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Integrating Deep Learning and Explainable Artificial Intelligence Techniques for Stock Price Predictions: An Empirical Study Based on Time Series Big Data

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Nada Marey
Demonstrator at Accounting Department, Faculty of Commerce, Tanta University, Egypt.
nada_marey@commerce.tanta.edu.eg
Ahmad A. Abu-Musa
Professor of Accounting Information Systems, Faculty of Commerce, Tanta University, Egypt.
ahmed.aboumousa@commerce.tanta.edu.eg
Mona Ganna
Lecturer at Accounting Department, Faculty of Commerce, Tanta University, Egypt.
mona.gana@commerce.tanta.edu.eg

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Abstract

This paper proposes an approach to improving the accuracy of predicting stock prices. The approach is built on integrating Long-Short-Term Memory (LSTM) networks, a Deep Learning (DL) technique, with Shapely Additive Explanations (SHAP), an Explainable Artificial Intelligence (XAI) technique. This integration is expected to improve predictive accuracy and model explainability. Leveraging the strengths of LSTM in capturing complex sequential patterns in financial time series big data, the model incorporates technical indicators to enhance its performance in forecasting stock movements. Deep learning is known to have a "black box" nature, so incorporating XAI techniques aims to offer detailed insights into how input features contribute to model outputs. This integration of XAI enhances the interpretability of predictions and enables users to understand the underlying rationale of the model, fostering greater trust among investors and financial professionals. The study utilized stock price data from the Yahoo Finance Website. The model processed forecasting of Google stock prices. The practical utility of this approach is demonstrated through the decision-making module, which provides actionable buy, sell, or hold recommendations, showcasing its potential in real-world investment scenarios. Our results indicate a balanced synergy between prediction accuracy and explainability, establishing a transparent and reliable AI-driven financial forecasting framework.

Keywords: Deep Learning (DL), Explainable Artificial Intelligence (XAI), Long short-term memory (LSTM), Shapely Additive Explanations (SHAP), Stock Price Prediction.

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1. Introduction

The problem of accurately predicting stock market movements remains one of the most challenging tasks in financial analysis due to the volatile and complex nature of financial markets (Gandhmal & Kumar, 2019). Numerous factors, including economic indicators, investor sentiment, and global events, interact in ways that are often difficult to model using traditional statistical approaches (Sable et al., 2023). With the rise of machine learning, particularly deep learning, there has been significant progress in capturing the non-linear patterns and dependencies inherent in financial time series data (Ambasht, 2024). However, despite the enhanced predictive capabilities of these models, a critical challenge persists: the interpretability of deep learning models (Arrieta et al., 2020). Financial professionals and investors require transparency to trust and act upon predictions made by these models (Arsenault et al., 2018). The "black box" nature of many deep learning models impedes their adoption in critical financial decision-making contexts where understanding the rationale behind a prediction is as important as the prediction itself (Rane et al., 2023).

The existing literature has explored various methods to improve the accuracy of stock price predictions using deep learning. However, there is a notable gap in addressing the transparency of these predictions (Valensky & Mohaghegh, 2023). Explainable AI (XAI) has emerged as a critical research area to bridge this gap, providing tools and techniques to make the decision-making process of complex models more interpretable (Arsenault et al., 2018). However, most studies have either focused on traditional machine learning models or have yet to integrate XAI methods with deep learning models applied to time series data, particularly in the context of stock market predictions. This research seeks to fill this gap by developing a stock prediction model that not only leverages the power of deep learning but also incorporates XAI techniques to offer clear and actionable insights to users. This study aims to enhance the

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usability and trustworthiness of predictive models in financial markets, providing a framework that balances accuracy with interpretability.

The methodology employed in this research centers around developing a deep learning-based stock prediction model, which is further enhanced with XAI techniques to provide transparency in its predictions. The model uses a Long-Short-Term Memory (LSTM) network trained on a large dataset of historical stock prices sourced from Yahoo Finance. The data is preprocessed and scaled to optimize the model's performance, and several technical indicators, such as Moving Averages (MA50, MA100, and MA200), are incorporated to improve prediction accuracy.

To address the explainability challenge, the model is integrated with Shapley Additive Explanations (SHAP) values, which provide a detailed breakdown of how each feature influences the model's predictions. Additionally, the model includes a decision-making module that offers buy, sell, or hold recommendations based on predicted price movements and a clear explanation of each recommendation's rationale using the XAI tools' outputs.

The paper is organized as follows: The following section covers the framework. Section 3 deals with literature review and hypothesis development. Section 4 presents the research methodology. Section 5 reports the results and discusses them. Finally, section 6 discusses conclusions and directions for future research.

2. The Theoretical Framework

The advancement in information technology and the internet has contributed to the creation of vast amounts of data about economies and companies' equities. Consequently, investment companies use different AI techniques to better understand the patterns of these available data (Strader et al., 2020). Although AI does not have a globally accepted definition (Dobrev, 2004; Wang, 2019), it encompasses a range of techniques designed to simulate human intelligence in machines (Dunsin et al., 2024). Nilsson (2009: 13) defined AI as an "activity devoted to making machines intelligent, and intelligence is that quality that enables an entity to function appropriately and with foresight in its environment." AI has been used in many fields,

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such as medicine, scheduling, automated trading, business practices, translating languages, automating inventions, and recognizing faces (Nilsson, 2009). Incorporating AI techniques in financial markets and stock prediction has supported the ability to analyze and deal with big data (Ambasht, 2024).

Early phases of AI techniques relied on rule-based systems (RBS). These systems depend on feeding it with "facts about the world" through rules (Masri et al., 2019, p. 1). These systems are mainly developed in expert systems that replace or assist humans in solving specific problems (Moret-Bonillo, 2018; Masri et al., 2019). The major disadvantage of the early phases of AI techniques is its sequentiality, as it is difficult for these systems to mimic human responses in a changing and uncertain environment (Moret-Bonillo, 2018).

