layer plays a central role in sustaining user engagement and reinforcing positive behaviors. Actions such as analyzing stocks, watching educational content, and revisiting the system regularly are rewarded with points and unlockable badges, creating a sense of achievement and progression. This rewards-based framework encourages repetition and deeper interaction, which are crucial for long-term retention and practical learning. The user profile system stores investment decisions, performance feedback, and achievement records, turning what would otherwise be a static tool into a dynamic, personalized learning journey.

LITERATURESURVEY

Chong et al., 2017 examined the predictability of three different machine learning methods: principal component analysis, autoencoder, and the restricted Boltzmann machine. They used high frequency lagged stock returns as input data. They applied it to the Korean stock market and found that the DNNS performs better than the linear autoregressive model in the training set, while the regressive model does better in the test set. This discrepancy was explained by pointing out that the predicted part of a stock return is more influenced by the first three lagged returns of itself rather than the lagged returns of other stocks. Fischer and Krauss (Fischer & Krauss, 2018) focused on the performance of the short-term memory (LSTM) networks. They found that LSTM performance exceeds the methods of memory-free classification like the random forest, deep neural network, and the logistic regression classifier. However, the RAF was better performing in one case, during the global financial crisis. On the other hand, Ballings et al. (Ballings et al., 2015) found that the best algorithms as ranked from best to worst as follows: Random Forest, Support Vector Machines, AdaBoost, Neural Networks, K-Nearest Neighbors, and Logistic Regression. Similarly, Patel et al., (Patel et al., 2015) compared four prediction models, namely the ANN, SVM, the Random Forest, and the Naive-Bayes, and found that Random Forest showed the best performance among all. Zhong and Enke (Zhong & Enke, 2017b) found that the combining ANN with PCA (principal component analysis) gives more accuracy. In another study (Zhong & Enke, 2017a), they found that the ANNs gave higher classification accuracy compared to logistic regression. Moghaddam et al. (Moghaddam et al., 2016) investigated the ability of artificial neural networks (ANN) to predict the daily NASDAQ stock exchange rate. Their methodology used both short-term past stock prices and the day of the week as input. They found that there are no distinct differences between using thepast four days or the past nine days as input. Likewise, Pehlivanli et al. (Pehlivanli et al., 2016) found that predictionsusing a reduced dataset yield better results than predictions using a full dataset. Malagrino et al. (Malagrino et al., 2018) used Bayesian Networks to see to what extent global indices influence the main index iBOVESPA (Sao Paulo, Brazil). Their model can serve as a basic block to more complex applications. Boyacioglu and Avci (Boyacioglu & Avci, 2010) used adaptive network-based fuzzy inference system ANFIS on the Istanbul Stock Exchange and found the model to have an accuracy success rate of 98.3%. Zhang et al. (Zhang et al., 2016) created a new system altogether. It used a heuristic algorithm that cuts stock data into multiple clips. These clips are classified. While, X. Zhang, Li, and Pan created a new approach named status box method, which classifies stock point into three categories of boxes—each box indicates different stock status. Their results show that the status box method has better classification accuracy and can solve the stock turning points classification problem.

Technical indicators remain a cornerstone of stock market analysis, with the Relative Strength Index (RSI) being among the most widely used tools. Introduced by J. Welles Wilder in 1978, RSI is a momentum oscillator that measures the magnitude of recent price changes to evaluate overbought or oversold conditions in a stock. Several studies have reaffirmed RSI's reliability as a leading indicator in both bull and bear markets. Integration of RSI with machine learning models, such as in hybrid AI systems, has shown to further enhance prediction accuracy. Despite their utility, these indicators often require contextual understanding, which novice users may lack without a guided framework.

Gamification has emerged as a potent educational and behavioral tool across various sectors, including health, education, and finance. In finance, platforms like Robinhood and Acorns have implemented elements of gamification such as streak tracking, rewards, and engaging interfaces to enhance user participation. Research shows that gamification improves user engagement, motivation, and information retention, particularly when it includes elements of challenge, achievement, and feedback. However, these platforms often stop short of integrating structured learning pathways or personalized educational feedback, which limits their effectiveness in building long-term investment knowledge.

