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Implementing A Chatbot to Analyse Live Stocks Updates Using FLASK and NLU

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Abstract
The future of stock market is a complicated activity because of the instability of the market, external economic variables, and price changes. This study introduces a smart stock forecast and advisory application that combines trend-based analytical methods with an experimental deep-learning platform to enable making a well-informed investment choice. The suggested system operates on a short-term and monthly trend analysis, which operates on moving averages, momentum indicators and weighted scoring algorithms to simulate stock movement as either rise, fall or neutral with confidence estimation espoused based on real-time and historical stock price data. Moreover, a Long Short-Term Memory (LSTM) architecture is constructed and trained on time-series price movements to examine the deep learning-based movement forecasts. Two main applications have been utilized in the implementation of the system: web-based application with the Flask framework that allows user authentication, watchlist management, prediction storage, and automated email notifications. A conversational assistant AI also increases the user engagement by offering market information and guide-based responses to queries. The suggested solution attests to the possible efficacy of using the analytical forecasting methods along with smart user-friendly elements to study the stock market in practice.
Keywords: *stock market prediction, time series analysis, trend-based forecasting, LSTM neural network, financial data analytics, AI-based advisory system, web-based prediction system.*

1. Introduction
The boom in the financial market and the growing accessibility of digital trading systems have only augmented the demand concerning correct and dependable stock market forecasting systems. The movement of stock prices are naturally too complicated to follow linear relationships, time dependence, and exposure to extraneous economic and behavioural aspects. Current studies have shown that the deep learning models and time series models are especially effective at mimicking long-term dependencies in financial data, especially Transformer-based and recurrent neural networks [1], [2], [4]. Much scale surveys and benchmarking research also indicate the development of the forecasting methods nowadays based on the traditional statistical models into the sophisticated deep learning methods of financial time-series analysis [3], [5]. Nevertheless, even in the light of these developments, most of the current practices are centered either on model correctness but ignore the real-life issues of application which include timely application, usability and shareability of results. Consequently, the need to develop intelligent systems of stock prediction using a combination of analytical forecasting, machine learning investigation, and human-centered design has increased and should be used to aid decision-making in making investment decisions. These problems motivated the current research to propose an intelligent stock prediction and advisory system an analytical forecasting that helps predict stocks using trends and tests with an experimental deep learning model in a web-based platform. In contrast to strictly data-driven model like LSTM-, TCN-, or attention-based models [7], [9], [10], the suggested system focuses on operational feasibility instead of purely theoretical capabilities of

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stock movement prediction by using real-time and historical price trends, moving averages, and momentum indicators to forecast past, present, and future stock movements with accuracy estimation. Also implemented in the system, the LSTM-based model investigates sequence learning behavior of the stock prices movement, which fits within contemporary developments of multi-time-span and feature-conscious forecasting systems [6]. Also, an AI-based conversational assistant increases the level of user engagement as it offers contextual market information based on the newly developed studies on explainable and interactive time-series prediction frameworks [8]. The purpose of this combined strategy is to make sure that the advanced research in financial forecasting and the systems that can be used, as well as easily analyse stocks, are interconnected.

