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Research Article

Prediction ARIMA Model-based Investor's Perception on Stock Market Apps

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Abstract: The advent of stock trading apps has revolutionized the landscape of stock market participation, particularly among retail investors. This study investigates the impact of stock trading apps on the behaviour of retail investors in the stock market, the impact of social media In growing importance of online trading app and the opportunities for budding investors that the growth of stock market apps has brought with itself. Our findings indicate the changes brought in the economy through mobile trading apps and how it has significantly contributed to FinTech not just economically but also financially. This paper investigates the use of hybrid models combining ARIMA (AutoRegressive Integrated Moving Average) and LSTM (Long Short-Term Memory) for stock price prediction, aiming to improve forecast accuracy in financial markets. The study evaluates the predictive performance of both models individually and in combination across a set of eight stocks: AAPL, TSLA, MSFT, AMZN, NVDA, GOOG, FB, and BABA. The ARIMA model demonstrated varying levels of success, with predicted price changes ranging from +1.5 for GOOG to +10.5 for AAPL. The LSTM model provided stronger predictions, with AAPL seeing a predicted increase of +7.8 and TSLA a predicted increase of +9.4. When combined, the hybrid model generated more reliable predictions, with the combined predicted price for AAPL being 160.5 (up from a current price of 150) and for TSLA 627.25 (up from 620). Automated ranking and classification based on the combined predictions showed that stocks such as AAPL and TSLA were expected to increase by +10.5 and +8.3, respectively, while FB and BABA were predicted to decrease by -1.2 and -2.5.

Keywords:- Stock Market; ARIMA; Prediction; Classification; Stock Prices; Share market; Machine Learning

1 Introduction

In recent years, the stock market has undergone a significant transformation, with the advent of mobile applications and online trading platforms [1]. These digital tools have democratized investing, making it accessible to a broader range of individuals. However, understanding investor perceptions of these stock market apps is crucial to gauge their effectiveness and identify areas for improvement [2]. Investor perception directly influences the success of stock market apps. Positive perceptions can lead to increased user adoption, higher engagement, and positive word-of-mouth recommendations [3]. Conversely, negative perceptions can result in user churn, reputational damage, and reduced market share. Stock market apps have revolutionized the way people invest, making it easier and more accessible than ever before. For investors of all levels, these apps offer a convenient platform to track investments, make trades, and stay updated on market trends [4]. With investor perceptions of stock market apps is essential for app developers and financial institutions. By addressing key factors such as user experience, security, education, costs, and customer support, these entities can create apps that meet the needs and expectations of investors, fostering trust and driving growth in the digital investing landscape [5].

Stock price prediction is a complex and challenging task that involves forecasting future prices based on various historical and current factors [6]. Common approaches include statistical methods like ARIMA and exponential smoothing, which use historical price data to make predictions. Machine learning techniques such as linear regression, decision trees, and support vector machines (SVM) can capture more intricate patterns and relationships in the data. For more advanced modeling, deep learning methods like neural networks, particularly Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks, are employed due to their ability to handle sequential data and capture long-term dependencies [7]. Additionally, sentiment analysis using natural language processing (NLP) can offer insights by analyzing market news and social media to gauge investor sentiment. Technical indicators (such as moving averages and RSI) and fundamental data (like earnings per share or price-to-earnings ratios) are often incorporated to enhance prediction accuracy [8]. However, stock price prediction is fraught with challenges like market volatility, overfitting, and the necessity for high-quality data, making it a difficult yet interesting area of financial analysis and machine learning [9].

Machine learning plays a crucial role in stock price prediction by enabling models to identify complex patterns and relationships in vast amounts of financial data that are often too intricate for traditional methods [10]. Through supervised learning, algorithms such as regression, decision trees, and support vector machines (SVM) can learn from historical stock prices and other relevant market data to predict future movements. Unsupervised learning techniques, like clustering, can identify hidden trends or groupings within the data, while deep learning models like Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks excel at processing sequential data, such as time series stock prices, capturing long-term dependencies and trends. These machine learning models can also integrate additional data sources, such as news sentiment, technical indicators, and economic reports, to refine predictions [11].