A subset of AI is Machine Learning (ML) (Naeem et al., 2023). ML focuses mainly on allowing computers to learn from data given through constructing hypotheses rather than rules (Nilsson, 2009; Naeem et al., 2023). ML can deal with and analyze large amounts of data as it builds inductive inferences from data (Nilsson, 2009). There are three learning modes: Supervised, Unsupervised, and Semi-Supervised learning (Naeem et al., 2023). Each of these modes has its techniques. In supervised learning, techniques such as Linear Regression and Ridge Regression are used to predict continuous outcomes, while Logistic Regression, Decision Trees, and Random Forests are employed for classification tasks (Kanaparthi, 2024). Support Vector Machines (SVM) and K-nearest neighbors (KNN) are also popular classification methods (Kanaparthi, 2024). In unsupervised learning, clustering techniques like K Means, Hierarchical Clustering, and DBSCAN group similar data points (Naeem et al., 2023). While dimensionality reduction methods such as Principal Component Analysis (PCA) and t-distributed Stochastic Neighbor Embedding (t-SNE) help in reducing the number of features in the dataset (Naeem et al., 2023). Semi-supervised learning combines labeled and unlabeled data to improve model performance, employing techniques such as Label Propagation and Self-training (Duarte & Berton, 2023).

Moving to Deep Learning (DL), a subset of ML, utilizes neural networks with multiple layers to model complex patterns in data (Sharifani & Amini, 2023). Feedforward Neural

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Networks, such as Multi-Layer Perceptrons (MLP), are foundational models in DL (Ahmed et al., 2023). Another type of artificial neural network is the Convolutional Neural Network (CNN) (Hussain, 2019). CNN is specialized in image data and spatial hierarchies, providing robust feature extraction capabilities (Sharifani & Amini, 2023). Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU), are effective in processing sequential data and capturing long-term dependencies (Moghar & Hamiche, 2020).

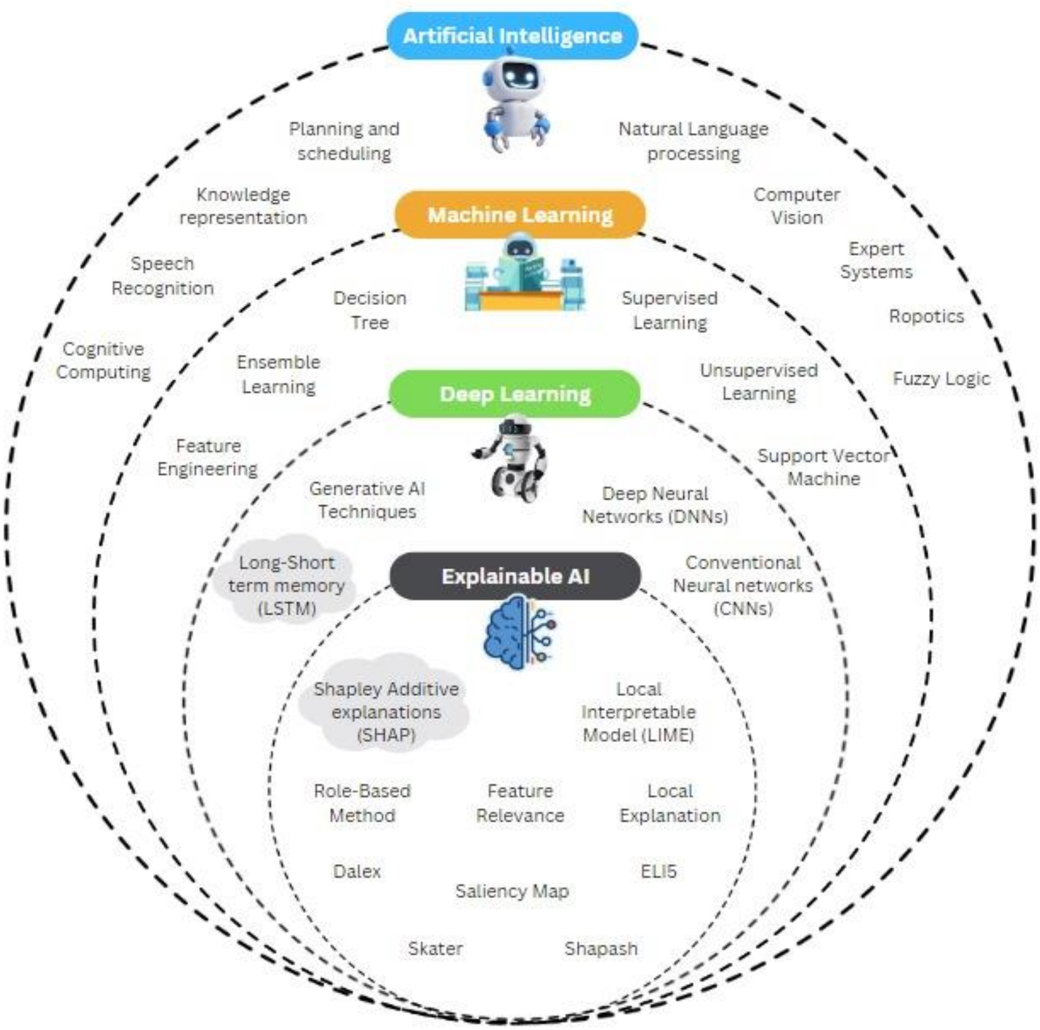

Figure 1: The relationship between Artificial Intelligence, Machine Learning, Deep Learning, and XAI [Source: The Researchers].

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As explained above and shown in Figure 1, there is a hierarchical relationship between AI, ML, and DL. AI includes all the technologies and methods that enable machines to solve problems that typically depend on human intelligence (Xiong et al., 2020). Within AI, ML is the subset that focuses on developing algorithms that allow systems to solve problems and learn and improve from data (Sharifani & Amini, 2023). ML includes supervised and unsupervised learning techniques, decision trees, and support vector machines. Further down the hierarchy, DL is a specialized branch of ML that deals with complex patterns in large unstructured datasets utilizing techniques of neural networks (Vora & Iyer, 2020).

A recent class of machine learning algorithms is Generative AI (GenAI) (Sun et al., 2022). GenAI is considered an evolution of AI ability from only recognizing to its ability to generate solutions (Schneider, 2024). GenAI can learn from texts and generate new content (Sun et al., 2022). Despite the revolutionary impact of introducing GenAI, its models in various fields are complex and challenging to understand (Bryan-Kinns et al., 2024). This drawback led to the invention of explainable AI (XAI) that aims to make complex GenAI models more understandable to users (Bryan-Kinns et al., 2024). Techniques such as deep neural networks (DNNs), convolutional neural networks (CNNs), and long-short-term memory (LSTM) networks are core techniques of deep learning that enable the GenAI and XAI applications (Shahroudnejad, 2021).

