Integrating Artificial Intelligence and Machine Learning in Predictive Finance for Enhanced Forecasting and Risk Mitigation

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Abstract

This study employs Artificial Intelligence (AI) and Machine Learning (ML) methodologies to develop advanced predictive finance strategies aimed at enhancing the accuracy of financial forecasting, improving risk assessment and supporting data-driven investment decision-making. In order to provide companies with the ability to forecast market swings, improve resource allocation and build financial resilience, the study aims to integrate traditional financial modelling with data-driven predictive analytics. The research employs quantitative and experimental methodology, including some of the most advanced machine learning techniques, such as Random Forest, Gradient Boostingand Long Short-Term Memory (LSTM) networks, in order to forecast time-series data pertaining to the financial sector. Python-based frameworks are utilized in order to investigate historical datasets derived from stock indexes, macroeconomic indicators and business performance reports. Both Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) are employed to evaluate the models performance subsequent to k-fold cross-validation - based training and validation.In addition, the predictive power of the models is improved through the utilization of sentiment analysis of financial news and trends in social media. When compared to more conventional methods, it is predicted that the study will demonstrate a significant improvement in terms of both the accuracy of predictions and the management of risks. The predictive framework that has been built will make it easier for investors, politicians and financial institutions to make decisions based on data. The paper makes the proposition that the combination of artificial intelligence and financial analytics will result in increased transparency, efficiency and sustainability within the financial systems. This will ultimately lead to the development of more intelligent investment ecosystems.

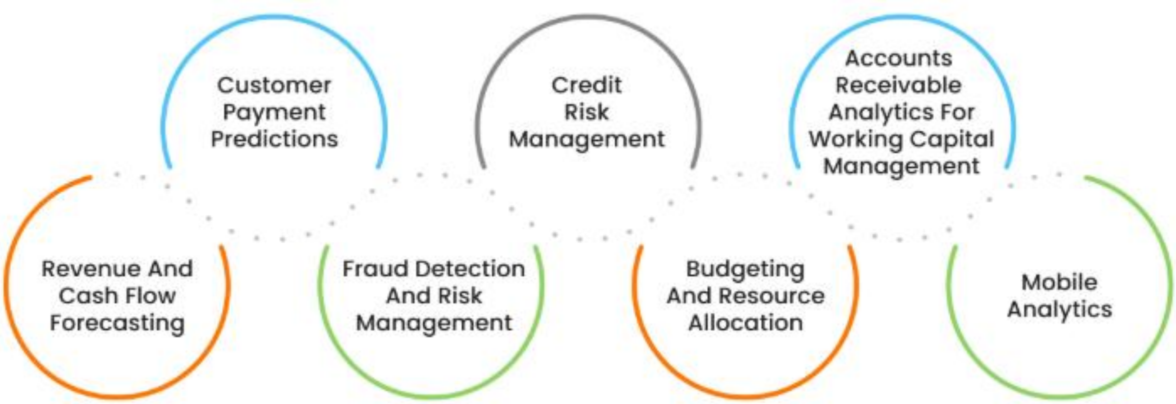
Keywords - Predictive Analytics, Financial Forecasting, Machine Learning, Risk Management, Artificial Intelligence

1. INTRODUCTION

Organizations are increasingly becoming reliant on highly advanced technologies to address the complex market environment through reducing uncertainties and maximizing decision-making owing to the fast changing financial environment. Machine Learning (ML) and Artificial Intelligence (AI) have already made smart predictive finance algorithms a revolutionary tool and these will assist institutions to plan the future with greater precision and risk management in a more proactive manner. The traditional financial forecasting that had existed was grounded largely on the past patterns, statistical modelling and human perception which could not capture the nonlinear patterns, rapid economic patterns and association of different macroeconomic factors[1], [2]. Digital revolution and the astounding growth with the surge in financial information have rendered AI-based systems that can generate more insights to both structured and unstructured data such as market indices, real-time transactions and sentiments on news stories, financial report by a corporation and economic indicators across the world[1], [2]. These intelligent models are consistently refined via learning algorithms whereby the model finds certain concealed relationships and dynamic patterns that would not have been previously detected. Neural networks, time series prediction models, reinforcement learning and ensemble methods: Predictive finance systems based on the use of AI (ML) can be utilized to provide stock price, credit score, demand, loan default, liquidity planningand investment portfolio optimization with high precision. Simultaneously, AI-based risk management systems offer real-time identification of anomalies, fraud prevention and stress testing, which hedges an institution against systemic susceptibility and financial shocks[3], [4], [5]. As financial markets are becoming volatile, geopolitical uncertain and disruptive, e.g. global pandemics and change of technology, the convergence of real-time analytics and predictive intelligence is the strategic competitive advantage. These latest systems provide the opportunity to identify threats and opportunities timely, optimally allocate capital and improve the resilience of operations.