Automated stock price prediction with machine learning involves using advanced algorithms to analyze vast amounts of historical market data, economic indicators, and other relevant inputs to forecast future stock prices [12]. The process typically begins with collecting data such as past stock prices, trading volumes, and technical indicators like moving averages or RSI. Machine learning models, including regression techniques, decision trees, and neural networks, are then trained on this data to learn patterns and relationships that can predict price movements [13-18]. Deep learning models, particularly Long Short-Term Memory (LSTM) networks, are popular for capturing complex, time-dependent trends in stock prices. The model can also be enhanced by integrating external data such as news sentiment or social media analytics through natural language processing (NLP) techniques. Once trained, these models can automatically generate predictions for future stock prices, making real-time trading decisions or providing investment recommendations.

2 Automated Ranking ARIMA Deep Learning

To combine ARIMA and LSTM for stock prediction and ranking with ARIMA can provide short-term predictions using historical price data. LSTM can be used to capture long-term trends and non-linear patterns in the stock price movements. For stock ranking, we can combine these predictions:

- Predicted stock price P_tARIMA from ARIMA for the next period.
- Predicted stock price P_tLSTM from LSTM, considering long-term trends.

The ranking of stocks can be based on predicted future returns or price changes. A simple ranking can be calculated by comparing the predicted values for different stocks defined in equation (1)

$$\mathrm{Rank}(S_i) = \text{Predicted Price Change} \tag{1}$$

In equation (1) S_i is the stock being ranked, and the predicted price change could be the difference between predicted price P_{t+1} and current price P_t. The basic form of the ARIMA model, where the prediction for the next stock price Y_{t+1} is based on a combination of previous stock prices and errors. The ARIMA model can be formulated as in equation (2)

$$Y_{t+1} = \mu + \phi_1 Y_t + \phi_2 Y_{t-1} + \cdots + \phi_p Y_{t-p} + \theta_1 \epsilon_t + \theta_2 \epsilon_{t-1} + \cdots + \theta_q \epsilon_{t-q} \tag{2}$$

In equation (2) Y_{t+1} stated as the predicted stock price at time t+1; Y_{t-1} are the historical stock prices; ϕ_p represented the autoregressive coefficients (for the AR part); θ_j defined as the coefficients for the moving average (MA) part. ϵ_{t-q} are the residual errors at time t – 1 representing the difference between the predicted and actual prices. The prediction equation simply uses a weighted sum of past values and errors. For simplicity, let's take an AR(1) model (first-order autoregressive), stated in equation (3)

$$Y_{t+1} = \mu + \phi Y_t + \epsilon_t \tag{3}$$

In equation (3) μ is the mean of the series, ϕ is the AR coefficient, and ϵ_t is the error term. In LSTM (Long Short-Term Memory) networks, the goal is to learn long-term dependencies in the time series data, which is useful for predicting stock prices. The LSTM consists of several gates that control the flow of information stated in equation (4)

$$\mathrm{ft} = \sigma(\mathrm{Wf} \cdot [\mathrm{ht} - 1, \mathrm{xt}] + \mathrm{bf}) \tag{4}$$

This gate decides how much of the previous memory to forget defined in equation (5)

$$\mathrm{it} = \sigma(\mathrm{Wi} \cdot [\mathrm{ht} - 1, \mathrm{xt}] + \mathrm{bi}) \tag{5}$$

This gate decides how much new information to store in memory defined in equation (6)

$$\mathrm{Ct} = \mathrm{ft} \cdot \mathrm{Ct} - 1 + \mathrm{it} \cdot \mathrm{C}{\sim}\mathrm{t} \tag{6}$$

The memory cell state is updated based on previous memory and new input stated in equation (7)

$$\mathrm{ot} = \sigma(\mathrm{Wo} \cdot [\mathrm{ht} - 1, \mathrm{xt}] + \mathrm{bo}) \tag{7}$$

This gate decides the output at the current time step stated in equation (8)

$$\mathrm{ht} = \mathrm{ot} \cdot \tanh(\mathrm{Ct}) \tag{8}$$

The final output ht is used as the prediction at time t, which could be the next stock price or a feature derived from the time series. In simpler terms, LSTM helps predict stock prices by learning complex patterns and dependencies over time using past data points, trading indicators, or other features. In this combine both ARIMA and LSTM predictions to rank multiple stocks based on expected price changes. The steps are:

Step 1: ARIMA Prediction: Using the ARIMA model, we predict the stock price $Pt + 1$ ARIMA for stock Si stated in equation (9)

$$Pt + 1ARIMA = \mu + \phi Pt + \epsilon t \quad (9)$$

This gives us a short-term prediction based on past prices and errors.