Arrieta et al. (2020) Have provided a deep understanding of the term "explainability" in the context of AI. Their paper distinguished between interpretability and explainability terms usually used interchangeably in research. Interpretability is a "passive" or inherent attribute of a model (Arrieta et al., 2020, p. 4). Interpretability indicates the extent to which the model is understandable, transparent, and faithful to users (Rane et al., 2023; Ade, 2024). On the other hand, explainability is a model's "active" attribute, representing any intentional action or process undertaken by the model to elucidate or describe its internal workings (Arrieta et al., 2020, pp. 4–5). It means the ability of the model to explain the reasons behind the specific outcome or prediction provided by DL or ML models (Rane et al., 2023).

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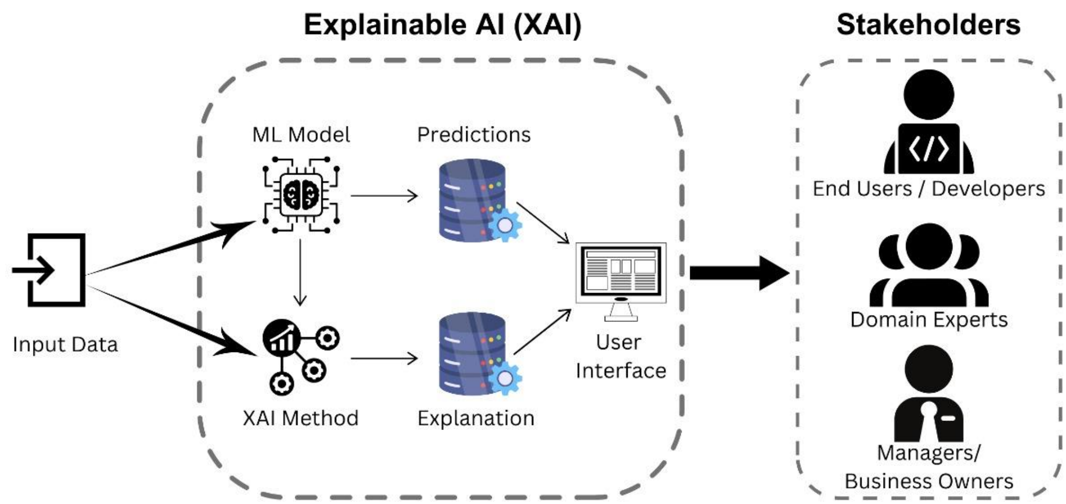

Figure 2: Explainable AI (XAI) [source: the researchers].

Figure 2 illustrates the concept of Explainable AI (XAI), emphasizing how machine learning models produce predictions and how those predictions can be explained to stakeholders. The ML model processes input data and generates predictions. The user interface stores and communicates the predictions of ML and explanations derived through XAI. The explanations help stakeholders answer questions about how and why the model made certain decisions. Understanding the model's behavior is vital for them to make informed decisions, ensure accountability, and foster trust in AI systems.

3. Literature Review and Hypotheses Development

Stock markets are essential for economies and affect various economic fields, such as education, employment, and technology (Sable et al., 2023). The size of the global stock market is tremendous. According to the World Federation of Exchanges, total market capitalization is US $ 111 trillion at the end of 2023 (WFE, 2023). This evolution of financial markets is characterized by non-stationarity, volatility, nonlinearity, nonparametric, random, and complex nature, and colossal data volume (e.g., Chopra & Sharma, 2021; Sable et al., 2023; Ambasht, 2024). Consequently, providing accurate stock price predictions is challenging yet highly desirable (Farmer et al., 2012).

Over the years, the stock market prediction field has captivated the interest of researchers, financial analysts, and investors. Researchers are highly interested in developing models that can provide accurate forecasts for stock prices (Shen et al., 2012). The literature on stock price prediction is derived from two leading schools of research: 1) the fundamental analysis and 2) the technical analysis (Petrusheva & Jordanoski, 2016). Several approaches and models have been developed in each of the two types of analysis. While fundamental analysis depends mainly on the information provided in the financial statements, technical analysis depends on the stock price information and technical indicators to predict future movements in stock prices (Abad et al., 2004). The fundamental analysis is out of the scope of this paper. This study focuses on the technical analysis that depends on the assumption that trends in stock prices repeat themselves and that historical prices can be used in forecasting future prices and determining the best decision for investors (whether to buy, hold, or sell) (Petrusheva & Jordanoski, 2016).

Technical stock price prediction has started by utilizing some statistical and time series techniques, such as the Exponential Smoothing Model (ESM) (Billah et al., 2006), Seasonal Autoregressive Integrated Moving Average (SARIMA) (Yoo et al., 2007), and other models (Sable et al., 2023). These statistical approaches, though practical in the past, have increasingly shown their limitations in capturing the complexity of market movements, especially as datasets grow more extensive and more intricate (Gandhmal & Kumar, 2019). With the advent of artificial intelligence (AI) and machine learning (ML), especially DL techniques, the stock market prediction field has seen a surge of excitement and potential. These advancements have allowed significant strides in modeling the non-linear patterns observed in stock market data (Chen et al., 2001). Consequently, the rest of this literature review section will review the previous studies that utilized AI, ML, and DL techniques. This literature review aims to define the gap in this field of research, locate the current study among the stream of research within the stock price prediction field, and develop the research hypotheses.

3.1 Predicting Stock Prices Using Machine Learning Models

Machine learning models, such as Support Vector Machines (SVM), Decision Trees, and Random Forests, have successfully predicted stock price movements (Illa et al., 2022). Among the various ML techniques, SVM is the most popular technique researchers have used for predicting stock market movements in the literature (Lin & Marques, 2024). Gururaj et al. (2019) conducted an experimental study to compare the pros and cons of linear regression and SVM in predicting the stock price of Coca-Cola. The experiment results showed that the SVM model performs better than linear regression in stock price prediction (Gururaj et al., 2019). Bhattacharjee & Bhattacharja (2019) have also conducted a comparative study between traditional statistical methods and machine learning methods to predict the stock prices of Apple and Tesla companies. The results supported the superiority of ML techniques over the statistical approach in prediction accuracy (Bhattacharjee & Bhattacharja, 2019).