Educational finance tools and simulators, such as Investopedia's stock simulator or Coursera-based financial literacy courses, offer structured content but lack real-time integration with market data and personalization. Furthermore, few tools combine analytical rigor with motivational design to keep users actively learning. The system proposed in this paper seeks to bridge this gap by embedding gamification within an AI-powered stock analysis engine. By offering dynamic visual feedback, actionable insights, and educational content in tandem, the system not only supports informed investing but also promotes financial literacy and confidence in beginners.

III .METHODOLOGY

A. Proposed Method

The proposed system is a gamified, AI-powered stock analysis tool aimed at making investment education engaging and accessible for beginners. It combines financial learning with real-time stock analysis using the Alpha Vantage API. Users interact with the system through a command-line interface where they can access educational guides, watch curated video content, and analyze selected stocks based on their risk tolerance and available balance.

A core feature of the system is its stock analysis engine, which evaluates short-term trends, calculates technical indicators like the Relative Strength Index (RSI), and offers investment predictions. Depending on whether a stock is trending bullish, bearish, or sideways, the system suggests optimized investment amounts and alternative stocks for diversification. The tool also visualizes price trends over a 14-day period using plots for clearer understanding.

To encourage consistent learning and interaction, the system integrates gamification elements. Users earn points for completing actions such as watching videos, reading guides, and running stock analyses. As they accumulate points, they unlock badges that reflect their level of engagement and progress in understanding the stock market.

All user data, including points, badges, and investment history, is stored in a local JSON profile. This makes it easy to track individual growth and maintain personalized feedback. The overall design not only supports informed decision-making but also fosters motivation and continuous learning, making it ideal for users new to investing.

B. Proposed Architecture

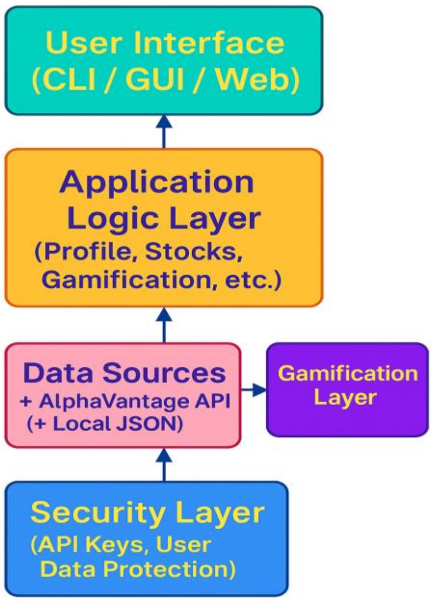

Fig 3 : Proposed Block diagram

The Stock Investment Assistant system is structured into four main layers: User Interface, Application Logic, Data Management, and Security. The User Interface (currently a command-line setup) collects user inputs and displays investment guides, stock analysis, and profile progress. The Application Logic layer handles core functionalities like managing user profiles, awarding points and badges, analyzing stock trends using Alpha Vantage data, suggesting investments, and providing educational resources. The Data Layer integrates real-time external data from APIs and stores user progress locally in a JSON file for persistence. Security measures focus on safe handling of API keys and protecting user information. A gamification system is embedded to enhance user engagement, motivating users through points, badges, and simulated investment tracking, making the learning and investment process both educational and interactive.

IV. SYSTEM IMPLEMENTATION

The developed stock analysis and gamification system is built using Python and integrates the Alpha Vantage API for fetching real-time stock market data. It enables users to input multiple stock tickers, analyze trends over the past 14 days, and predict market movement using percentage change and simple statistical heuristics. The system calculates average daily fluctuations and predicts market direction as bullish, bearish, or sideways. To visualize these trends, Matplotlib is employed to plot stock closing prices, offering users an intuitive understanding of short-term market behavior. In addition, the system uses the Relative Strength Index (RSI) to support technical analysis, giving further insight into whether a stock is overbought or oversold.

The interactive flow is initiated by loading a user profile from a JSON-based persistent storage. If the profile does not exist or is reset, a new profile is initialized with default values. The profile stores accumulated points, earned badges, and past investment decisions, promoting user engagement through gamification. Points are awarded for actions like running an analysis, watching educational videos, or viewing beginner guides. As users accumulate points, the system dynamically awards badges at thresholds (10, 50, and 100 points), encouraging continued interaction and learning.