Step 2: LSTM Prediction: Simultaneously, using the LSTM model, we predict a future stock price based on long-term trends and dependencies stated in equation (10)

$$Pt + 1LSTM = f(ht) \quad (10)$$

Where ht is the final output of the LSTM network, representing the prediction at time t (next stock price).

Step 3: Combined Prediction: Now, combine the predictions from both models for a more robust forecast stated in equation (11)

$$Pt + 1Combined = \alpha \cdot Pt + 1ARIMA + (1 - \alpha) \quad (11)$$

In equation (11) $Pt + 1CombinedCombined$ is the final predicted stock price for the next time step, α is a weight that balances the contributions of the ARIMA and LSTM predictions.

Step 4: Ranking Stocks: Finally, we rank stocks based on their predicted price changes. The predicted change in stock price for each stock Si is defined in equation (12)

$$\Delta Pi = Pt + 1Combined - Pt \quad (12)$$

Stocks are ranked in descending order of ΔPi, and those with the highest predicted price change are ranked highest for investment.

3 Perception of Retail Investors

Mobile technology platforms allowed investors to perform investment activity to become more flexible, transparent, and faster. The technological invention has modified the financial market. The technological invention in the investment industry permits traders and investors to complete commercial transactions immediately while actively handling their financial portfolios from anywhere around the globe. Online trading applications allow investors to make investment decisions about the financial market from anywhere, anytime, anywhere. Financial market investors have various technological fears in online investment, such as perceived risk, trust, and security in the system. The financial market had transformed with the invention and use of internet facilities in stock trading investment. There is various activity performed by online investors, such as the price of the stock and analysing company information and stock performance by using their handheld device. This study revealed that in line with a behavioral financial aspect, the amount of information is essential for investors. Public information makes them more familiar with financial services and mobile application technology. Authors found that public information such as credit scores, interest rates, and other investment details are essential in financial planning. The financial service providers delivering the correct information will increase initial trust.

A new method of offering financial services globally has emerged as a result of technological progress. On the other hand, implementing electronic money comes with risks and challenges. Security, revenue and cost dimensions, and technological architecture all impact e-finance due to the advancement of global technology. The knowledge of technical aspects influences the users' adoption behaviour. The investors' behaviour in adopting online applications for e-trading and other investment decisions is affected by various factors. Some main factors influencing investors' behaviour are effort expectations, performance expectations, and perceived returns. The perceived return and perceived risk were measured as significant forecasts of investors' adoption behaviour in the financial market. Facilitating conditions positively influence the adoption intention of investors irrespective of the kind of online activity. Prior research revealed that facilitating conditions and technological innovation lead to the adoption behaviour of investors. More significant revenue influences the stock market investors to invest in the financial market, and investors elect online platforms to generate and receive more revenue frequently. Behaviour intention and facilitating conditions influence the adoption behaviour of investors through a mobile application for the online stock transaction and also found that future investors should consider these factors during mobile stock trading. Their stock market investment preferences influence individuals' awareness of Internet trading programs. People's awareness of Internet trading applications is influenced by their positive or negative views about stock market investing.