Despite the notable superiority of ML models over statistical models, ML models often struggle with the high dimensionality and sequential nature of financial time series data (Lee & Kim, 2020). Due to this drawback in ML models, researchers incorporated DL models such as LSTM to overcome ML problems (e.g., Lee &Kim, 2020; Moghar et al., 2020)

3.2 Predicting Stock Prices Using Deep Learning Models

Deep learning models, particularly Long Short-Term Memory (LSTM) networks, have emerged as a powerful alternative due to their ability to handle sequential dependencies and large datasets (Lindemann et al., 2021). LSTMs are a class of recurrent neural networks (RNNs) designed to remember long-term dependencies, making them particularly suitable for time series prediction tasks such as stock market forecasting (Moghar & Hamiche, 2020). In their experimental study, Siami-Namini & Namin (2018) compared the traditional Autoregressive Integrated Moving Average (ARIMA) method and LSTM networks to test which method will provide a more accurate prediction of time series data. They used historical data from 1985 to 2018 from the Yahoo finance website. The results showed that the LSTM model outperformed the ARIMA model with an 84% to 87% reduction in error rates (Siami-Namini & Namin, 2018).

Despite the effectiveness of deep learning models in improving predictive accuracy, one critical challenge is their lack of interpretability (Chakraborty et al., 2017). The "black-box" nature of deep learning models makes it difficult for users to understand how predictions are generated, and this is particularly problematic in financial markets, where decision-makers rely not only on the accuracy of predictions but also on understanding the rationale behind these predictions (Hussain, 2019). Investors and financial professionals require transparency to trust and make decisions based on AI-driven models (Arrieta & Del Ser, 2020). Without interpretability, even highly accurate models may fail to gain traction in real-world financial applications (Li et al., 2019).

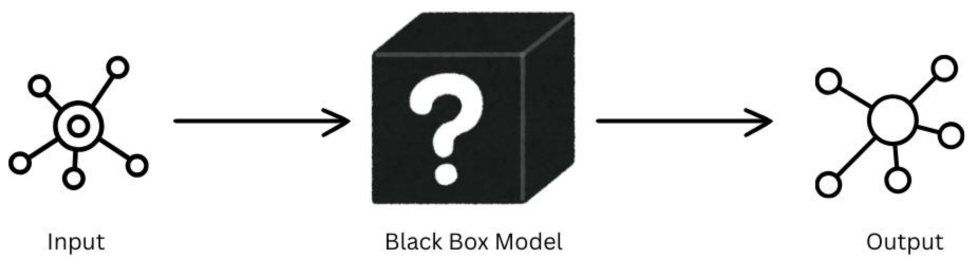

Figure 3: The Black box nature of deep learning models [Source: The Researchers].

Figure 3 illustrates the "Black Box" nature of deep learning models, highlighting the lack of transparency in how these models operate. Input data is processed through the model. However, the internal processes—the steps taken to transform the input into an output—are not easily interpretable and understood by humans. Consequently, the model's decision-making process is opaque. This raises concerns about why a particular output is produced from a given input (Arsenault et al., 2018). This opacity makes it difficult to explain or trust the model's predictions, emphasizing the need for techniques to interpret or explain the inner workings of such complex models.

3.3 The Integration of XAI in Stock Prediction Models

The drawbacks of DL techniques have sparked interest in a new area of research: XAI (Arsenault et al., 2018). XAI refers to tools and techniques designed to make complex models, such as deep learning networks, more interpretable (Dwivedi et al., 2023). By explaining how specific inputs affect model outputs, XAI aims to enhance transparency and trust in AI systems (Guidotti et al., 2018). Several techniques have been proposed in the XAI, including Shapley Additive Explanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) (Salih et al., 2024). These methods allow for a detailed breakdown of feature contributions, helping users understand the inner workings of models without sacrificing accuracy (Arrieta et al., 2020).

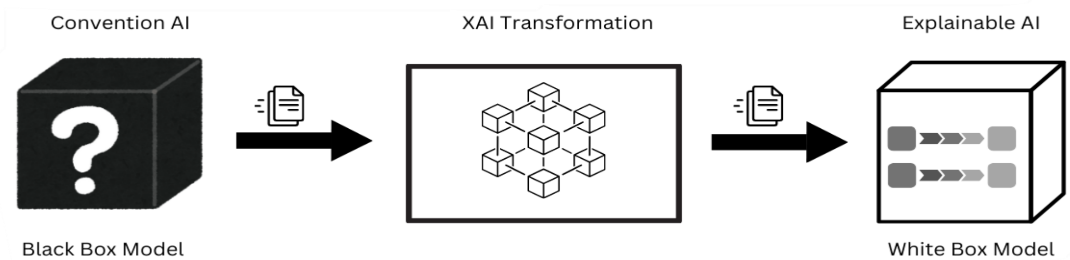

Figure 4: XAI Transformation from Blackbox model to Whitebox model. [Source: the researchers].

Figure 4 illustrates the transformation process from a conventional AI "black box" model to an "explainable AI" (XAI) "white box" model. The black box model initially represents an AI system where the decision-making process is hidden and not easily interpretable. The model's inner workings are analyzed and decoded through XAI transformation techniques, generating explanations for its predictions and making the process more transparent. This transformation leads to a "white box" model with clear and understandable decision logic. The explainable model enhances interpretability, accountability, and trust, allowing stakeholders to understand how and why the AI system makes a specific decision.

While XAI has gained traction in traditional machine learning, its integration with deep learning models, particularly for time series big data in stock market predictions, remains underexplored as previous studies have focused on improving the accuracy of predictions using more sophisticated models or better training techniques, often at the expense of model interpretability (Ambasht, 2024). So, there is a clear need to balance the trade-off between accuracy and transparency in financial markets, where decision-making must be reliable and explainable (Arsenault et al., 2018).

In response to this gap, recent studies have begun to explore integrating XAI techniques into deep learning models like SHAP, which has emerged as a powerful tool for explaining complex models (Vimbi et al., 2024). It is based on cooperative game theory and provides a unified measure of feature importance by distributing the contribution of each feature fairly among the predictions (Ekanayake et al., 2022). SHAP has been applied successfully in various domains, including healthcare, credit scoring, and finance (Van Den Broeck et al., 2022). However, its application in the context of LSTM networks for stock market predictions is still in its infancy. Most existing studies have focused on traditional machine learning models rather than deep learning architectures, leaving room for further research (Valensky & Mohaghegh, 2023).

