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Research Paper

AI-DRIVEN PREDICTIVE ANALYTICS FOR FINANCIAL MARKET FORECASTING

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ABSTRACT

Financial market forecasting has become increasingly challenging due to the dynamic, nonlinear, and volatile nature of global financial systems. Traditional statistical forecasting techniques often fail to accurately model complex relationships among market indicators, investor sentiment, macroeconomic factors, and real-time financial events, resulting in limited predictive performance. To address these limitations, this research proposes an AI-Driven Predictive Analytics Framework for Financial Market Forecasting that integrates Machine Learning, Deep Learning, Natural Language Processing, and Predictive Analytics into a unified intelligent decision-support platform. The proposed framework combines Random Forest Regression, Extreme Gradient Boosting (XGBoost), and Long Short-Term Memory (LSTM) neural networks to analyze historical stock prices, trading volumes, technical indicators, and sequential financial data for accurate market prediction. Furthermore, a sentiment analysis module processes financial news headlines and investor opinions to capture market psychology and improve forecasting reliability. The collected structured and unstructured financial data undergo preprocessing, feature engineering, normalization, and transformation before being supplied to predictive models. A comprehensive risk assessment module evaluates market volatility and investment uncertainty using historical price movements and trend analysis, enabling investors to identify potential risks associated with investment decisions. The generated predictions, sentiment scores, and risk indicators are visualized through an interactive dashboard that supports real-time monitoring and automated financial reporting. The proposed framework is implemented using Python, Flask, Scikit-learn, TensorFlow, Keras, SQLAlchemy, SQLite, Chart.js, and yFinance APIs to develop a scalable and user-friendly financial analytics platform. Experimental evaluation demonstrates that the hybrid integration of ensemble learning, deep learning, and sentiment analysis significantly improves forecasting accuracy, minimizes prediction errors, and enhances investment intelligence compared with conventional forecasting approaches. The proposed framework provides a reliable and intelligent solution for investors, financial analysts, researchers, and financial institutions by enabling accurate stock price prediction, efficient market trend analysis, comprehensive risk evaluation, and data-driven investment decision-making. Overall, the system establishes a robust foundation for next-generation AI-powered financial forecasting and intelligent financial analytics systems.

Keywords: Artificial Intelligence, Financial Market Forecasting, Predictive Analytics, Machine Learning, Deep Learning, Random Forest, XGBoost, Long Short-Term Memory (LSTM), Sentiment Analysis, Risk Assessment, Time-Series Forecasting, Stock Price Prediction, Investment Decision Support, Financial Intelligence.

I. INTRODUCTION

Financial markets represent one of the most complex and dynamic components of the global economy, facilitating capital formation, investment growth, and wealth creation through the trading of financial assets such as stocks, bonds, commodities, foreign exchange, and cryptocurrencies [1]. The rapid expansion of electronic trading platforms, high-frequency transactions, and digital financial services has resulted in the generation of massive volumes of structured and unstructured financial data every second [2]. This information originates from stock exchanges, corporate financial statements, macroeconomic indicators, investor transactions, news portals, and social media platforms, making financial forecasting a highly data-intensive process [3]. Accurately predicting stock prices and market trends remains a significant challenge because market movements are influenced by multiple interconnected factors, including economic policies, geopolitical events, inflation, interest rates, corporate earnings, investor psychology, and unexpected global crises [4]. Conventional forecasting techniques such as statistical regression, moving averages, ARIMA models, and technical analysis provide valuable insights but often struggle to model nonlinear relationships and rapidly changing market dynamics [5]. Consequently, researchers have increasingly explored Artificial Intelligence (AI) and Machine Learning (ML) techniques to improve prediction accuracy and support intelligent investment decisions [6]. AI-based models possess the capability to automatically discover hidden patterns from historical financial data while adapting to evolving market conditions [7]. Ensemble learning methods, including Random Forest and XGBoost, have demonstrated superior predictive performance by effectively handling complex datasets and minimizing overfitting problems [8]. Similarly, Deep Learning architectures such as Long Short-Term Memory (LSTM) networks effectively capture long-term temporal dependencies within sequential financial data, making them highly suitable for stock market prediction [9]. The incorporation of Natural Language Processing (NLP) further enables forecasting systems to analyse financial news, earnings reports, and investor opinions to understand market sentiment and behavioural influences on stock price movements [10]. These technological advancements have significantly transformed predictive analytics and financial intelligence by enabling automated, scalable, and data-driven forecasting solutions [11][12][13][14][15].