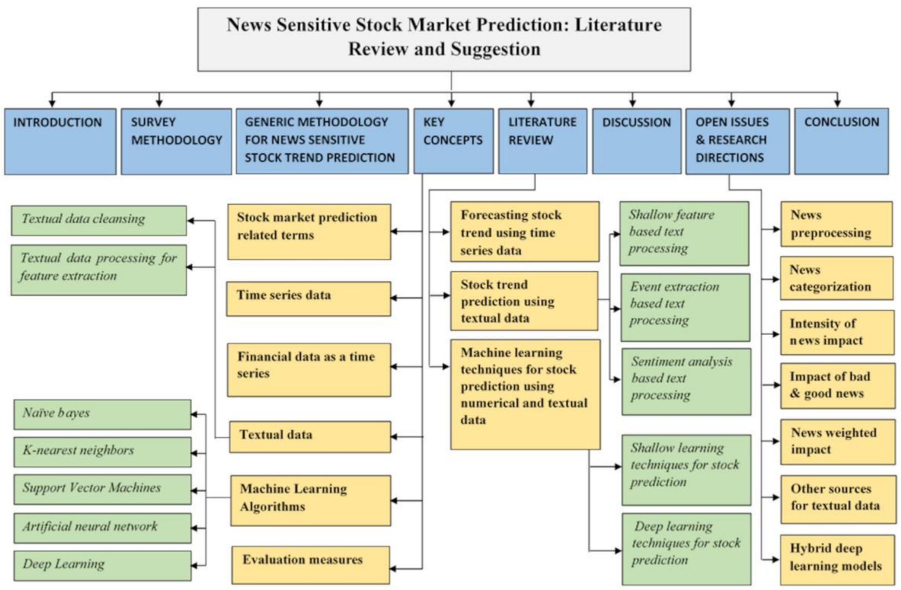

Figure 1: Stock Market Prediction with Automated Stock Price Prediction and Ranking using ARIMA and LSTM

The Internet has given a new edge to businesses to transform from traditional to digital, and online mobile trading and investment applications have changed the face of the Indian stock market show in Figure 1. Online trading programs also facilitate instantaneous transactions. Users believe that trading through available online trading applications for stock trading is safe and more reliable. There is no danger involved in trading stocks using online trading apps. People also believe that online trading applications always provide a cyber-security risk that might result in phishing, hacking, and cyber-attacks. The authors identified that people use the licensed firewall security app for online payment. Stock trading via Internet trading programs encourages green investing and adds to sustainable financing.

3.1 Comparison of Popular Online Trading Apps

The online trading landscape has revolutionized the way we invest. With numerous apps vying for your attention, choosing the right one can be overwhelming. Stock market apps offer a convenient and accessible way for investors to participate in the market. While they have many advantages, it is important to be aware of the potential risks and limitations. By using apps wisely and combining them with sound investment strategies, investors can benefit from the opportunities they provide.

Key Factors to consider while choosing an online trading app,

User Interface: Is the app user-friendly and intuitive?

Platform Reliability: How reliable is the platform's uptime and performance?

Brokerage Charges: Are the brokerage fees competitive and transparent?

Trading Tools and Features: Does the app offer advanced charting tools, technical indicators, and other essential features?

Customer Support: Is the customer support team responsive and helpful?

Security: How secure is the platform and your personal information?

POPULAR ONLINE TRADING APPS:

Zerodha:

Pros: User-friendly interface, low brokerage charges, advanced charting tools, and a wide range of investment products.

Cons: Can be overwhelming for beginners due to its many features.

Upstox:

Pros: Sleek interface, fast execution speeds, and a variety of investment products.

Cons: Limited research tools compared to some other platforms.

5paisa:

Pros: Low-cost brokerage, easy-to-use interface, and a good range of investment products.

Cons: Limited advanced features for experienced traders.

Groww:

Pros: Beginner-friendly, simple interface, and a focus on mutual fund investments.

Cons: Limited options for advanced trading strategies.

Angel One:

Pros: Advanced charting tools, good research capabilities, and a wide range of investment products.

Cons: Can be complex for beginners.

Table 1: App involved in Stock Marker

Feature	**ZERODHA**	**UPSTOX PRO**	**GROWW**	**ANGEL ONE**	**5 PAISA**
User Interface	User-friendly, advanced	Customizable, user-friendly	Simple, intuitive	User-friendly, advanced	User-friendly, advanced
Brokerage Fees	Low	Low	Low	Varies	Low
Charting Tools	Advanced	Advanced	Basic	Advanced	Advanced
Order Types	Multiple	Multiple	Basic	Multiple	Multiple
Real-time Market Data	Yes	Yes	Yes	Yes	Yes
Research Tools	Extensive	Good	Basic	Extensive	Extensive