The financial industry stands to benefit from integrating XAI with deep learning models as stock markets are driven by numerous factors, including economic indicators, investor sentiment, and global events, all of which interact in ways that are difficult to model (Bustos & Pomares-Quimbaya, 2020). Applying XAI techniques to deep learning models makes it possible to provide insights into how each factor influences stock price predictions. This can be particularly useful for investors and financial analysts who require clear explanations to guide their decisions (Rane et al., 2024). A model that predicts stock price movements and explains why specific predictions are made could revolutionize how financial professionals approach market forecasting (Jiang, 2021).

Moreover, using LSTM networks in financial time series data is particularly promising (Siami-Namini & Namin, 2018). LSTMs are well-suited to capturing the long-term dependencies in stock price movements, often influenced by past market trends and external factors (Nelson et al., 2017). However, without explainability, the effectiveness of LSTM models is limited in practice (Maarif et al., 2023). This research aims to provide a more comprehensive solution that balances predictive accuracy with interpretability by incorporating SHAP into LSTM networks. This combination can help bridge the gap between model performance and real-world usability in the financial sector.

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The study proposes a framework integrating SHAP into LSTM-based deep learning models for stock price prediction. The proposed research aims to fill the gap in the existing literature by developing a deep learning model that combines the predictive power of LSTM networks with the interpretability provided by XAI. The hypotheses developed suggest that this integration will improve transparency and user trust and lead to more accurate and actionable predictions in the context of stock market forecasting.

Given the gaps identified in the literature, this research develops the following hypotheses:

H1. Integrating Long Short-Term Memory (LSTM) networks into the stock prediction program provides accurate stock price predictions.

H2. Incorporating Explainable AI (XAI) techniques into the stock prediction program enhances the clarity and interpretability of the predictions.

4. Research Methodology

This paper followed a deductive approach in which insights are gathered from existing literature and used to develop the research hypotheses (Saunders et al., 2009). Then, an inductive approach follows, focusing on developing and implementing the stock prediction model. In the literature review and hypotheses development section, researchers have identified the research gap in the previous literature. Researchers also developed hypotheses that will be tested in the empirical part of the research. This section explains the dataset and its preprocessing, the model selection and architecture, model training, model evaluation, feature interpretation using SHAP, decision-making based on predictions, model deployment, and model validation.

4.1 Data Collection and Preprocessing

The first step in building the model is to collect the data through accessing a dataset. The data about historical stock price data was sourced using the *yfinance* library, which allows seamless access to financial data from Yahoo Finance. The dataset spans a chosen time range, typically from a past date to the present day, depending on the stock prediction timeline. The

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stock data for specific ticker symbols, such as "GOOG," was downloaded for this study. The study period covers data from January 2012 to August 2025. Researchers used a future end date to enable the model to run to the latest date it is used without any need to modify the date every time the model is in use.

The key metrics collected included open, high, low, and Closed prices and trading volume. The data was preprocessed to prepare for model training, which involved normalizing the stock prices using the MinMaxScaler. This normalization process guarantees that the values are uniform, making them appropriate for deep-learning models to make time-series predictions.

4.2 Model Selection and Architecture:

Researchers selected Long Short-Term Memory (LSTM) neural networks as they have a proven ability to handle sequential data and capture long-term dependencies. This critical feature is required when predicting stock prices based on historical data.

The architecture consists of multiple LSTM layers, starting with an LSTM layer containing 50 units, followed by a Dropout layer to prevent overfitting. Additional LSTM layers with different configurations, such as 60 or 80 units, were added, along with more Dropout layers, to ensure the model generalized well during training. Finally, a Dense output layer with a single neuron was used to predict the closing stock price. The model was compiled using the Adam optimizer, with the Mean Squared Error (MSE) serving as the loss function, which is standard for regression tasks like stock price forecasting.

4.3 Training the Model

The dataset was split into training and testing sets, with 80% of the data allocated for training and 20% reserved for testing. The model was trained using the preprocessed training data, where it learned to predict future stock prices based on historical trends. The training involved running the model for a specific number of epochs, typically around 100, and using a suitable batch size. The batch size used is 32. The training ensured the model converged properly and could generalize well to new data without overfitting.

4.4 Model Evaluation

The performance of the LSTM model was evaluated using metrics like Mean Squared Error (MSE) and Mean Absolute Error (MAE), which measure the deviation of the predicted stock prices from the actual values. A comparison plot was generated to visually assess the model's predictions, showing the predicted prices against the actual stock prices. This visualization helped confirm the model's ability to capture stock price trends effectively.

4.5 Feature Interpretation Using SHAP

SHAP values enhanced the model's interpretability. SHAP values offer insights into how each input feature contributes to the model's predictions. This is particularly important when dealing with neural networks, often seen as black-box models. A SHAP force plot was generated to visualize the impact of individual features on specific predictions, providing a clear understanding of the decision-making process behind the model's forecasts.

4.6 Decision-Making Based on Predictions

Based on the model's predictions, buy, sell, or hold decisions were made by comparing predicted prices with actual prices. A buy decision was recommended if the predicted price was significantly higher than the current price. Conversely, a sell decision was advised if the predicted price was lower. In cases where the predicted price change was minimal, a hold recommendation was made. These decisions were displayed through a user-friendly interface built with Streamlit, allowing users to interact with the model's outputs and view real-time predictions.

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4.7 Model Deployment

The LSTM model was deployed using a Streamlit-based web application, which allows users to make real-time predictions about stock prices. By loading a pre-trained model into the web app, users could obtain predictions without retraining the model every time. This deployment enabled users to access stock price forecasts and decision-making support anytime.

4.8 Model Validation

In order to ensure the robustness and generalizability of the model, k-fold cross-validation was employed. This technique divided the dataset into subsets to evaluate how well the model performed across various parts of the data. Additionally, out-of-sample testing was conducted on a hold-out set that the model had not seen during training. This helped assess the model's ability to predict stock prices on new, unseen data. Finally, a sensitivity analysis was performed to examine the model's sensitivity to changes in input features, ensuring that the predictions remained stable and reliable across various scenarios.