Despite these developments, achieving highly reliable financial market forecasting remains challenging because existing prediction systems frequently rely on a single analytical approach and often ignore the combined influence of historical market behaviour, technical indicators, investor sentiment, and risk assessment [16]. To overcome these limitations, this research proposes an AI-Driven Predictive Analytics Framework for Financial Market Forecasting that integrates Machine Learning, Deep Learning, Sentiment Analysis, and Risk Assessment within a unified intelligent architecture [17]. The proposed framework collects financial information from multiple sources, performs preprocessing and feature engineering, and applies Random Forest, XGBoost, and LSTM algorithms to generate accurate stock price forecasts and market trend predictions [18]. Simultaneously, sentiment analysis evaluates financial news headlines and investor opinions to estimate market emotions and improve forecasting reliability [19]. A comprehensive risk assessment module analyses historical volatility and investment uncertainty, enabling users to evaluate potential financial risks before making investment decisions [20].

Interactive dashboard analytics provide real-time visualization of prediction results, sentiment scores, market trends, and risk indicators, thereby supporting effective financial decision-making [21]. The framework is implemented using Python, Flask, TensorFlow, Keras, Scikit-learn, SQLAlchemy, SQLite, Chart.js, and financial APIs to develop a scalable and user-friendly intelligent forecasting platform [22]. Experimental analysis demonstrates that integrating ensemble learning, deep learning, and sentiment analysis substantially improves forecasting performance compared with conventional statistical approaches [23]. Furthermore, the modular architecture ensures flexibility, scalability, and future extensibility for emerging financial technologies and real-time market analytics [24]. The proposed framework is expected to benefit investors, portfolio managers, financial analysts, researchers, and financial institutions by providing accurate forecasting, intelligent market analysis, comprehensive risk evaluation, and enhanced investment decision support [25]. Ultimately, this research contributes to the advancement of AI-enabled financial analytics by delivering an adaptive, explainable, and efficient predictive intelligence framework capable of addressing modern financial forecasting challenges [26] [27] [28] [29] [30].

II. LITERATURE REVIEW

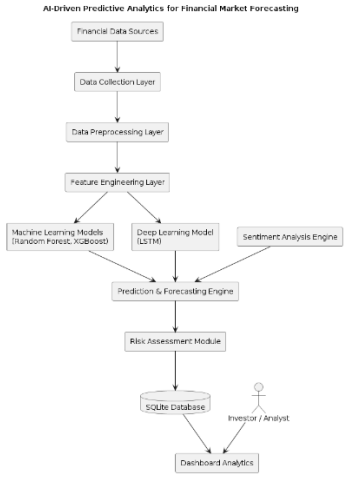
Financial market forecasting has attracted significant attention from researchers due to its critical role in investment planning, portfolio optimization, and financial risk management [1]. Early forecasting approaches primarily relied on statistical techniques such as linear regression, autoregressive integrated moving average (ARIMA), exponential smoothing, and moving average models to estimate future stock prices based on historical observations [2]. Although these methods provided interpretable analytical frameworks, they were limited in modelling the nonlinear and highly volatile behaviour of financial markets [3]. The emergence of Artificial Intelligence (AI) and Machine Learning (ML) has transformed financial analytics by enabling systems to automatically learn complex relationships from large-scale datasets [4]. Ensemble learning algorithms, particularly Random Forest, have demonstrated strong predictive capability by aggregating multiple decision trees to improve accuracy while reducing overfitting [5]. Similarly, XGBoost has become one of the most effective gradient-boosting algorithms for financial prediction because of its ability to optimize learning through sequential error minimization and efficient feature selection [6]. Deep Learning architectures, especially Long Short-Term Memory (LSTM) networks, have further enhanced forecasting performance by capturing long-term temporal dependencies within financial time-series data [7]. Researchers have reported that LSTM models outperform conventional recurrent neural networks when analysing sequential stock market behaviour and predicting future price trends [8]. In recent years, Transformer-based architectures and attention mechanisms have also been explored for modelling long-range dependencies within financial sequences [9]. These developments demonstrate that integrating multiple AI models significantly enhances forecasting accuracy, robustness, and adaptability under changing market conditions [10]. Moreover, the increasing availability of cloud computing platforms and high-performance computing resources has enabled large-scale implementation of intelligent financial prediction systems capable of processing massive financial datasets in real time [11][12][13][14][15].