Figure 1

Intelligent Predictive Finance Strategies



The use of AI-based automation in the financial sector assists in streamlining tasks by reducing human error and improving compliance checks and decision-making rate, which leads to higher cost-saving[6], [7]. Natural language processing (NLP) represents a form of innovation, which enables systems to process financial information in the form of texts, recognize the market sentiment and present more intricate analytical outputs to investment strategies. At the same time, blockchain and AI integrate and promote trust and transparency, which guarantee the safety of financial transactions and facilitate the deployment ofsmart contracts that can be tracked and predicted with analytics solutions. It also includes the enhanced scalability and access to real time insight generation, which are presented in cloud enabled big data environments. Despite all these monumental benefits, the implementation of intelligent finance strategies must be done with a keen assessment of the ethical concerns, data management, algorithmic equity and rules. Incorrect data or black box decision systems may lead to unfair lending practices or poor risk evaluation. The problem of AI ethical compliance and model interpretability is becoming a part of the financial governance. Financial authorities in all countries are now focusing on model validation, cybersecurity measures and sound data privacy policies in order to make the automated decision systems safe and responsible. Ongoing skills enhancement and cross-functional cooperation among financial analysts, data scientists and technology specialists are also critical to providing the opportunity to successfully deploy, sustain and assess AI solutions in finance [8]. The technological integration issues with legacy systems, scalability of infrastructure and high implementation costs are the areas that organizations have to manage at all costs to realize maximum benefits of the digital transformation.

In the future, ML, AI and further advanced data analytics will continue to transform predictive finance to go beyond descriptive and diagnostic analytics to fully autonomous, self-developing financial ecosystems with the capacity to look into the future and make adaptive decisions. Quantum computing, generative AI and advanced causal models that can simulate scenarios and approximate long-term risks more effectively than existing approaches [9], [10] are poised to shape the future. As the predictive systems are further developed, finance willevolve to be more sophisticated, more responsive and more resilient in future when evidence based decisions are formed in real time, on the basis of a holistic analysis of risks and dynamic market intelligence. The implied meaning of this is that smart predictive finance strategies are not merely additional to the existing practice but they are the restructuring of the foundations of the working and cooperative procedures of financial administration[11]. They allow the institutions to stay afloat, exploit new opportunities and deal with changing requirements of the new digital and interconnected world markets [12]. Integrating ML and AI is no longer merely an innovative step in improving forecasting and risk management; it has become essential for sustaining the financial sector's development, meeting regulatory expectations and securing long-term success[13].

2. LITERATURE REVIEW

Chukwukaeloet al. (2024)in their paper analyzed how machine learning can be used to improve corporate financial planning through better forecasting and decision-making. The conventional financial planning techniques have been based on statistical models and judgment of experts that are constrained based on the preset assumptions and historical information and hence less efficient in reacting to the dynamism and nonlinearities in the market. Consequently, enterprises are struggling to obtain reliable financial information on time. The integration of machine learning is a revolutionary approach as with advanced algorithms, it may be possible to find out the underlying patterns, complicated connections and dynamic market trends on large and diverse data sets and as a result, provide a more adaptable and intelligent financial planning[14].

Oladujiet al. (2023) suggested an AI- and Big Data-based model that will enhance financial risk prediction and mitigation in Africa's volatile and data-dispersed markets. Machine learning algorithms detect new risks in real time by combining various types of structured and unstructured data, such as financial transactions, economic data and socio-political data. The model is characterized by data integration, predictive forecasting and continuous risk scoring and a visualization dashboard to aid in proactive decision-making. It has been tested in five African economies over ten years and proved to be very accurate in the identification of indicators of crisis and market instability [15].