5. Results and Discussion

This section explains the results of applying the LSTM and SHAP model on stock price prediction for the companies chosen. The pre-trained LSTM model loads and downloads historical stock data from Yahoo Finance using the `*yfinance*` library. The model predicts stock price movements based on user input for stock symbols. As it is mentioned in the previous section, researchers used stock data of Google company.

Accordingly, the first stock symbol used is 'GOOG,' and the stock data for the selected period is displayed directly. This provides an interactive experience, allowing users to track stock price trends over time. By presenting key metrics such as the closing price and moving averages, the model highlights the historical patterns in stock performance, helping users understand the context of the model's predictions.

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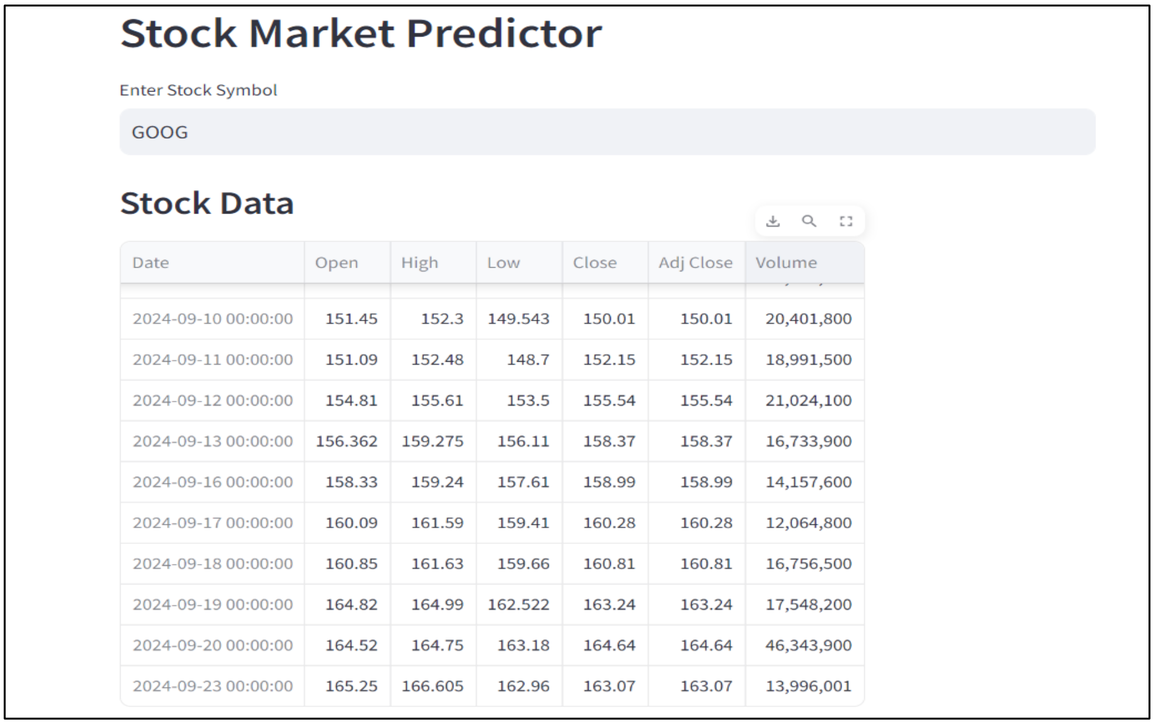
Figure 5 shows a sample of the historical stock data collected from the *yfinance* database. Open, high, low, and close prices and the trade volume on that date are collected for the period chosen. Data are daily data about each of the mentioned metrics. The data reflects stock prices from January 2012 to the current model running date.



Stock Market Predictor

Enter Stock Symbol

GOOG

Stock Data

Date	Open	High	Low	Close	Adj Close	Volume
2024-09-10 00:00:00	151.45	152.3	149.543	150.01	150.01	20,401,800
2024-09-11 00:00:00	151.09	152.48	148.7	152.15	152.15	18,991,500
2024-09-12 00:00:00	154.81	155.61	153.5	155.54	155.54	21,024,100
2024-09-13 00:00:00	156.362	159.275	156.11	158.37	158.37	16,733,900
2024-09-16 00:00:00	158.33	159.24	157.61	158.99	158.99	14,157,600
2024-09-17 00:00:00	160.09	161.59	159.41	160.28	160.28	12,064,800
2024-09-18 00:00:00	160.85	161.63	159.66	160.81	160.81	16,756,500
2024-09-19 00:00:00	164.82	164.99	162.522	163.24	163.24	17,548,200
2024-09-20 00:00:00	164.52	164.75	163.18	164.64	164.64	46,343,900
2024-09-23 00:00:00	165.25	166.605	162.96	163.07	163.07	13,996,001

Figure 5: The historical stock data from Yahoo Finance for Google company.

The next step the model performs is calculating and displaying various technical indicators. Researchers used the 50-day, 100-day, and 200-day moving averages (MA50, MA100, and MA200). These indicators are crucial in stock market analysis as they allow users to visualize the stock's short-, medium-, and long-term trends. Moving averages help smooth out short-term volatility (Billah et al., 2024). The plotted stock price charts against these moving averages provide insights into potential market shifts, where crossovers between moving averages often indicate buy or sell signals. This visualization helps users understand the underlying trends influencing stock price movements, offering an additional layer of analysis to complement the model's predictions. Figures 6, 7, and 9 present diagrams of prices compared to MA50, MA100,

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and MA200 consecutively. Figures 8 and 10 show the comparison between MA50 and MA100 and between MA100 and MA200 consecutively.