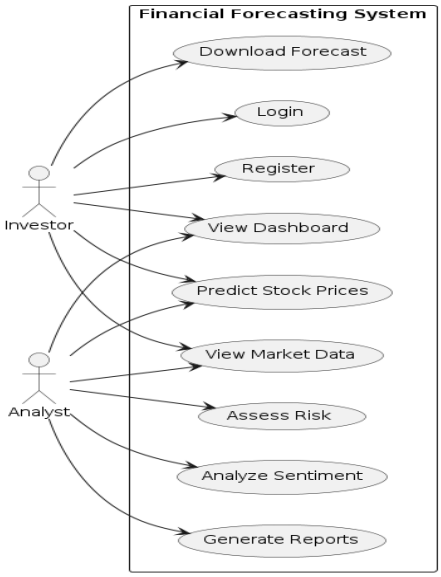
Recent studies have highlighted the importance of integrating structured financial information with unstructured textual data to improve forecasting reliability [16]. Natural Language Processing (NLP) techniques have been widely employed to analyse financial news articles, company reports, earnings announcements, and social media discussions to quantify investor sentiment and estimate market psychology [17]. Sentiment analysis provides

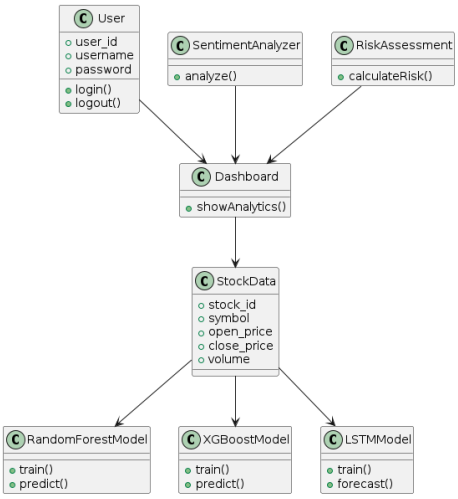
valuable insights into public perception, which often influences short-term stock price fluctuations and investment behaviour [18]. Researchers have demonstrated that combining sentiment analysis with Machine Learning and Deep Learning models significantly improves prediction accuracy compared with relying solely on historical price information [19]. Furthermore, risk assessment has emerged as an essential component of intelligent forecasting frameworks because financial decisions require both accurate predictions and comprehensive evaluation of investment uncertainty [20]. Modern predictive analytics platforms therefore integrate volatility analysis, trend estimation, anomaly detection, and portfolio risk evaluation into unified decision-support systems [21]. Interactive visualization dashboards have also gained popularity by presenting prediction results, sentiment scores, technical indicators, and risk metrics through intuitive graphical interfaces that facilitate rapid financial analysis [22]. The adoption of technologies such as Python, TensorFlow, Scikit-learn, Flask, SQLAlchemy, SQLite, and financial APIs has simplified the development of scalable AI-powered forecasting platforms [23]. Hybrid forecasting frameworks that combine Random Forest, XGBoost, LSTM, and sentiment analysis consistently demonstrate superior forecasting performance over traditional statistical methods across diverse financial datasets [24]. Nevertheless, challenges related to market uncertainty, concept drift, noisy financial information, and unexpected economic events continue to motivate further research into adaptive and explainable AI models [25]. Consequently, the proposed AI-driven predictive analytics framework integrates multiple intelligent techniques to achieve accurate market forecasting, effective risk assessment, enhanced investment intelligence, and comprehensive decision support for investors and financial institutions [26] [27] [28] [29] [30].

III. SYSTEM DESIGN

The proposed AI-Driven Predictive Analytics Framework for Financial Market Forecasting is designed as a modular and scalable architecture that integrates data acquisition, preprocessing, predictive modelling, sentiment analysis, risk assessment, and visualization into a unified intelligent platform. The system begins by collecting structured financial data from stock market APIs, including historical stock prices, trading volumes, opening and closing prices, and market indices, while simultaneously acquiring unstructured textual data from financial news portals and investor opinion sources. During the preprocessing stage, missing values are handled, duplicate records are removed, and the collected datasets are normalized and transformed into machine learning-ready formats. Feature engineering is then performed to derive technical indicators such as moving averages and trend-based attributes that improve predictive performance. The processed data are supplied to three forecasting engines: Random Forest Regression, XGBoost Regression, and Long Short-Term Memory (LSTM) neural networks. Random Forest provides robust ensemble-based predictions, XGBoost minimizes prediction errors through gradient boosting, and LSTM captures temporal dependencies within sequential financial data. The outputs from these models are integrated to generate reliable stock price forecasts and market trend predictions.