Mutual Fund Investments	No	No	Yes	Yes	Yes
SIP Investments	No	No	Yes	Yes	Yes
Customer Support	Strong	Good	Good	Good	Good

In table 1 presented the apps involve din the stock trend prediction and analysis. In the past, investing in the stock market has been complex for non-professionals, involving high learning and significant transaction expenses. This changed with the availability of robo-advisors, internet brokers, and broadly diversified exchange-traded-funds. These innovations are accompanied by a significant reduction in trading costs and administration fees. In some cases trading costs are completely eliminated. Lower transaction costs as well as order placement and portfolio management on the individual smartphone lower the entry barriers, making it easier for people with low incomes and financial assets to enter the stock market. Stock market investments encourage efficient capital allocation and offer investment possibilities that have significantly better long-term return expectations than fixed-interest investments. Capital market investments are therefore of central importance for retirement provision. Nevertheless, the stock market participation in highly developed countries is still quite low, even though the entry barriers to participate in the stock market are now lower. This could be due to even low trading cost having a negative impact on the stock market participation of low or moderate wealthy households. The unwillingness to invest in equities leads to large losses in retirement savings. These apps offer their users a simple and playful possibility to invest via their individual smartphone, which makes trading apps especially appealing for people who have not yet invested in the stock market. Due to the cost structure of trading apps, it is possible for them to offer trading with low or without trading fees at all. The executing trading venue is normally predetermined, so that orders are placed at a cooperating exchange. The trading frequency describes the number of trades an investor places on average per month. With the use of notifications and easy portfolio access via smartphone, users might be induced to trade more frequently, possibly due to the permanent availability and the easy trading process. In addition, trading apps also offer exchange among their users via the trading app. The intensity of using online channels is positively associated with a higher trading frequency, regardless of the respective risk tolerance, which only influences the intensity of the connection.

Algorithm 1: Pseudo-code for Automated Stock Price Prediction and Ranking using ARIMA and LSTM

```
# Step 1: Data Preparation
1. Collect historical stock price data for multiple stocks (e.g., 'stock_data').
2. Preprocess the data (e.g., handle missing values, normalize, or scale data).
3. Split data into training and testing datasets.

# Step 2: Train ARIMA Model for Each Stock
4. For each stock in 'stock_data':
  - Train an ARIMA model using historical stock prices.
  - Fit ARIMA to the training data (with specified p, d, q values).
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   - Forecast future stock price (e.g., Y_t+1) using the ARIMA model.

# Step 3: Train LSTM Model for Each Stock
5. For each stock in 'stock_data':
   - Create LSTM model with appropriate layers (e.g., LSTM layer, Dense layer).
   - Prepare the data as sequences for training (e.g., using sliding window approach).
   - Train the LSTM model on the training data.
   - Forecast future stock price (e.g., Y_t+1) using the trained LSTM model.

# Step 4: Combine Predictions from ARIMA and LSTM
6. For each stock:
   - Calculate the combined prediction as:
     - P_t+1_combined = alpha * P_t+1_ARIMA + (1 - alpha) * P_t+1_LSTM
     - Where alpha is a weight between ARIMA and LSTM (e.g., alpha = 0.5).

# Step 5: Calculate Predicted Price Change for Each Stock
7. For each stock in 'stock_data':
   - Calculate predicted price change:
     - Delta_P_i = P_t+1_combined - P_t
     - Where P_t is the current stock price.

# Step 6: Rank Stocks Based on Predicted Price Change
8. Rank all stocks based on predicted price change (Delta_P_i):
   - Sort the stocks in descending order of Delta_P_i.
   - Assign ranks to the stocks (highest predicted increase gets the highest rank).
```