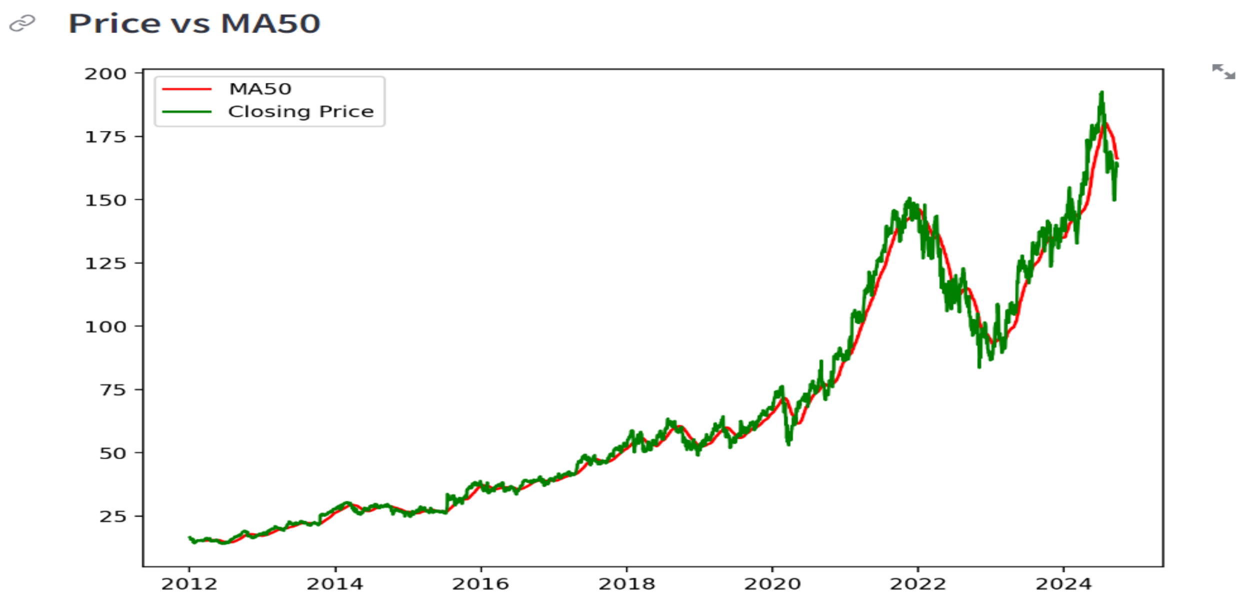

Figure 6: The stock price versus the 50-day moving average

Figure 7: The stock price versus the 100-day moving average.

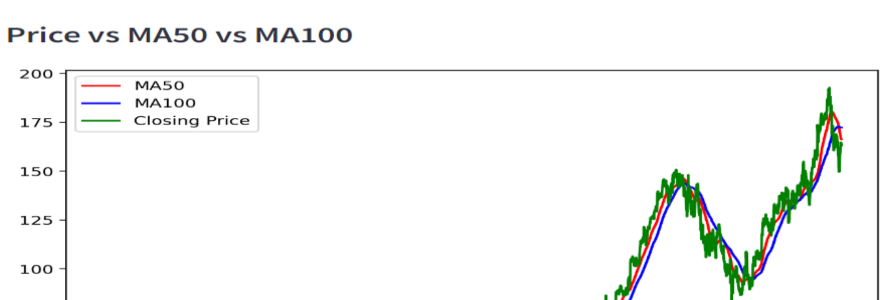

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Figure 8: The stock price versus 50-day versus 100-day moving averages.

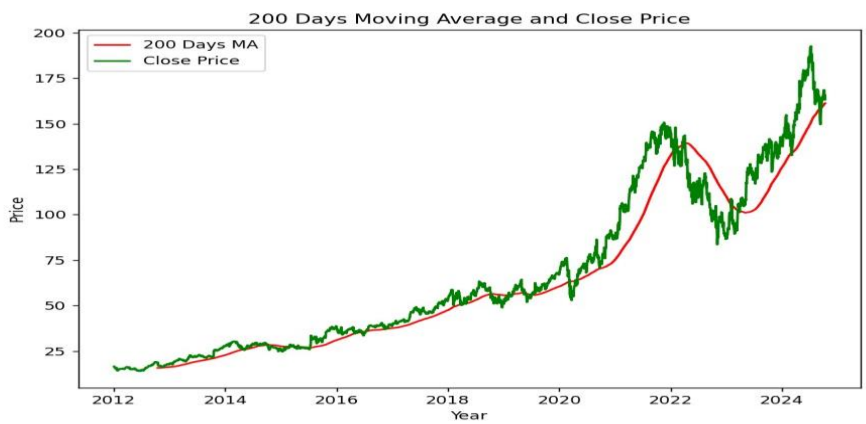

Figure 9: The stock price versus the 200-day moving average.

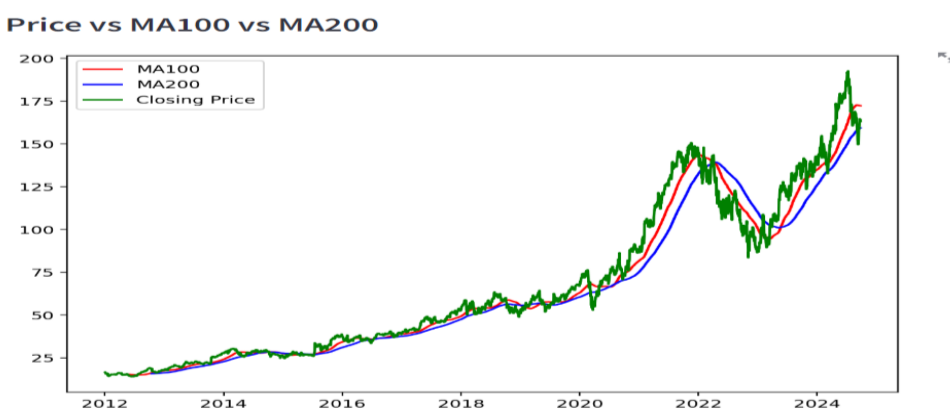

Figure 10: The stock price versus 50-day versus 100-day versus 200-day moving averages.

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The model prepares the data for prediction by scaling and creating input data sequences for the LSTM model. The scaled data is fed into the LSTM model, which predicts future stock prices. After making predictions, the model inversely scales the data back to its original form to make the predicted prices interpretable. A comparison of the predicted and actual stock prices is plotted, allowing users to assess the model's accuracy visually. However, the model's predictions have some limitations, particularly during periods of high volatility, where the complexity of market conditions leads to slight deviations between the predicted and actual prices (as shown in figure 11). However, the close alignment between the predicted and actual stock prices indicates that the LSTM model effectively captures stock price trends, making it a reliable tool for forecasting short-term price movements.