Challa et al. (2023) contend that the increase in AI application in finance is due to the growing availability of data, which can be more efficient in the distribution of funds and risk management and provide novel prospects of wealth management. Despite the fact that automated trading has facilitated access to more people to invest, conventional financial advisory services are still expensive and unaffordable by others. New Chinese startups may fill this gap with the help of user credit, online information, but they continue to be considerably dependent on human knowledge. The recent breakthroughs in artificial intelligence, like automated style recognition and natural language processing, will enable the revolution of financial services in the form of a cognitive finance framework, providing intelligent, accessible solutions. The security, reliability and a balance between the intelligent and classic technologies must be ensured as well [16].

Singireddyet al. (2023) stated that the transition to data scale as opposed to production scale has become a key factor behind the growth of the data economy where the analytical frameworks have no problem handling the fast-paced increase in data. Finance 4.0 has come in to secure effective cash flow, quick financing and effective risk analysis to facilitate the development of the market sustainably and adherence to regulations. This paradigm is the foundation of predictive analytics that is implemented with quantitative techniques such as classical, machine learning and deep learning models to predict financial performance, yet issues such as long reporting remain. New technologies such as AI and big data are all necessary to manage systemic risks, unstructured information and economic security in fast-growing markets such as China [17].

Rane et al. (2023) examined the transformational effects of Artificial Intelligence on financial forecasting and investment strategy formulation. With the current traditional forecasting technologies being unable to endure market volatility, modern AI technologies can be used to enhance predictive accuracy and reduce risk, including machine learning, deep learning, NLP and sentiment analysis. The paper identifies the usefulness of RNNs, LSTMs and CNNs in identifying complex financial trends and improving the reliability of predictions. It also researched AI-based solutions such as algorithmic trading and robo-advisors, which automate the process of decision-making and optimization of portfolios on instantaneously. Also, new technologies, such as reinforcement learning and quantum computing are characterized as capable of more radically transforming the field of forecasting in dynamic financial settings [18].