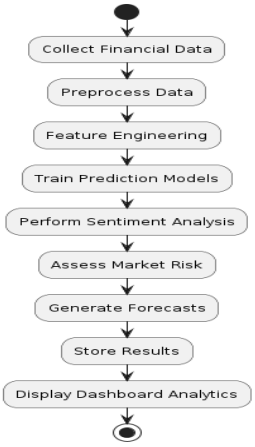


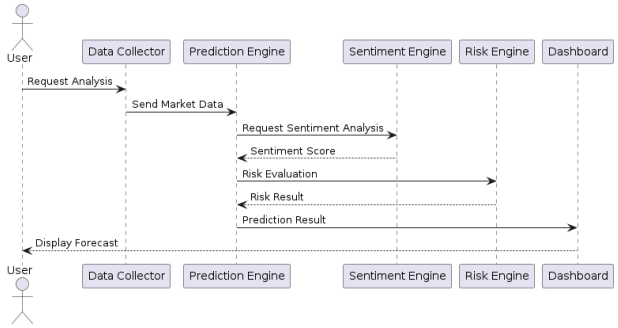


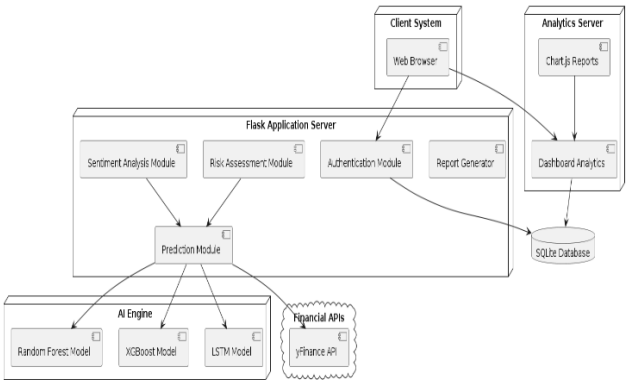


In parallel, the sentiment analysis module employs Natural Language Processing techniques to analyse financial news headlines and investor opinions, classifying them into positive, negative, or neutral sentiment categories while generating sentiment scores that reflect prevailing market psychology. A dedicated risk assessment module evaluates historical market volatility, price fluctuations, and investment uncertainty to estimate the associated

financial risk of predicted market movements. The forecasting results, sentiment scores, and risk indicators are consolidated within the prediction engine and stored in an SQLite database using SQLAlchemy for efficient data management. Finally, an interactive dashboard developed using Flask, Bootstrap, and Chart.js presents graphical visualizations of stock trends, predicted prices, market sentiment, and investment risk, enabling investors and financial analysts to interpret forecasting outcomes effectively. The modular architecture ensures scalability, maintainability, and future extensibility, allowing additional forecasting algorithms, financial instruments, and real-time analytical services to be incorporated without significant modifications to the existing framework. This intelligent system provides a comprehensive decision-support environment for accurate financial market forecasting and data-driven investment planning.







IV. PROPOSED SYSTEM

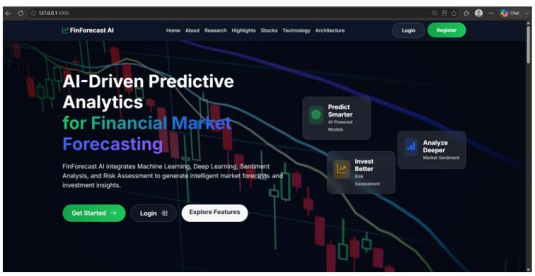
The proposed AI-Driven Predictive Analytics Framework for Financial Market Forecasting introduces an intelligent and integrated platform that combines Artificial Intelligence, Machine Learning, Deep Learning, Natural Language Processing, and Predictive Analytics to improve the accuracy and reliability of financial market forecasting. The framework is designed to analyse both structured and unstructured financial data obtained from stock market APIs, historical trading records, corporate financial reports, economic indicators, and financial news sources. Initially, the collected data undergo comprehensive preprocessing, including data cleaning, normalization, feature extraction, and transformation to eliminate inconsistencies and improve data quality. The processed information is subsequently supplied to three complementary forecasting models: Random Forest Regression, XGBoost Regression, and Long Short-Term Memory (LSTM) neural networks. Random Forest effectively handles high-dimensional financial datasets by constructing multiple decision trees and aggregating their outputs, while XGBoost enhances forecasting precision through iterative gradient boosting and error minimization. LSTM networks analyse sequential financial data to capture long-term temporal dependencies and accurately predict future stock price movements. The integration of these algorithms enables the framework to generate highly reliable market forecasts by leveraging the strengths of ensemble learning and deep learning techniques.