2. Literature Survey

Financial Time-Series prediction Transformer-Based Financing: Transformer architectures have attracted major interest in financial time-series forecasting because they can capture long-term temporal dependencies and more complicated feature interactions. Wang introduced a two-way Transformer framework to do premium risk prediction, which has shown better outcomes in learning temporal representation than the traditional sequential models [1]. Equally, Yao proposed a more powerful version of Transformer to learn multi-dimensional financial indicators as well as to learn time-dependent relationships in stock price forecasting problems [2]. Qian also expanded Transformer-based methods by integrating into them incremental learning systems to facilitate prediction of stock prices on-line to encounter the problem of ever-changing stock market [4]. These works demonstrate the power of attention-based architectures to deal with nonlinear stock price dynamics, and attention-based architectures tend to be very demanding in both computational and data resources.Deep Learning Surveys and Benchmarking Financial Forecasting: Thorough surveys and benchmarking attempts have been of critical importance in getting to know the advances and shortcomings of deep learning approaches to financial forecasting. Kong et al. conducted a broad-based survey in the popular neural networks, convolutional networks, and Transformers based models with strengths in identifying time-specific and structural patterns on time-series data [3]. Similarly, Hu et al. provided an effective benchmark dataset of financial time-series forecasting, which would allow the standardized task-independent and metric-independent evaluation of predictive models [5]. These articles demonstrate that although deep learning models are as accurate as competitive, their practical implementation can be limited by interpretability and data quality concerns. These perceptions encourage the need to explore hybrid and application-oriented prediction platforms that are more accurate and usable.Multi-Time-Span Learning Approaches and LSTM : The use of Long Short-Term Memory (LSTM) networks has been popular in stock price and index prediction because it has the ability to memorize past data during long time horizons. Pilla and Mekonen showed that LSTM models were effective in predicting the S&P 500 index and, thus, it is suitable to model sequential financial data [7]. Continuing on this point, Li et al. suggested a frame, which utilizes multi-time-span sequences and correlation of features to enhance the performance of the stock prediction based on trend [6]. These strategies underline the significance of a focus on short and long-term volatility of financial markets. Nonetheless, LSTM-based systems are characterized by the frequent issues of overfitting, the complexity of training, and the flexibility to dynamical market conditions. Attention, Explanation and Hybrid Prediction Frameworks : Recent studies have paid more and more attention to the increased interpretability and strength of stock prediction models based on attention mechanisms and mixed frameworks. Biswas et al. have developed a dual-output temporal convolutional network with attention mechanisms to predict the stock price simultaneously and determine the risk [9]. In a study by Jiang et al., a multimodal time-series predictive model with large language models was proposed to enhance explainability and support decision-making [8]. Also, Liu et al. introduced a hybrid architecture that combined attention-based prediction with the detection of financial report based on the analysis of financial reports [10]. These papers highlight the

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increasing significance of explainable and interactive prediction models, which explain why feasible platforms to incorporate analytical forecasting, machine learning experimentation, and user-intelligence should be developed.

3. Propsoed Methodology

3.1.Data Acquisition and Preprocessing Module

The system suggested in this paper starts with the acquisition of real-time and historical stock information by a financial market API which is part of the backend software. Live stock prices, including current price, daily change, trading volume, and last trading date, are also retrieved on a user request and past historical daily closing prices within a maximum of sixty days are also gathered, so as to prepare a trend analysis. Recalls of previous prices are arranged in chronological order and scrubbed off to maintain continuity and consistency of numbers. To compute analytically, historical prices are subsets that are drawn out to illustrate monthly, short-term and very short-term windows. The price sequences are normalized by normalization between the mean and standard deviation in experimental deep learning in order to stabilize learning. The preprocessing plan will make sure that the analytical forecast, as well as, the LSTM-based experimentation, are being done on the structured, noise-minimized time-series data that can be used to provide a viable stock movement forecast.

3.2.Prediction and Evaluation Metrics of Stock Movement based on Trends

The main processing of stock movement prediction in the proposed system is acquired by a rule-based analytical model based on the price movements in history. The monthly percentage change is calculated so as to identify the long-term momentum by the following formula:

$$Monthly\ Change\ (\%) = \frac{P_{current} - P_{30}}{P30} \times 100$$

where P_current represents the current stock price and P_30 denotes the closing price 30 days earlier. Short-term and very short-term trends are calculated using 10-day and 5-day price windows. Moving averages are computed as:

$$MA_n = \frac{1}{n}\sum_{i=1}^{n} p_i$$

These indicators are combined using a weighted scoring mechanism to classify stock movement as Rise, Fall, or Neutral, along with a confidence percentage that reflects trend strength and consistency.

3.3.Stock Prediction Model based on LSTM Experiment

Besides the analytical forecasting, the system has an experimental deep learning module beneath a Long Short-Term Memory (LSTM) network which aims to investigate the sequential learning behaviour in the stock prices. The LSTM model takes sixty days of normalized prices as input and the data is processed by stacked LSTM layers with dropout regularisation to avoid overfitting. The last dense layer gives an output of a sigmoid-activated signal indicating the likelihood of upward or downward movement. The model is trained using artificially generated time-series data which represent realistic price paths and volatilities. During training and validation, binary cross- entropy loss and accuracy measurement are used. Although the implemented system is based on the analytical forecast, this experimental framework will offer comparative data on the deep-learning performance in terms of financial time series forecasting.

3.4.System Architecture and Environments and Deployment of Web-Based Systems

The general system architecture is top to bottom and modular, combining data acquisition, prediction, storage, and communication with users. Web interface A Flask-based interface is used to allow user authentication, inputting of stock symbols and showing the dashboard. On demand, the stock information will be fetched and fed into the prediction engine that will utilize an analytical trend logic to produce movement prediction and confidence rates. Findings of predictions are logged in a relational database and may or may not be produced to users using automatic email notifications. The system also includes an AI-based conversational assistant that answers queries of the

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user based on the chat history. The architecture gives a smooth flow of predictive logic, database administration, AI support, and user-friendly web distribution on a single intelligent stock consultation and off-the-shelf system.