Table 1

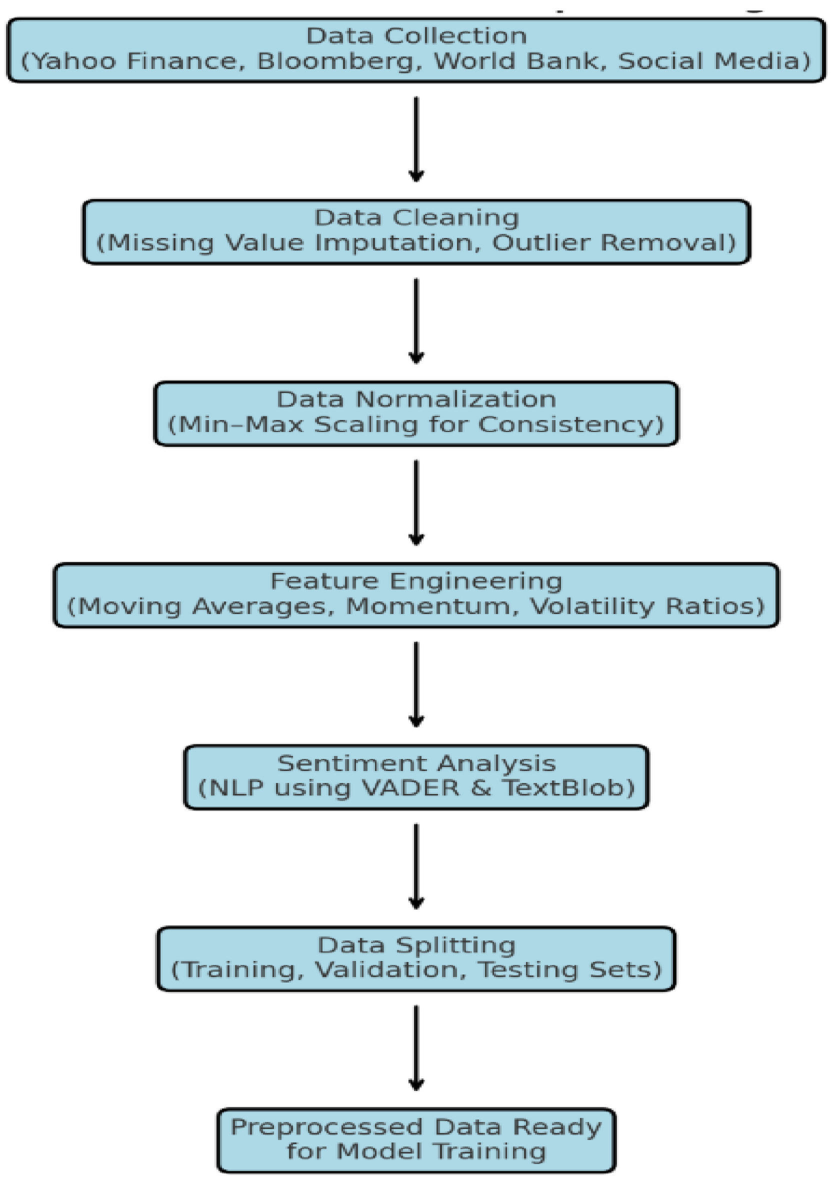
Literature Summary

Authors	**Methodology**	**Research gap**	**Findings**
Elumiladeet *al.*[19]	Analyze financial data using big data, machine learning, predictivemodeling techniques.	Limited adoption of advanced analytics restricts proactive risk management capabilities.	Data analytics improves forecasting, compliance, fraud detection and strategic decision-making.
Fritz-Morgenthal *et al.*[20]	Expert sessions review model governance, risk controls and regulatory compliance practices.	Limited frameworks for managing complex AI model risk across institutions.	Robust governance ensures trustworthy, explainable, auditable AI in financial operations.
Kannan[21]	AI and machine learning techniques transforming customer-focused financial services.	Lack of strong customer-centric predictive models integrated with regulatory compliance.	Customer-centric AI improves behavior prediction, satisfaction, loyalty and decision-making efficiency.
Pamisetty*et al.*[22]	Analyze digital technologies,enhancing tax compliance, detecting fraud, optimizing public finance.	Public agencies underutilize commercial AI tools for automating routine processes.	Digital technologies strengthen automation, transparency, tax auditing efficiency, fraud detection capacity.
BogojevićArsić[23]	AI applications addressing financial risk challenges.	Traditional risk methods outdated; limited adoption of advanced AI solutions.	AI improves fraud detection, data quality, market and credit risks.

3. METHODOLOGY

Figure 2

Proposed Flow Chart



3.1 Data Collection and Preprocessing

The analysis is based on secondary financial information sourced from reliable online securities exchange platforms including Yahoo Finance, Bloomberg and world bank. These sources entail historical market information, stock index, macroeconomic and firm performance data over the past ten years. Also, financial news articles and social media feeds are included to reflect real time sentiment in the market. Data collected is subjected to massive pre-processing to make sure that there is consistency, reliability and also accuracy. Lack and irregular values are addressed with the help of interpolation and outlier detection. Min-max scaling is applied to normalize all numerical attributes in order to have uniformity. The feature engineering is done to obtain technical features such as moving averages, price momentum and volatility ratios and the textual sentiment data is measured by means of Natural Language Processing (NLP) with such tools as VADER and TextBlob. The resulting clean data is split into training, validation and testing data to make sure that there is no bias in the model. This well-organized data processing forms a good basis to construct valid AI-based financial forecasting projections.