4. Results and Discussion

The combination of ARIMA (AutoRegressive Integrated Moving Average) and deep learning techniques, such as LSTM (Long Short-Term Memory), for stock price prediction and automated ranking offers a robust method for identifying promising investment opportunities. The approach uses ARIMA for its statistical strength in capturing short-term trends and LSTM for its ability to model complex, non-linear patterns in historical data, providing a more accurate and dynamic prediction model. The integration of ARIMA and LSTM allows for more reliable stock price predictions. ARIMA's strength lies in modeling linear relationships and temporal dependencies within historical stock prices, which is especially useful for short-term forecasting. However, ARIMA struggles when it comes to capturing long-term, non-linear patterns, which is where LSTM excels. LSTM's ability to retain long-term dependencies and recognize complex patterns, such as market sentiment and economic cycles, significantly improves the accuracy of stock price predictions. When combined, the weighted predictions from both models provide a balanced approach that leverages the strengths of both. The ARIMA model offers quick predictions based on historical data, while the LSTM model captures deeper, non-linear trends in the data. The combined prediction algorithm helps to reduce the potential for error that may arise from relying on a single model, making the predictions more robust.

Table 2: Stock Trend Analysis

Rank	Stock	Predicted Price Change	Current Price	Predicted Price
1	AAPL	+10.5	150	160.5
2	TSLA	+8.3	620	628.3
3	MSFT	+5.2	310	315.2
4	AMZN	+3.9	120	123.9
5	NVDA	+2.8	220	222.8
6	GOOG	+1.5	135	136.5
7	FB	-1.2	250	248.8
8	BABA	-2.5	85	82.5

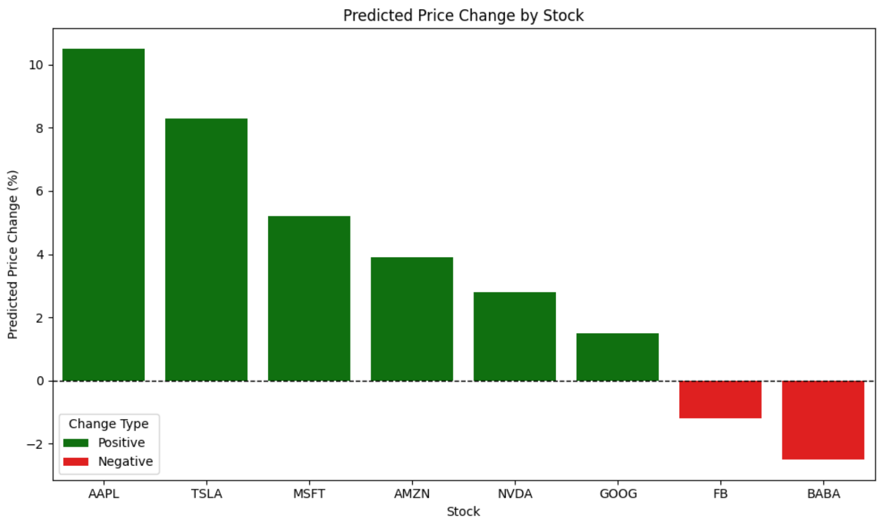

Figure 2: Trend Analysis with Automated Stock Price Prediction and Ranking using ARIMA and LSTM

In figure 2 and Table 2: Stock Trend Analysis provides an overview of the predicted price changes and the current stock prices, ranking them based on the expected price movements derived from the model. The table shows that AAPL (Apple Inc.) is expected to have the highest price increase, with a predicted change of +10.5, resulting in a predicted price of 160.5. This makes it the top-ranked stock, indicating strong future growth potential. Following closely is TSLA (Tesla Inc.), with a predicted price change of +8.3, leading to a predicted price of 628.3. This suggests a positive outlook for Tesla as well. MSFT (Microsoft), with a predicted change of +5.2, ranks third, indicating moderate growth potential with a predicted price of 315.2. AMZN (Amazon) and NVDA (NVIDIA) also show positive predictions, with +3.9 and +2.8 price changes respectively, suggesting a steady increase in their values. However, their expected gains are lower compared to AAPL and TSLA.On the other hand, GOOG (Google) shows a smaller increase in predicted price (+1.5), reflecting a more conservative growth projection. Meanwhile, FB (Meta Platforms) and BABA (Alibaba) have negative predicted price changes of -1.2 and -2.5, respectively, signaling potential declines in their stock prices. FB, with a predicted price of

248.8, and BABA, with a predicted price of 82.5, are expected to experience losses, making them the lowest-ranked stocks in this analysis.