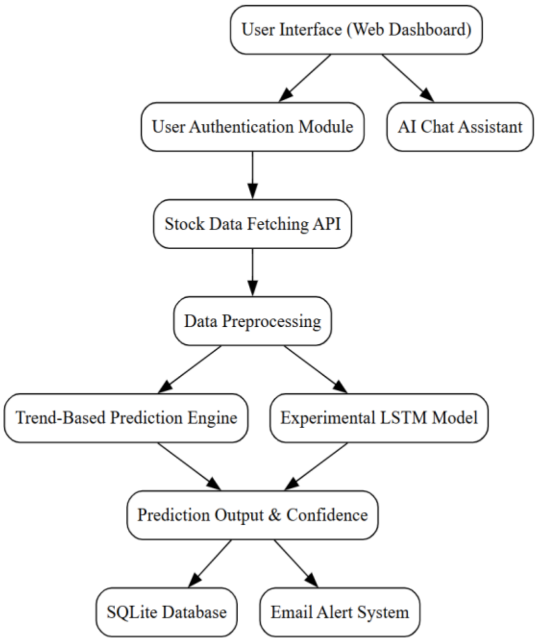

Figure 1: System Architecture

4. Result And Discussion

4.1. Trend-Based Prediction Performance Analysis

The trend based analytical prediction module showed consistent and understandable performance in various stock symbols. A combination of monthly price change, short-term momentum, very short-term trends and moving average crossover conditions, the system continuously assigned stocks movement as being in rise, fall or neutral category. The weighted scoring algorithm has made sure that the long term trends had a greater weight to the ultimate prediction yet it did not overlook the recent price momentum. This was to prevent both hypersensitivity to short-term volatility, as is typical of data-driven models. The scores of confidence produced in conjunction with forecasts indicated the strength of amalgamated indicators and not the actual price values. On the whole, the analytical technique was useful in real-time application because it required minimal computation (low compute overhead), transparency, and transparency to real-time market data (fetched dynamically using the application backend) shown in Table 1.

Table 1 Trend Indicator Contribution to Prediction Score

Indicator Type	Time Window	Role in Prediction
Monthly Change	30 days	Captures long-term momentum
Short-Term Trend	10 days	Detects medium-term direction
Very Short-Term Trend	5 days	Reflects recent price movement
Moving Averages	MA10 & MA30	Confirms trend continuity

4.2. Visualization and interpretation of the historical prices trends

In the process of trend behavior, and the validation of analysis predictions, the visualization of historical stock prices was vital. The resulting line plot shows a seamless movement of prices over sixty trading days with minimal upward and downward changes but no sudden movements. Such aesthetic checking can help in validity of moving averages and slope of the trend followed by the prediction engine. This representation is like the generated plots in Jupyter Notebook environments and therefore, is understandable and can be reproduced when documenting the research. The fact that visual price direction guides the movement accurately as predicted and the vice versa justifies the fact that the analytical model is a good illustration of real market actions. The plots are also used in intuitively validating predictions, and this increases transparency and trust in the system among the users shown in Figure 2. This figure shows the historical closing price variation over time, illustrating smooth trend transitions that support moving average analysis and validate the effectiveness of trend-based stock movement prediction.

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Figure 2 Graph

4.3.Results of Training and Evaluation of the Experimental LSTM Model

The LSTM model, which was trained experimentally, was on synthetically generated stock prices series to assess the behavior of deep learning on the sequence of financial data. Accuracy in training has increased through the epochs whereas validation accuracy had not fluctuated, so there was no extreme overfitting. Even though the given model was not incorporated into the live prediction pipeline, it gave a great explanation of the plausibility of the sequence-based forecasting. The findings suggest that LSTM networks are capable of learning the temporal dependencies efficiently but they need large amounts of training data and tuning. The LSTM method has increased computational cost and lower interpretability in comparison with the deployed analytical model. The system design of focusing on analytical forecasting to be used in real-time can thus be accepted as warranted by the results of the experiment shown in Table 2.