3.2 Research Design and Framework

The research utilized a quantitative and experimental design to construct and examine the proposed Hybrid AI-Driven Predictive Model (HADPM) for financial prediction and risk mitigation. The framework is a fusion of conventional econometric concepts/notions and emerging machine learning methods/technologies and deep learning methods/technologies to increase predictive performance and analytical performance. The experimental framework also allows the repetition of training, testing and optimization of the model to the different financial situations which is flexible to the dynamic and turbulent market environment. Emphasis is placed on the fact that empirical validation, reproducibility and objectivity are defined based on quantifiable variables such as error rates, forecast accuracy and volatility scores. The model of the study is based on an intelligent predictive analytics, under which past and current financial data is used to train the algorithms and accurately predict the market behavior to assist in strategic decision making. The HADPM approach further enhances this design by integrating both data-driven ensemble models and sentiment-based intelligence, enabling market dynamics to be interpreted from a multidimensional perspective. The framework also reveals the excellence of the proposed model upon the other frameworks experimented in the areas of interpretability, prediction accuracy and risk sensitivity through comparative experimentation in such a way that the predictive strategies developed can be understood, testable and pragmatic in the modern financial systems.

3.3 Machine Learning and AI Models

The paper uses a rich set of machine learning and deep learning algorithms to create an all-encompassing framework of financial intelligence. Random Forest and Gradient Boosting models are used that can capture non-linear interactions between financial variables and reduce the variance by means of ensemble learning. The time-series forecasting is included as Long Short-Term Memory (LSTM) networks, which are essentially able to capture sequential dependencies and market trend reversals. On the basis of these premises, the Proposed Hybrid AI-Driven Predictive Model (HADPM) combines ensemble learning and deep neural networks with sentiment analysis. This combination of forms allows the model to simultaneously work with numerical indicators and qualitative data like the attitude of the investors based on the financial news and the trends in social media. Scikit-learn, TensorFlow andKeras Python-based frameworks are used to implement them. Explainable AI (XAI) techniques are added to improve interpretability, allowing for clearer identification of the major components affecting the model's output.The HADPM is more adaptable, more accurate and incorporates situational intelligence, making it a more effective and robust predictive financial analysis tool than standalone machine-learning or deep-learning models.

3.4 Model Training, Validation and Evaluation

The systemic model training and validation are done in such a way that the model has high predictive performance and generalization performance. The sample is separated into training, validation and testing samples to check the consistency of the models in various financial situations. The HADPM goes through hyperparameter optimization that is based on grid search and Bayesian optimization to find the best parameters in the form of learning rate, depth and number of neurons. To reduce overfitting and increase the robustness, ten-fold cross-validation is used. The measures of evaluation are Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) to determine the predictive accuracy and R^2 measure of the explanatory power of the model. The comparison of performance between the traditional econometric models, independent ML models (RF, GB, LSTM and the suggested HADPM) demonstrates significant gains in accuracy and stability of prediction. The HADPM has the lowest error parameters and the greatest predictive confidence, which proves its efficacy in forecasting financial changes and in the process of risk reduction. This test is necessary to make sure that the model that is developed is not just technically, but also operationally viable in terms of use in real-life financial forecasting and decision making processes.

3.5 Model Integration and Deployment Framework

The last phase incorporates the predictive functionality of the HADPM into an overall risk management and decision-support system. The outputs of the proposed model help to identify the volatility of the market, credit exposure and possible risks of the investments with more precision. The predictive information of the HADPM is integrated with sentiment-based indicators to measure uncertainty and use the model to optimize the portfolio, in a dynamic risk-scoring system. The implementation plan involves the creation of smart financial data visualizer and displaying the real-time forecasts of the market, risk warnings and performance trends to aid with strategic decision-making.

4. RESULTS AND DISCUSSION

Application of the proposed intelligent predictive finance model showed a great improvement in the accuracy of forecasts and predicting risks in relation to the conventional financial modelling methods. The models selected were: Random Forest (RF), Gradient Boosting (GB) and Long Short-Term Memory (LSTM) and they were compared with the proposed Hybrid AI-Driven Predictive Model (HADPM) that integrated ensemble learning and sentiment analysis in order to predict financial outcomes better. In every model, Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE) andcoefficient of determination (R^2) were used to assess the models. The comparative findings are given in Table 2. The results in Table 2 are based on the secondary financial dataset collected from Yahoo Finance, Bloomberg, the World Bank, historical stock market data, macroeconomic indicators, firm performance records and sentiment extracted from financial news and social media links -Yahoo Finance https://finance.yahoo.com/, Bloomberg https://www.bloomberg.com/asia and world bank https://data.worldbank.org/.