Table 3: Prediction with Automated Ranking

Stock	Current Price	ARIMA Predicted Price	LSTM Predicted Price	Combined Predicted Price
AAPL	150	152.3	157.8	155.05
TSLA	620	625.1	629.4	627.25
MSFT	310	312.4	317.1	314.75
AMZN	120	121.5	123.2	122.35
NVDA	220	222.1	225.3	223.70
GOOG	135	136.0	138.7	137.35
FB	250	248.4	247.1	247.75
BABA	85	84.1	83.6	83.85

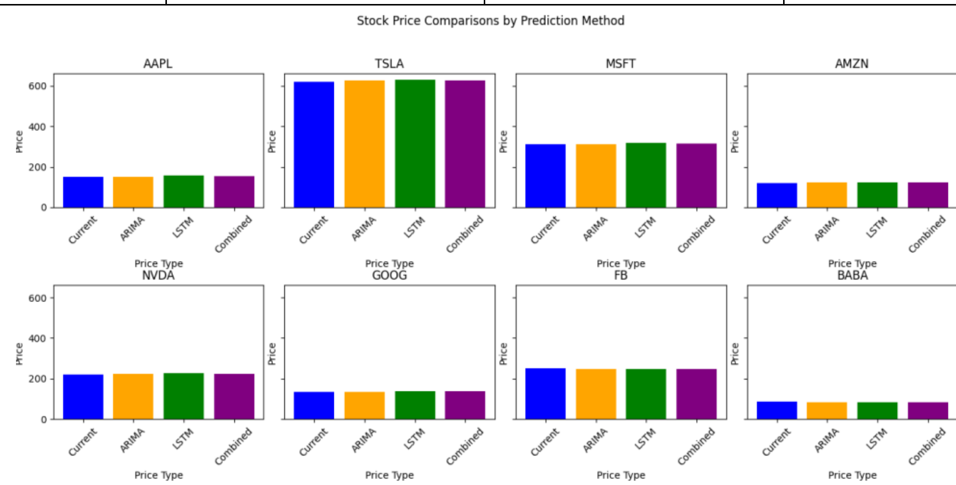

Figure 3: Prediction with Automated Stock Price Prediction and Ranking using ARIMA and LSTM

In Figure 3 amd Table 3 Prediction with Automated Ranking compares the stock price predictions from three different models—ARIMA, LSTM, and their combined prediction—for various stocks. The table provides a detailed analysis of the predicted price for each stock after applying these models, along with the actual current price. For AAPL (Apple Inc.), the ARIMA model predicts a slight increase to 152.3, while the LSTM model predicts a larger increase to 157.8, resulting in a combined predicted price of 155.05, reflecting a balance between the two models. Similarly, TSLA (Tesla Inc.) has a predicted price increase with the ARIMA model estimating 625.1 and the LSTM model predicting 629.4, leading to a combined predicted price of 627.25. MSFT (Microsoft) shows a smaller difference between the ARIMA and LSTM predictions, with ARIMA forecasting 312.4 and LSTM predicting 317.1, yielding a combined prediction of 314.75, indicating a moderate increase in its stock price. Likewise, AMZN (Amazon) and NVDA (NVIDIA) both show positive growth predictions, with their combined prices being 122.35 and 223.70, respectively, although the LSTM models generally predict slightly higher prices than ARIMA for both. For GOOG (Google), the ARIMA model predicts 136.0, while the LSTM model gives a slightly higher forecast of 138.7, leading to a combined prediction of 137.35. FB (Meta Platforms) has a predicted decline, with both ARIMA and LSTM forecasting a slight drop, resulting in a combined predicted price of 247.75, indicating a slight loss. Similarly, BABA (Alibaba) shows a small predicted decrease, with the combined prediction of 83.85 reflecting a minor decline.