To support new investors, the system includes a built-in guide covering foundational stock market concepts, strategies, and metrics. Furthermore, it curates a playlist of beginner-friendly YouTube videos. These videos are accessible via direct browser launch through the system's CLI, with points awarded for participation. This multimedia integration is designed to make stock investing less intimidating and more educational, particularly for users with limited financial literacy.

For investment recommendations, the system calculates the amount to be invested in each stock based on the user's balance, risk tolerance (high or low), and predicted trend. It also suggests alternative stocks for diversification, based on the current trend classification. After analysis, a comparative report is displayed using the Tabulate library, summarizing each stock's trend, predicted change, RSI, investment amount, projected profit or loss, and alternatives. By combining predictive analytics, gamification, and educational content in a command-line interface, the system offers a comprehensive tool that is both informative and engaging for beginner investors.

A. Algorithm

The system employs a **percentage change-based trend prediction algorithm** that calculates the daily percentage change in a stock's closing prices over the past 14 trading days. This is derived from time series data provided by the Alpha Vantage API. The algorithm computes the mean of these daily changes to estimate the overall direction of the market for the selected stock. If the average daily change exceeds +0.5%, the stock is considered **Bullish**; if it falls below -0.5%, it is labeled **Bearish**. Changes within this range are classified as **Sideways**, indicating minimal momentum. This simple moving average approach offers a lightweight yet effective mechanism for trend prediction without relying on complex machine learning models.

To further support investment decisions, the system integrates the **Relative Strength Index (RSI)** calculation as a technical analysis indicator. RSI is computed over a standard 14-day period, identifying the speed and change of price movements. It is calculated using the average gain and average loss during the period and transforms this into a value between 0 and 100. A stock with an RSI above 70 is typically considered overbought, while one below 30 is considered oversold. This helps users assess potential entry or exit points, aligning technical insights with the directional prediction made by the trend algorithm.

The **investment allocation algorithm** is a rule-based function that considers the predicted trend and the user's declared risk tolerance (either "high" or "low"). Based on this, the algorithm applies a predefined multiplier to the user's total balance to compute a recommended investment amount. For example, a high-risk investor in a bullish market might allocate 60% of their balance to a particular stock, while a low-risk investor in a bearish market might invest only 5%. This heuristic-based allocation strategy simulates basic portfolio management principles without needing complex optimization models.

Finally, the **gamification logic** is implemented using a point and badge system. Actions such as viewing beginner guides, watching educational videos, or performing stock analyses earn the user points. The system maps certain point thresholds to badge awards (e.g., 10 points for "First Step", 50 for "Rising Star"). These achievements are persistently stored in a user profile JSON file. This reward system encourages frequent interaction, fosters learning, and enhances retention for new investors. The combination of analytical tools and gamification mechanisms results in an engaging and educational platform for stock market beginners.

B.Module Description

1) Data Processing Module

Data processing is the foundational step in any machine learning pipeline. For stock market prediction, the raw stock data (e.g., closing prices, volume, open price) must be cleaned and transformed to be useful for model training.

Data Cleaning: The first step involves handling missing values, duplicates, and outliers. For instance, if stock data has missing values, they can be imputed using various methods such as forward-fill, backward-fill, or interpolation.

Normalization: Stock data often comes in varying scales (e.g., prices could range from $10 to $500). Normalizing data ensures that features are on a comparable scale, which helps improve model performance. Techniques like **Min-Max Scaling** (scaling data between 0 and 1) or **Standardization** (scaling data to have a mean of 0 and standard deviation of 1) are commonly used.

Feature Engineering: This involves creating new features based on existing data. For example, you could compute the **Moving Average**, **Relative Strength Index (RSI)**, **Bollinger Bands**, and **Exponential Moving Average (EMA)**. These technical indicators often provide meaningful insights into stock price trends.

2. Feature Selection Module

Feature selection is the process of selecting the most relevant features to be used in model training. This reduces the complexity of the model and helps to avoid overfitting. Here are a few techniques commonly used for feature selection:

Correlation Matrix: A correlation matrix shows the relationship between different features. If two features are highly correlated (e.g., closing price and volume), one can be removed to reduce redundancy and prevent overfitting.

Recursive Feature Elimination (RFE): This technique iteratively removes the least important features based on model performance (e.g., using a linear regression model). It ranks features based on their importance, and removes the least significant ones.

