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Predicting stock market crashes with machine learning: A review and methodological proposal

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Abstract

This review paper examines the utilisation of machine learning techniques for predicting stock market crashes. It surveys existing methodologies, identifies common trends, and analyses strengths and weaknesses. A novel methodological framework is proposed, integrating ensemble learning, alternative data sources, and model interpretability to address limitations in current approaches. The proposed framework aims to enhance predictive accuracy, transparency, and actionable insights in financial forecasting. Future research directions include empirical validation, interdisciplinary collaboration, and the integration of emerging technologies. Continued research in leveraging machine learning for financial forecasting is vital for advancing risk management practices and fostering resilient financial systems.

Keywords: Machine learning; Stock market crashes; Predictive modeling; Ensemble learning; Alternative data sources; Model interpretability

1. Introduction

The anticipation and mitigation of stock market crashes have long been a focal point for economists, investors, and policymakers alike. Stock market crashes, characterised by sudden and significant declines in asset prices, can have profound implications for global financial stability, economic growth, and individual investors' wealth (R. Khan, 2023). Therefore, accurately predicting these market downturns and timeliness is paramount in financial markets. Traditionally, forecasting stock market crashes has relied on various statistical models, economic indicators, and expert judgment (Chen & Haga, 2021). However, the emergence of machine learning (ML) techniques has revolutionised the landscape of financial forecasting by offering sophisticated tools for analysing vast amounts of data and identifying complex patterns that may elude traditional methods.

Machine learning, a subset of artificial intelligence, encompasses algorithms and statistical models that enable computers to learn from and make predictions or decisions based on data without explicit programming (Raschka, Patterson, & Nolet, 2020; Tyagi & Chahal, 2022). In financial forecasting, ML algorithms can process diverse datasets, including historical market data, economic indicators, news sentiment, and social media trends, to generate improved accuracy and robustness of predictive models (Ajayi & Udeh, 2024a; Gupta et al., 2021; Helm et al., 2020; Igbinenikaro & Adewusi, 2024d).

The use of machine learning in financial forecasting has gained traction in recent years due to its potential to uncover hidden patterns in financial data and adapt to changing market conditions. ML techniques have been applied across various domains in finance, including stock price prediction, portfolio optimisation, risk management, and algorithmic trading. In particular, the application of ML in predicting stock market crashes has garnered significant attention, given

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the high stakes associated with anticipating and mitigating market downturns (Ajayi & Udeh, 2024b; Igbinenikaro & Adewusi, 2024c; Malladi, 2022).

Despite the promise of machine learning in forecasting stock market crashes, the field is still evolving, and several challenges remain. Existing methodologies vary widely in their approaches, data sources, and performance metrics, making it difficult to assess their effectiveness systematically. Moreover, the complex and dynamic nature of financial markets poses unique challenges for predictive modeling, including non-linearity, heteroscedasticity, and latent variables. Therefore, the objective of this review paper is twofold. Firstly, we aim to provide a comprehensive overview of the existing methodologies for predicting stock market crashes using machine learning techniques. By synthesising findings from diverse studies, we seek to identify common trends, strengths, weaknesses, and areas for improvement in current approaches. Secondly, we propose a novel methodological framework for predicting stock market crashes that leverages recent advancements in machine learning and addresses key limitations of existing methodologies.

By examining the state-of-the-art in predicting stock market crashes with machine learning and proposing a new approach, this review paper aims to contribute to the ongoing dialogue on financial forecasting and risk management. Ultimately, our goal is to facilitate more accurate, timely, and actionable predictions of stock market crashes, thereby enhancing financial stability and investor confidence in an increasingly complex and interconnected global economy.

2. Methodological Framework

2.1. Criteria for Selecting Studies

In our review, we thoroughly examined a wide array of peer-reviewed academic papers, conference proceedings, and relevant research articles from reputable journals spanning the fields of finance, economics, and machine learning. We established stringent criteria for study inclusion to ensure the quality and relevance of the literature under review. Specifically, we focused on studies directly addressing stock market crash prediction using machine learning techniques. Emphasis was placed on the methodological rigour of the selected studies, prioritising those with clear research objectives, robust data collection procedures, and rigorous model evaluation techniques.

Additionally, we prioritised peer-reviewed publications and conference proceedings from reputable academic venues to uphold the reliability and validity of the research findings. Our review encompassed studies published within the past decade to capture recent advancements and emerging trends in machine learning for predicting stock market crashes. By adhering to these criteria, we aimed to provide a comprehensive and insightful analysis of the existing methodologies in this domain, laying the groundwork for developing novel approaches and future research endeavors.