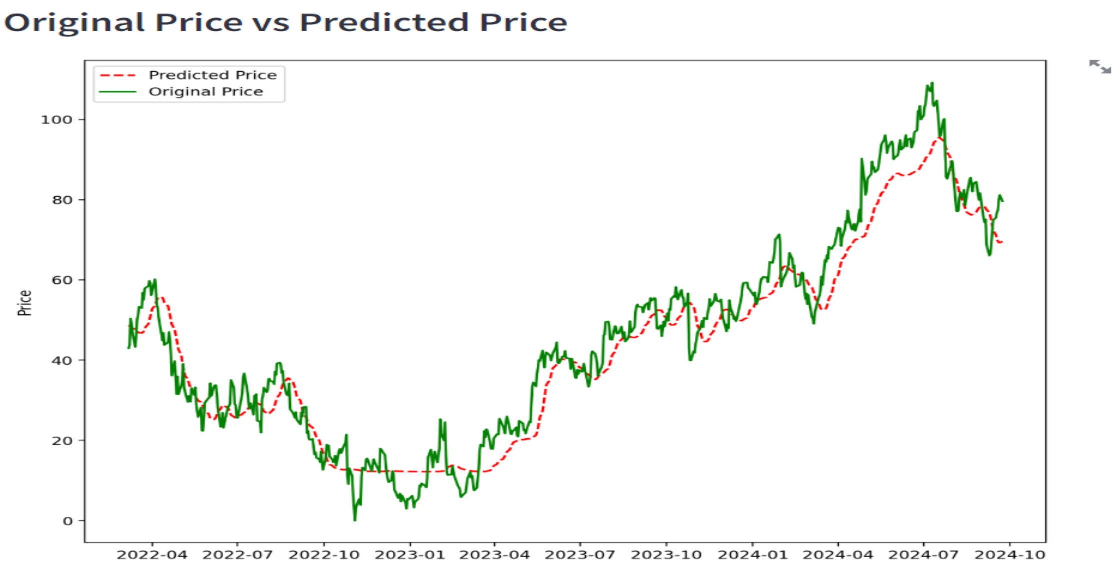

Figure 11: The stock's original price versus the stock's predicted price using the DL model.

Finally, the role of XAI rises, and SHAP values are used to interpret the model's predictions. SHAP values show how each input feature (such as past prices) contributes to the model's output. This transparency addresses the interpretability challenge often associated with deep learning models, making it easier for users to trust the predictions. Additionally, the code includes decision-making logic for buy, sell, or hold recommendations based on the predicted price change. If the predicted price increase exceeds a 2% threshold, a "Buy" recommendation is made, while a predicted decrease beyond 2% triggers a "Sell" recommendation. A "Hold"

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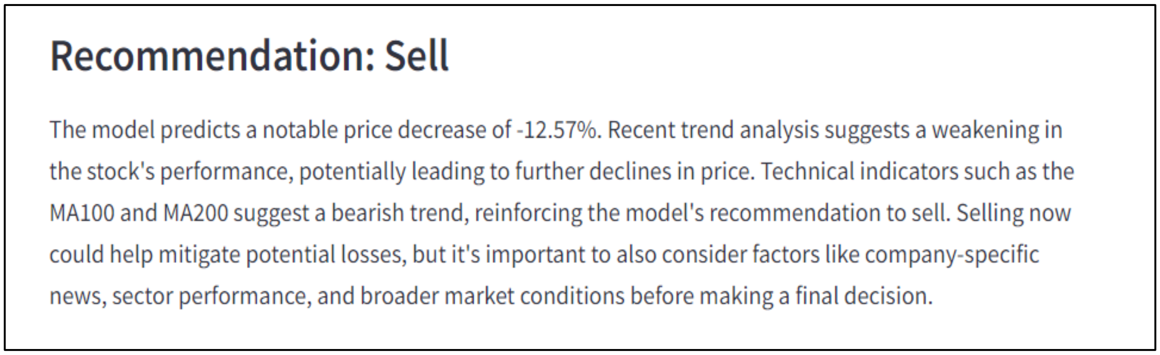
suggestion is provided when the price change is minimal. This decision-making process gives users actionable recommendations based on predicted price and technical indicators, making the tool practical for real-world investment strategies considering other market factors. Figure 12 shows the model's recommendation output.



Recommendation: Sell

The model predicts a notable price decrease of -12.57%. Recent trend analysis suggests a weakening in the stock's performance, potentially leading to further declines in price. Technical indicators such as the MA100 and MA200 suggest a bearish trend, reinforcing the model's recommendation to sell. Selling now could help mitigate potential losses, but it's important to also consider factors like company-specific news, sector performance, and broader market conditions before making a final decision.

Figure 12: The recommendation generated by the XAI using the DL model.

6. Conclusion and Directions for Future Research

This study aimed to integrate the LSTM technique and SHAP values to build a model for stock price prediction. The LSTM-based stock market prediction model results demonstrate its effectiveness in capturing short-term stock price trends and providing actionable recommendations. By leveraging deep learning techniques, specifically LSTM networks, the model succeeded in handling the sequential nature of financial time series data, making accurate predictions about future price movements. Additionally, integrating technical indicators, such as moving averages, enhanced the model's ability to contextualize its predictions within broader market trends. Using SHAP values adds a layer of interpretability, addressing the "black-box" nature of deep learning models and allowing users to understand the factors driving predictions. Moreover, the decision-making framework recommending buying, selling, or holding actions based on predicted price changes offered users practical guidance, making this model a valuable tool for novice and experienced investors.

While this model has shown promise, there are limitations that open the door for future research. The model used historical stock prices as the only factor for predicting future price trends. Future research can add additional features, such as macroeconomic indicators, news sentiment analysis, or company-specific events like earnings reports, to improve prediction accuracy further. Furthermore, the current model operates within a fixed training and testing period; future models could benefit from dynamic retraining mechanisms that adjust to new market conditions in real time. As discussed earlier, the model's ability to accurately predict high volatility periods remains challenging. Future research can work to improve the accuracy of model prediction. Finally, research into optimizing the balance between accuracy and interpretability, particularly for more complex deep learning architectures, could yield further advancements in building transparent and reliable stock prediction systems.

7. Data Availability

Stock-Market-Predictor is free, open-source software released under the GNU GPL license. Its source is the GitHub repository (https://github.com/NadaMarei/Stock-Market-Predictor-).

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