Lasso Regression: Lasso (Least Absolute Shrinkage and Selection Operator) is a type of regression that adds a penalty to the model's coefficients, encouraging sparsity in the feature set. Features with zero coefficients can be discarded, and the model is left with the most relevant features.

3. **Model Building and Training**

After preprocessing and feature selection, the next step is to build a predictive model. Several machine learning algorithms can be used for stock prediction:

Linear Regression: A simple approach where the model tries to predict a continuous variable (stock price) based on the relationship between input features (e.g., historical prices). It's often a baseline model to compare against more advanced techniques.

Random Forest and XGBoost: These are tree-based ensemble methods that perform better than linear models in many cases. They create a set of decision trees and use the majority vote (or average) to make predictions. These models tend to perform well when there are complex, non-linear relationships in the data.

Long Short-Term Memory (LSTM) Networks: LSTMs are a type of recurrent neural network (RNN) designed for sequential data. Since stock prices are time-series data, LSTM networks are well-suited for this kind of task. LSTMs can capture patterns over long periods and are often used for stock price prediction.

V. RESULT

When the user initiates the system, it begins by either loading an existing profile or creating a new one if none is found. This profile keeps track of accumulated points, badges earned, and investment activities. As the user interacts with various components of the system, such as viewing guides or analyzing stocks, they are rewarded with points. These points contribute to earning badges like "First Step" or "Market Wizard," which are awarded once specific milestones are reached, encouraging consistent learning and engagement.

Immediately after loading the profile, the system introduces the user to stock market fundamentals through a structured beginner-friendly investment guide. This is followed by a set of carefully chosen YouTube videos that cover essential concepts such as stock chart reading, technical analysis, and beginner investment strategies. When the user chooses to watch one or more of these videos, the system acknowledges this action by awarding additional points and updates the user profile accordingly, reinforcing learning through gamification.

Next, the system prompts the user to enter one or more stock tickers, a risk tolerance level (high or low), and their available investment balance. Using the Alpha Vantage API, it retrieves the last 14 days of daily stock data for each ticker. This data is analyzed to determine the market trend for each stock—bullish, bearish, or sideways—based on recent average percentage price changes. This immediate insight helps users gauge the short-term market outlook for each of their selected stocks.

Following the trend analysis, the system uses the user's risk preference and total balance to calculate a personalized investment amount per stock. It then estimates the potential profit or loss based on the predicted price change, giving users a data-driven approach to make investment decisions. This customization helps new investors align their strategies with both market behavior and personal financial comfort, making the system adaptable and user-focused.

To enhance the analysis, the system computes the Relative Strength Index (RSI) for each stock, a key technical indicator that reveals whether a stock is overbought or oversold. It also generates comparative line plots for each stock's recent price movement, allowing users to visually interpret the trend. This combination of numerical and graphical analysis offers users an intuitive understanding of stock behavior, even if they are unfamiliar with advanced trading tools.

In the final step, the system presents a detailed tabular report comparing all analyzed stocks, including trend direction, predicted percentage change, RSI value, investment recommendation, and estimated gain or loss. Additionally, it suggests alternative stocks based on the trend to diversify investment options. The session ends with an update to the user profile—awarding more points and potentially unlocking new badges—while displaying a summary of the user's current progress and investment insights, making the experience both educational and rewarding.

VI. CONCLUSION

In conclusion, the investment analysis system offers a holistic platform that combines education, personalized financial insights, and user engagement to support beginner investors. It begins by familiarizing users with the basics of stock markets through a structured guide and curated educational videos, rewarding their participation with points and badges to reinforce learning through gamification. The system then allows users to input stock tickers, risk tolerance, and available balance to provide trend analysis, personalized investment suggestions, and potential profit or loss estimates using real-time data from Alpha Vantage. By calculating technical indicators like the Relative Strength Index (RSI) and generating visual stock trend graphs, it enhances the analytical understanding of market behavior. Moreover, the system suggests alternative stocks based on current trends, giving users diversified options to explore. All interactions are stored in a user profile, which tracks progress, rewards achievements, and promotes further engagement. The tabulated results offer clarity, allowing users to compare multiple stocks at a glance. Overall, this tool simplifies complex financial concepts, encourages smart investing through data-driven suggestions, and creates a gamified experience that keeps users motivated. It stands out as an educational yet practical solution, perfectly tailored for those new to investing but eager to make informed financial decisions.

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