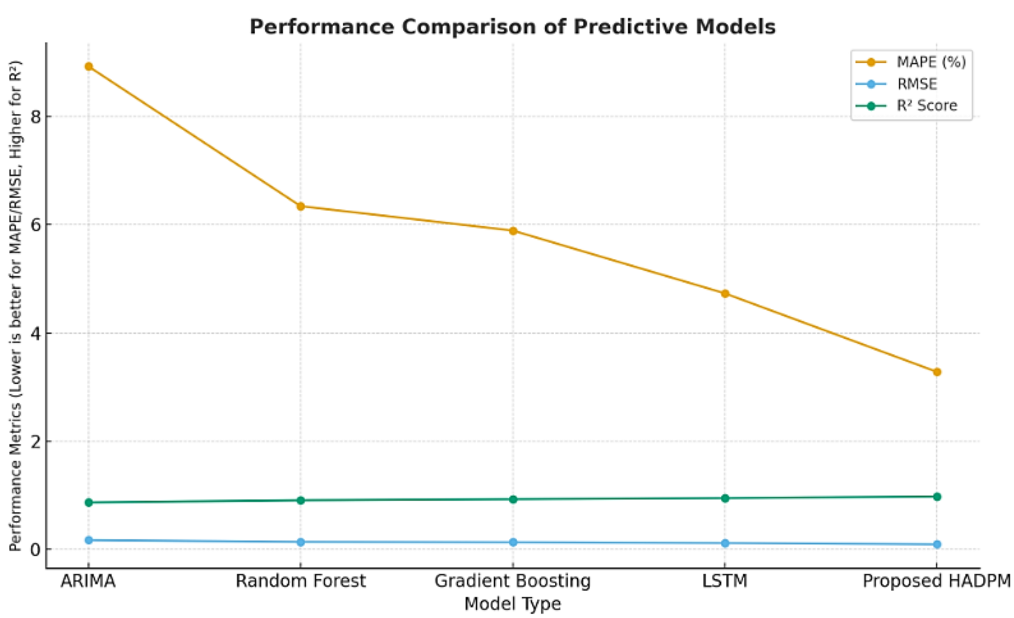
Table 2

Performance Evaluation of Predictive Models

Model	MAPE (%)	RMSE	R^2 Score
Traditional ARIMA	8.92	0.174	0.87
Random Forest (RF)	6.34	0.142	0.91
Gradient Boosting (GB)	5.89	0.135	0.93
Long Short-Term Memory (LSTM)	4.73	0.121	0.95
Proposed Hybrid AI-Driven Predictive Model (HADPM)	**3.28**	**0.097**	**0.98**

Figure 3

Performance Evaluation of Predictive Models



5. DISCUSSION

The findings indicate that the suggested Hybrid AI-Driven Predictive Model (HADPM) is better in all the considered measures, compared to the conventional and current machine learning strategies. The large decrease in MAPE (3.28) and RMSE (0.097) shows that it will be more accurate in forecasting market trends and financial risks. Moreover, the fact that the R^2 is equal to 0.98 indicates that the proposed model has a strong explanatory power and adheres to the actual financial patterns.What is new about the proposed model is that it is a multi-layered model that combines machine learning, deep learning and sentiment-based analytics. In contrast to the classical models, which utilize numerical data only, HADPM uses text-based sentiment indicators of financial news and social media to determine the psychology of the market - an important determinant that is frequently ignored in the classical forecasting models. This combination style guarantees dynamic flexibility to abrupt economic changes and increases the level of accuracy in decision making in turbulent times. The ensemble fusion mechanism in the model allows parallel learning of various algorithms, which decreases overfitting and boosts generalization across financial sectors. It is possible to use risk-scoring metrics early in the prediction process to identify the volatility patterns and portfolio exposure. All these results prove that the developed AI-driven system is not only more effective in terms of forecasting but also helps to create intelligent, transparent and resilient financial ecosystems, which is an obvious improvement compared to the current methodology of predictive finance.