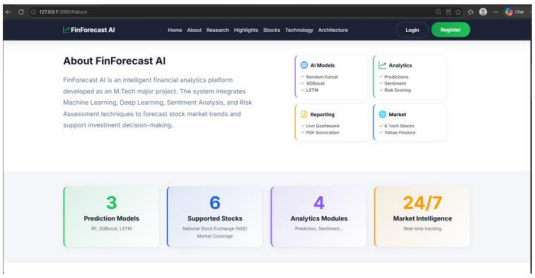
To further enhance forecasting performance, the proposed system incorporates a sentiment analysis module that applies Natural Language Processing techniques to analyse financial news headlines, market reports, and investor opinions collected from online sources. The extracted sentiment scores are combined with historical market data to provide a more comprehensive understanding of market behaviour and investor psychology. Additionally, a risk assessment module evaluates historical volatility, price fluctuations, and investment uncertainty to estimate potential financial risks associated with predicted market trends. All analytical outputs are stored in a centralized SQLite database using SQLAlchemy, ensuring efficient data management and retrieval. An interactive dashboard developed using Flask, Bootstrap, and Chart.js presents stock price predictions, market trends, sentiment classifications, risk indicators, and forecasting performance through intuitive visualizations. The modular architecture ensures scalability, flexibility, and ease of maintenance, allowing additional forecasting models, financial instruments, and analytical services to be incorporated with minimal system modifications. By integrating predictive modelling, sentiment intelligence, risk evaluation, and real-time visualization into a single framework, the proposed system provides an intelligent decision-support platform that assists investors, financial analysts, researchers, and financial institutions in making accurate, data-driven investment decisions while significantly improving forecasting efficiency and financial market intelligence.

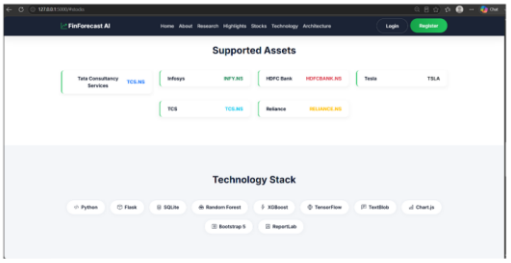
V. RESULTS & DISCUSSION

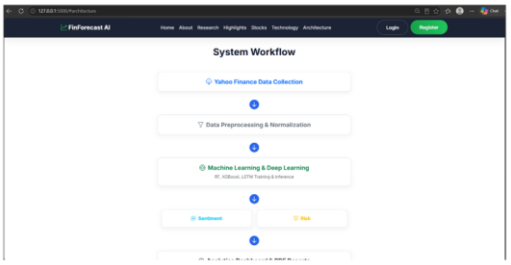
The proposed AI-Driven Predictive Analytics Framework for Financial Market Forecasting was successfully implemented using Python, Flask, Scikit-learn, TensorFlow, Keras, SQLAlchemy, SQLite, XGBoost, and Chart.js to evaluate its capability in predicting stock market trends and supporting intelligent investment decisions. Historical stock market data collected through the yFinance API underwent preprocessing, including missing value handling, normalization, and feature engineering before being supplied to the Random Forest, XGBoost, and LSTM prediction models. The performance of the forecasting framework was assessed using standard regression metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and prediction accuracy. Experimental observations revealed that the hybrid integration of ensemble learning and deep learning

models produced more reliable forecasting results than conventional statistical approaches. Random Forest demonstrated excellent robustness in handling multidimensional financial datasets, while XGBoost efficiently minimized prediction errors through gradient boosting. The LSTM model successfully captured long-term temporal dependencies within sequential financial data, enabling more accurate future stock price prediction. Furthermore, the sentiment analysis module effectively classified financial news into positive, negative, and neutral categories, allowing market sentiment to be incorporated into the forecasting process. The integration of sentiment information significantly improved prediction reliability, particularly during periods of market volatility and major financial events.