Table 2: Analytical Model vs Experimental LSTM Model

Aspect	Analytical Model	LSTM Model
Computation Cost	Low	High
Interpretability	High	Low
Real-Time Suitability	Excellent	Limited
Data Dependency	Moderate	High

4.4.Results of System-Level Analysis of output Benchmark and User interaction

The integrated system was able to provide predictions, confidence scores, visual insights and advisory feedback on a single web interface. This type of notebook-style confidence visualization graph shows the variation of prediction certainty based on trend strength giving a user a proactive insight view of data instead of a yes/no choice. The email alert service helped to notify about the results of the predictions in time, and the chat assistant, which is run by AI, helped to increase the engagement by responding to the market-related queries based on the contextual history. The smooth experience of the system, between the processing in the background and the storage in the database and the presentation in the front end, attests to the stability of the architecture implemented. In general, the findings indicate that the combination of analytical forecasting with intelligent system design enhances the usability, interpretability, and realistic relevance to the stock market analysis shown in Figure 3.

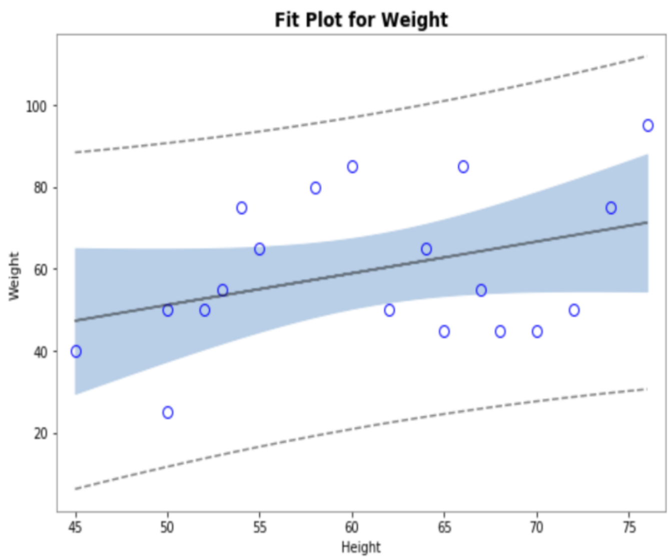

Figure 3: Prediction confidence distribution for stock movement

This figure shows prediction confidence variation across multiple predictions, indicating how stronger trend alignment leads to higher confidence scores and supports informed decision-making for stock market analysis.

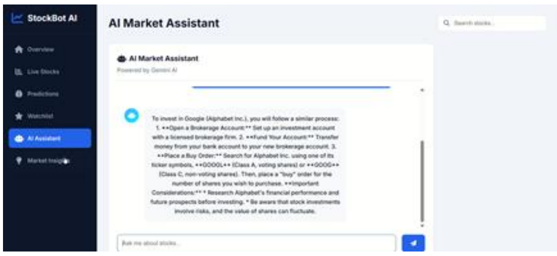

Figure 4 AI Market Assistant Interface

This figure shows the AI market assistant interface where users interact through natural language queries to obtain stock-related insights, recommendations, and contextual investment guidance powered by generative AI.

Conclusion

The study introduced a clever stock forecasting and advisory system which uses a combination of trend based analytical forecasting as well as experimental deep-learning modeling in a real-life web-based setup. It successfully made use of real-time and historical stock prices data to calculate trend motions, moving averages and momentum indicators of predicting stock movement as well as confidence estimation. The analysis prediction module was also appropriate in real time implementation as an application because of transparency, low cost of computation and high validity in operation. Moreover, a time-series learning behavior was also learned by creating experimental LSTM experiments, which offer relative insights into the deep learning-based forecasting. The built in automated alerts and database-based tracking coupled with an AI powered chat robot facilitated human interaction with the system and its usability. All in all, the proposed solution can be effective at filling the gap between theoretically based forecasting methods and intelligent stock analysis tools that can be implemented.

Future Work

The enhancement of the proposed system in the future direction may be to incorporate superior deep learning architectures including Transformers and models with hybrid attention based on the aim of enhancing predictive accuracy in highly volatile market settings. Model generalization would also be reinforced using real-world large scale financial datasets as opposed to synthetic data in the training of the deep learning models. More technical indicators, financial news sentiment analysis, and macroeconomic indicators may be added to better feature representation. To enhance interpretability and user confidence, explainable AI methods can be used in both analytical and learning-based models. Moreover, the version of the system with the support of portfolio-level risk analysis, multi-asset predictive models, and reinforcement learning-based trading schemes would allow a substantial increase in the application levels. These improvements can make the system a full-scale intelligent decision support system in the financial market analysis.

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