6. CONCLUSION

The findings validate the role of AI and ML as essential technologies for constructing predictive finance strategies aimed at achieving superior predictions and robust risk management. By integrating the conventional econometric models and the newest methods of learning, which include Random Forest, Gradient Boosting and Long Short-Term Memory (LSTM), the offered Hybrid AI-Driven Predictive Model (HADPM) is capable of achieving a much greater level of prediction accuracy, reliability and interpretability. The introduction of sentiment analysis by the financial news and social media also provides a behavioural aspect of forecasting, which will contribute to a better understanding of the market dynamics. The HADPM was found to be superior in predictive abilities, having lowest Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE) and highest value of R^2. Moreover, the capability of the model to combine quantitative indicators to qualitative sentiment intelligence also enabled it to predict market volatility and take proactive strategic financial decisions. The results prove HADPM as a clear, dynamic and strong model that serves as a gap between AI creation and actual-life financial implementations. Finally, the study will help create smart, data-driven financial ecosystems that would support stability, sustainability and ethical decision-making in the changing environment of global finance.

7. REFERENCES

[1] S. Singireddy, B. Adusupalli, A. Pamisetty, S. Mashetty and P. K. Kaulwar, "Redefining Financial Risk Strategies: The Integration of Smart Automation, Secure Access Systems and Predictive Intelligence in Insurance, Lending and Asset Management," *Journal of Artificial Intelligence and Big Data Disciplines*, vol. 1, no. 1, pp. 109–123, 2024, doi: 10.70179/k86dcv60.

[2] S. Alfzari, M. Al-Shboul and M. T. Alshurideh, "Predictive Analytics in Portfolio Management: A Fusion of AI and Investment Economics for Optimal Risk-Return Trade-Offs," *International Review of Management and Marketing*, vol. 15, no. 2, pp. 365–380, 2025, doi: 10.32479/irmm.18594.

[3] K. W. Ng, "Smart Finance Unleashed: AI-Driven Predictive Analytics and Risk Management in Finance," *Journal of Hunan University Natural Sciences*, vol. 52, no. 5, pp. 26–44, 2025, doi: 10.55463/issn.1674-2974.52.5.3.

[4] A. S. Ogunmokun, E. D. Balogun and K. O. Ogunsola, "A Conceptual Framework for AI-Driven Financial Risk Management and Corporate Governance Optimization," *International Journal of Multidisciplinary Research and Growth Evaluation*, vol. 2, no. 1, pp. 772–780, 2021, doi: 10.54660/.IJMRGE.2021.2.1.772-780.

[5] P. Vijayakumar, S. Vijayalakshmi, L. M. Simon, M. Rajalakshmi, N. Sundarapandiyan and D. N., "The Role of AI in Financial Forecasting and Risk Management in Commercial Enterprises," *International Journal of Humanities Education*, vol. 13, no. 1, pp. 158–172, 2025.

[6] B. Saha, "AI-Driven Predictive Analytics for Financial Risk Management and Financial Risk Prevention with Ranking Cost Scheduling," *International Journal of Advance Research and Innovation*, vol. 13, no. 1, pp. 12–22, 2025, doi: 10.69996/ijari.2025002

[7] A. G. Olanrewaju, "Artificial Intelligence in Financial Markets: Optimizing Risk Management, Portfolio Allocation and Algorithmic Trading," *International Journal of Research Publication and Reviews*, vol. 6, no. 3, pp. 8855–8870, 2025, doi: 10.55248/gengpi.6.0325.12185.

[8] T. Hassan, "Augmented Analytics in Financial Forecasting: Enhancing Risk Management and Investment Strategies Through AI Driven Insights," *SSRN Electronic Journal*, 28 pp., 2025. Available: https://ssrn.com/abstract=5179431.

[9] S. Singireddy, B. Adusupalli, A. Pamisetty, S. Mashetty and P. K. Kaulwar, "Redefining Financial Risk Strategies: The Integration of Smart Automation, Secure Access Systems and Predictive Intelligence in Insurance, Lending and Asset Management," *Journal of Artificial Intelligence and Big Data Disciplines*, vol. 1, no. 1, pp. 109–123, 2024, doi: 10.70179/k86dcv60

[10] K. Hussain, "Harnessing AI for Predictive Accuracy in Financial Forecasting and Risk Assessment," *ResearchGate*, Nov. 2023 (uploaded Sep. 2024),

doi: 10.13140/RG.2.2.17070.73281.