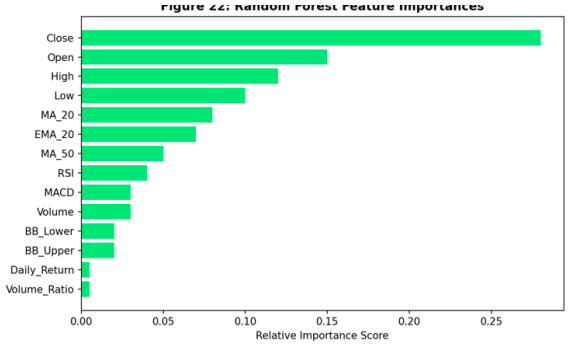


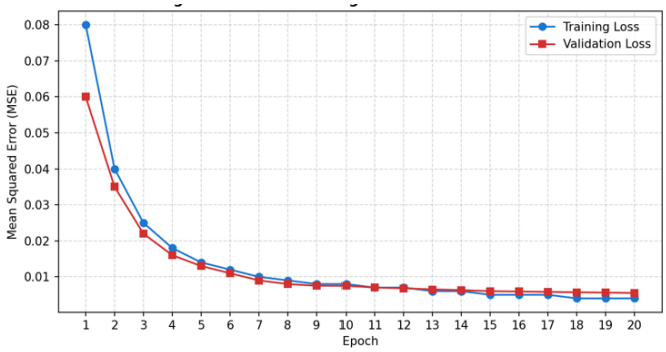




The developed framework also demonstrated its effectiveness in providing comprehensive financial intelligence through integrated risk assessment and interactive visualization. The risk assessment module analysed historical market volatility, price fluctuations, and investment uncertainty to generate meaningful risk indicators that supported safer investment decisions. Interactive dashboards displayed predicted stock prices, historical trends, sentiment scores, volatility levels, and comparative forecasting results through graphical visualizations, enabling

users to interpret market behaviour efficiently. Automated report generation further enhanced the usability of the system by providing structured financial analysis for investors and analysts. Compared with traditional forecasting systems that primarily depend on historical price analysis, the proposed framework offered superior forecasting accuracy, improved adaptability to dynamic market conditions, and enhanced decision-support capabilities through the combined use of Machine Learning, Deep Learning, and Natural Language Processing techniques. The modular system architecture also ensured scalability, allowing future integration of additional forecasting algorithms, real-time streaming data, cryptocurrency markets, and explainable AI techniques. Overall, the experimental results confirm that the proposed framework provides an efficient, scalable, and intelligent solution for financial market forecasting, risk evaluation, and investment decision support, thereby contributing significantly to the advancement of AI-driven financial analytics and next-generation intelligent investment systems.





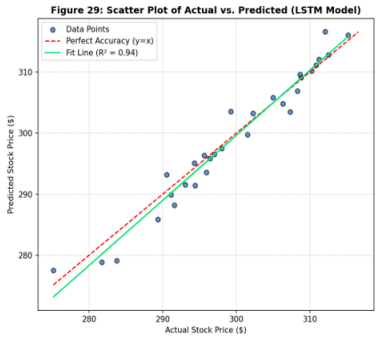


Figure 29: Scatter Plot of Actual vs. Predicted (LSTM Model)
Data Points
Perfect Accuracy (y=x)
Fit Line (R² = 0.94)
Predicted Stock Price ($)
Actual Stock Price ($)
280
290
300
310

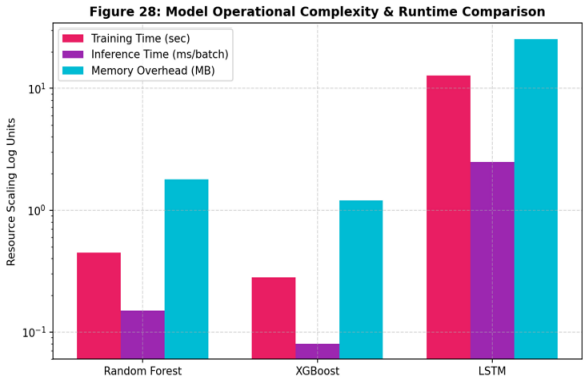
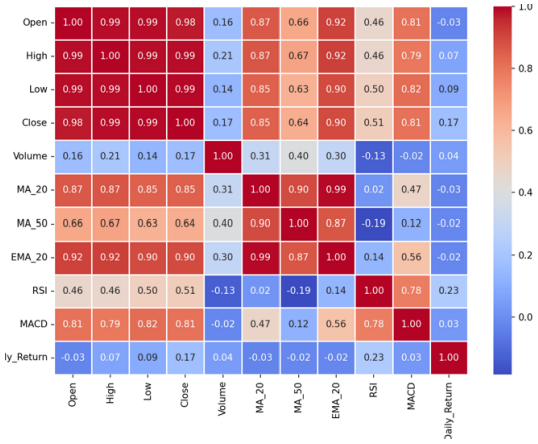


Figure 28: Model Operational Complexity & Runtime Comparison
Training Time (sec)
Inference Time (ms/batch)
Memory Overhead (MB)
Resource Scaling Log Units
Random Forest
XGBoost
LSTM