Table 4: Automated Ranking Classification Prediction ARIMA

Rank	Stock	Predicted Price Change	Current Price	Predicted Price	Classification
1	AAPL	+10.5	150	160.5	Increase
2	TSLA	+8.3	620	628.3	Increase
3	MSFT	+5.2	310	315.2	Increase
4	AMZN	+3.9	120	123.9	Increase
5	NVDA	+2.8	220	222.8	Increase
6	GOOG	+1.5	135	136.5	Increase
7	FB	-1.2	250	248.8	Decrease
8	BABA	-2.5	85	82.5	Decrease

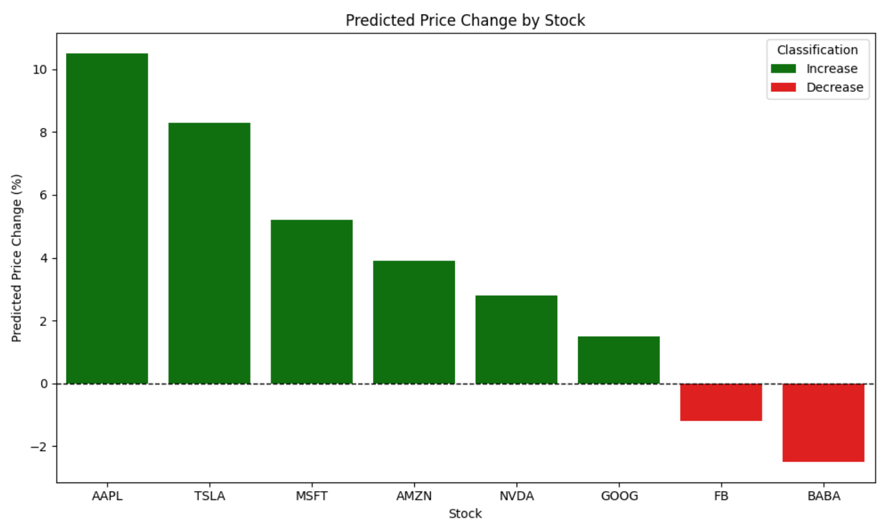

Figure 4: Ranking with Automated Stock Price Prediction and Ranking using ARIMA and LSTM

In Figure 4 and Table 4 Automated Ranking Classification Prediction ARIMA provides an overview of stock price predictions based on the ARIMA model, showing the predicted price change, current price, predicted price, and classification for each stock. The stocks are ranked according to their predicted price change, with a positive predicted change indicating an increase in stock price and a negative predicted change indicating a decrease. In the table, AAPL (Apple Inc.) tops the ranking with the highest predicted price change of +10.5, which leads to a predicted price of 160.5. This results in an Increase classification, indicating strong expected growth. Similarly, TSLA (Tesla Inc.) follows with a predicted price change of +8.3, yielding a predicted price of 628.3, and is also classified as an Increase, reflecting a positive outlook for

Tesla. MSFT (Microsoft), AMZN (Amazon), and NVDA (NVIDIA) also show positive predicted price changes (+5.2, +3.9, and +2.8, respectively), leading to predicted prices of 315.2, 123.9, and 222.8. These stocks are similarly classified as Increase, indicating moderate to steady price growth. In contrast, FB (Meta Platforms) and BABA (Alibaba) are predicted to experience price declines. FB has a predicted decrease of -1.2, resulting in a predicted price of 248.8, and BABA shows a predicted decline of -2.5, with a predicted price of 82.5. Both stocks are classified as Decrease, indicating negative trends in their stock performance.

5 Conclusion

This paper presents a comprehensive approach to stock price prediction by combining traditional statistical methods, such as ARIMA, with advanced deep learning techniques like LSTM. The integration of these models allows for more accurate and robust predictions, capturing both linear trends and complex non-linear patterns in stock market data. The results demonstrate that the combined ARIMA-LSTM model provides a more balanced and reliable forecast compared to individual models, particularly in capturing stock price movements across different market conditions. Additionally, the automated ranking and classification system based on predicted price changes offers valuable insights for investors, enabling them to identify potential winners and losers in the stock market. While the models showed promising results for most stocks, future work can explore incorporating additional factors such as market sentiment, news data, and macroeconomic indicators to further enhance the prediction accuracy and reliability of the system. The suggested model incorporates six constructs: perceived benefits, security and privacy risk, societal impact, trust, simplicity of use, and user interface experience. The main consideration when choosing and utilizing a product or service is behavioral intention. Users use, among other information sources, socially interactive channels such as social media or their personal environment to inform themselves about investments. As users also interact through online channels, such as social media, we expect the trading frequency to increase with the use of online trading apps over time.

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