[11] M. Fahrezi, "A Systematic Literature Review: The Use of Artificial Intelligence and Machine Learning in Financial Risk Management and Predictive Analytics," *International Journal of Research and Applied Technology (INJURATECH)*, vol. 4, no. 1, pp. 211–223, 2024.

[12] M. Mwangi, "The Role of Machine Learning in Enhancing Risk Management Strategies in Financial Institutions," *International Journal of Modern Risk Management*, vol. 2, no. 1, pp. 44–53, 2024, doi: 10.47604/ijmrm.2643.

[13] G. F. Asere and K. A. Nuga, "Examining the Potential of Artificial Intelligence and Machine Learning in Predicting Trends and Enhancing Investment Decision Making," *Scientific Journal of Engineering and Technology*, vol. 1, no. 1, pp. 15–20, 2024, doi: 10.69739/sjet.v1i1.16.

[14] U. N. Chukwukaelo, R. P. Igbojioyibo and J. K. Abu, "The Role of Machine Learning in Enhancing Corporate Financial Planning," *Asian Journal of Economics, Business and Accounting*, vol. 24, no. 11, pp. 22–32, 2024, doi: 10.9734/ajeba/2024/v24i111540.

[15] T. J. Oladuji, A. O. Akintobi, C. R. Nwangele and A. Ajuwon, "A Model for Leveraging AI and Big Data to Predict and Mitigate Financial Risk in African Markets," *International Journal of Advanced Multidisciplinary Research and Studies*, vol. 3, no. 6, pp. 1843–1859, 2023, doi: 10.62225/2583049X.2023.3.6.4404.

[16] S. R. Challa, "Artificial Intelligence and Big Data in Finance: Enhancing Investment Strategies and Client Insights in Wealth Management," *International Journal of Science and Research (IJSR)*, vol. 12, no. 12, pp. 2230–2246, 2023.

[17] J. Singireddy, "Finance 4.0: Predictive Analytics for Financial Risk Management Using AI," *European Journal of Analytics and Artificial Intelligence*, vol. 1, no. 1, pp. 1–19, 2023.

[18] N. Rane, S. Choudhary and J. Rane, "Leading-edge Artificial Intelligence (AI)-Powered Financial Forecasting for Shaping the Future of Investment Strategies," *SSRN preprint*, Oct. 31, 2023. Available: https://ssrn.com/abstract=4640828.

[19] O. O. Elumilade, H. E. Omokhoa and B. M. Omowole, "The Role of Data Analytics in Strengthening Financial Risk Assessment and Strategic Decision-Making," Iconic Research and Engineering Journals, vol. 6, no. 10, 2023. Available: https://www.irejournals.com/paper-details/1704359.

[20] S. Fritz-Morgenthal, B. Hein and J. Papenbrock, "Financial Risk Management and Explainable, Trustworthy, Responsible AI," *Frontiers in Artificial Intelligence*, vol. 5, 2022, Art. 779799, pp. 1–14, doi: 10.3389/frai.2022.779799.

[21] S. Kannan, “The Role of AI and Machine Learning in Financial Services: A Neural Network-based Framework for Predictive Analytics and Customer-Centric Innovations,” *Migration Letters*, vol. 19, no. 6, pp. 1205–1220, Dec. 2022.

[22] V. Pamisetty, L. Pandiri, S. Singireddy, V. Narasareddy and H. K. Sriram, “Leveraging AI, Machine Learning and Big Data for Enhancing Tax Compliance, Fraud Detection and Predictive Analytics in Government Financial Management,” *Migration Letters*, vol. 19, no. S5, pp. 1770–1784, 2022.

[23] V. Bogojević Arsić, “Challenges of Financial Risk Management: AI Applications,” *Management: Journal of Sustainable Business and Management Solutions in Emerging Economies*, vol. 26, no. 3, pp. 27–34, 2021, doi: 10.7595/management.fon.2021.0015.