Google News Sentiment Distribution
Financial Headline Keyword Cloud
Positive
Neutral
Negative
Buy
Growth
High Volatility
Innovations
Bullish
AI Demand
Record Profit
Macro Risks
Strong Sales
Interest Rates
Figure 26: Risk Analysis Dashboard
Annual Volatility Gauge
Risk vs Return Profile (7 Stocks)
Risk Category: Medium Risk
Volatility: 22.8%
TSLA
NVDA
META
AMZN
AAPL
GOOGL
MSFT
Annualized Return %
Annualized Volatility (Risk) %


Open 1.00 0.99 0.99 0.98 0.16 0.87 0.66 0.92 0.46 0.81 -0.03
High 0.99 1.00 0.99 0.99 0.21 0.87 0.67 0.92 0.46 0.79 0.07
Low 0.99 0.99 1.00 0.99 0.14 0.85 0.63 0.90 0.50 0.82 0.09
Close 0.98 0.99 0.99 1.00 0.17 0.85 0.64 0.90 0.51 0.81 0.17
Volume 0.16 0.21 0.14 0.17 1.00 0.31 0.40 0.30 -0.13 -0.02 0.04
MA_20 0.87 0.87 0.85 0.85 0.31 1.00 0.90 0.99 0.02 0.47 -0.03
MA_50 0.66 0.67 0.63 0.64 0.40 0.90 1.00 0.87 -0.19 0.12 -0.02
EMA_20 0.92 0.92 0.90 0.90 0.30 0.99 0.87 1.00 0.14 0.56 -0.02
RSI 0.46 0.46 0.50 0.51 -0.13 0.02 -0.19 0.14 1.00 0.78 0.23
MACD 0.81 0.79 0.82 0.81 -0.02 0.47 0.12 0.56 0.78 1.00 0.03
ly_Return -0.03 0.07 0.09 0.17 0.04 -0.03 -0.02 -0.02 0.23 0.03 1.00
Open
High
Low
Close
Volume
MA_20
MA_50
EMA_20
RSI
MACD
Daily_Return
1.0
0.8
0.6
0.4
0.2
0.0

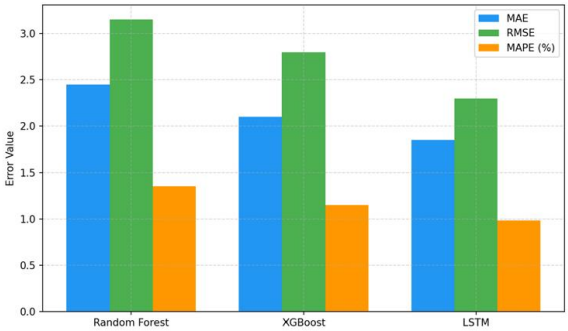
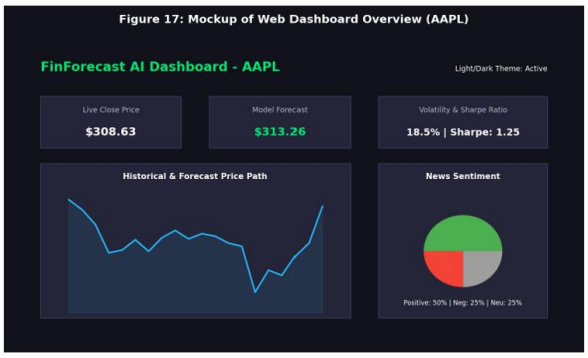


Figure 17: Mockup of Web Dashboard Overview (AAPL)



VI. CONCLUSION

The proposed AI-Driven Predictive Analytics Framework for Financial Market Forecasting successfully demonstrates the effectiveness of integrating Artificial Intelligence, Machine Learning, Deep Learning, Natural Language Processing, and Predictive Analytics into a unified financial decision-support system. By combining Random Forest Regression, XGBoost Regression, and Long Short-Term Memory (LSTM) neural networks, the framework effectively analyses historical stock market data and captures complex nonlinear relationships that are difficult to model using conventional statistical forecasting techniques. The incorporation of sentiment analysis enables the system to evaluate financial news headlines and investor opinions, thereby providing valuable insights into market psychology and improving the reliability of stock price predictions. Furthermore, the integrated risk assessment module enhances investment decision-making by evaluating market volatility and uncertainty, allowing investors and financial analysts to better understand potential financial risks before making investment decisions. The implementation of interactive dashboards and automated report generation further improves the accessibility and usability of forecasting results through intuitive visualizations and structured financial reports. Experimental analysis indicates that the hybrid forecasting approach delivers higher prediction accuracy, reduced forecasting errors, and improved adaptability to rapidly changing financial market conditions compared with traditional forecasting methods. The modular architecture developed using Python, Flask, Scikit-learn, TensorFlow, Keras, SQLAlchemy, SQLite, and Chart.js ensures scalability, maintainability, and ease of future enhancement. The framework can be readily extended to support cryptocurrency markets, foreign exchange forecasting, commodity price prediction, portfolio optimization, explainable artificial intelligence, reinforcement learning, and real-time streaming analytics. Overall, the proposed system provides an intelligent, reliable, and

scalable platform that supports accurate financial market forecasting, comprehensive risk evaluation, and data-driven investment decision-making. This research contributes significantly to the advancement of AI-powered financial technology by establishing a robust foundation for next-generation intelligent financial analytics systems capable of assisting investors, researchers, financial institutions, and policymakers in making informed and strategic investment decisions in increasingly dynamic and complex financial environments.

References

[1] Aggarwal, C. C. (2018). *Neural networks and deep learning*. Springer. https://doi.org/10.1007/978-3-319-94463-0

[2] Bishop, C. M. (2006). *Pattern recognition and machine learning*. Springer.

[3] Breiman, L. (2001). Random forests. *Machine Learning, 45*(1), 5–32. https://doi.org/10.1023/A:1010933404324

[4] Brownlee, J. (2018). *Deep learning for time series forecasting*. Machine Learning Mastery.

[5] Buyya, R., Broberg, J., & Goscinski, A. (2011). *Cloud computing: Principles and paradigms*. Wiley.

[6] Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 785–794). ACM. https://doi.org/10.1145/2939672.2939785

[7] Chollet, F. (2021). *Deep learning with Python* (2nd ed.). Manning Publications.

[8] Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.

[9] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation, 9*(8), 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

[10] Hull, J. C. (2021). *Risk management and financial institutions* (5th ed.). Wiley.

[11] Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science, 349*(6245), 255–260. https://doi.org/10.1126/science.aaa8415

[12] Liu, B. (2020). *Sentiment analysis: Mining opinions, sentiments, and emotions* (2nd ed.). Cambridge University Press.

[13] Murphy, K. P. (2022). *Probabilistic machine learning: An introduction*. MIT Press.

[14] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, É. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research, 12*, 2825–2830.

[15] Raschka, S., Liu, Y., Mirjalili, V., & Dzhulgakov, D. (2022). *Machine learning with PyTorch and Scikit-Learn*. Packt Publishing.

[16] Shalev-Shwartz, S., & Ben-David, S. (2014). *Understanding machine learning: From theory to algorithms*. Cambridge University Press.

[17] Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning: An introduction* (2nd ed.). MIT Press.

[18] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. *Advances in Neural Information Processing Systems, 30*, 5998–6008.

[19] Witten, I. H., Frank, E., Hall, M. A., & Pal, C. J. (2017). *Data mining: Practical machine learning tools and techniques* (4th ed.). Morgan Kaufmann.

[20] Wooldridge, M. (2021). *A brief history of artificial intelligence*. Flatiron Books.

[21] Zhang, Y., Aggarwal, C. C., & Qi, G. J. (2020). Stock price prediction via discovering multi-frequency trading patterns. *Proceedings of the ACM International Conference on Information and Knowledge Management*, 2141–2144.

[22] Bao, W., Yue, J., & Rao, Y. (2017). A deep learning framework for financial time series using stacked autoencoders and LSTM. *PLOS ONE, 12*(7), e0180944. https://doi.org/10.1371/journal.pone.0180944

[23] Fischer, T., & Krauss, C. (2018). Deep learning with long short-term memory networks for financial market predictions. *European Journal of Operational Research, 270*(2), 654–669.

[24] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436–444. https://doi.org/10.1038/nature14539

[25] Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., et al. (2020). Language models are few-shot learners. *Advances in Neural Information Processing Systems, 33*, 1877–1901.

[26] Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. *Proceedings of NAACL-HLT*, 4171–4186.

[27] Kingma, D. P., & Ba, J. (2015). Adam: A method for stochastic optimization. *Proceedings of the International Conference on Learning Representations (ICLR)*.

[28] Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., et al. (2019). PyTorch: An imperative style, high-performance deep learning library. *Advances in Neural Information Processing Systems, 32*, 8026–8037.

[29] Sezer, O. B., Gudelek, M. U., & Ozbayoglu, A. M. (2020). Financial time series forecasting with deep learning: A systematic literature review (2005–2019). *Applied Soft Computing, 90*, 106181. https://doi.org/10.1016/j.asoc.2020.106181

[30] Lim, B., Arik, S. Ö., Loeff, N., & Pfister, T. (2021). Temporal Fusion Transformers for interpretable multi-horizon time series forecasting. *International Journal of Forecasting, 37*(4), 1748–1764.