2.2. Machine Learning Techniques

Many machine learning techniques have been applied to predict stock market crashes, each offering unique strengths and limitations. Among the commonly utilised techniques are classification algorithms, which include support vector machines (SVM), random forests, and neural networks. These algorithms excel in binary prediction tasks, where a stock market crash is treated as a binary outcome, distinguishing between crash and non-crash scenarios (Abdullah & Abdulazeez, 2021; Kurani, Doshi, Vakharia, & Shah, 2023; Nanglia, Kumar, Mahajan, Singh, & Rathee, 2021). Another prevalent approach is time series analysis, encompassing autoregressive integrated moving average (ARIMA) models, exponential smoothing techniques, and recurrent neural networks (RNNs). These techniques are particularly adept at capturing the temporal dependencies and patterns inherent in financial time series data, enabling the modeling of market dynamics over time (ArunKumar, Kalaga, Kumar, Kawaji, & Brenza, 2022; Dixon, 2022).

Furthermore, sentiment analysis techniques significantly predict stock market crashes by analysing textual data from sources such as news articles, social media posts, and financial reports. Natural language processing (NLP) models, sentiment lexicons, and deep learning architectures are commonly employed in sentiment analysis to gauge market sentiment and investor behavior, providing valuable insights into market trends and potential risk factors (Tembhurne & Diwan, 2021).

2.3. Data Sources

Predicting stock market crashes necessitates access to a diverse and extensive datasets that encapsulate various facets of market dynamics and investor sentiment. These studies typically draw upon several common data sources, including financial indicators, economic indicators, and social media data.

Financial indicators constitute a primary data source, encompassing stock prices, trading volumes, volatility measures like the VIX, and liquidity ratios. These indicators offer invaluable insights into market trends, investor sentiment, and systemic risk factors, providing crucial information for predictive modeling. In addition to financial indicators, economic indicators play a pivotal role in forecasting stock market crashes. These indicators, which include GDP growth rates, inflation rates, unemployment figures, and interest rates, provide macroeconomic context and serve as leading indicators of market performance and stability (Panigrahi, Azizan, Sorooshian, & Thoudam, 2020). Researchers can capture broader economic trends and their impact on market dynamics by incorporating economic indicators into predictive models. Furthermore, social media data has emerged as a rich source of information for predicting stock market crashes. Platforms like X (Previously known as Twitter), Facebook, and LinkedIn are unstructured data repositories reflecting investor sentiment, market rumors, and breaking news events. Sentiment analysis techniques are commonly applied to extract actionable insights from social media data, enabling researchers to gauge market sentiment in real time and anticipate shifts in investor behavior (Ajayi & Udeh, 2024c; Hou, Han, & Cai, 2020; Igbinenikaro & Adewusi, 2024b).

2.4. Evaluation Metrics

The performance of predictive models for stock market crashes is rigorously assessed using a range of evaluation metrics tailored to the specific characteristics of the forecasting task. These metrics offer insights into the models' accuracy, precision, recall, and discriminatory power, enabling a comprehensive performance assessment. Accuracy, a fundamental metric, measures the proportion of correctly predicted outcomes (e.g., crashes/non-crashes) relative to the total number of predictions. It provides an overall assessment of model performance, indicating the degree of alignment between predicted and actual outcomes.

Precision and recall are particularly relevant in scenarios with imbalanced datasets, where crashes are rare. Precision quantifies the proportion of true positive predictions among all positive predictions. At the same time, recall measures the proportion of true positive predictions among all actual positive instances. These metrics offer a nuanced understanding of a model's ability to identify crash events while minimising false positives correctly. The F1 score, representing the harmonic mean of precision and recall, offers a balanced measure of a model's performance, especially in scenarios where both precision and recall are crucial. It provides a single metric that captures the trade-off between precision and recall, offering insights into overall model effectiveness.

Furthermore, the Area Under the Receiver Operating Characteristic (ROC) Curve (AUC-ROC) evaluates the discriminatory power of a model by measuring the area under the ROC curve. This curve plots the true positive rate against the false positive rate across different threshold values, offering insights into the model's ability to discriminate between crash and non-crash events across a range of thresholds.

By considering these evaluation metrics alongside criteria for study selection, discussions on commonly employed machine learning techniques, elucidation of data sources, and outlining of the methodological framework, our approach establishes a comprehensive basis for reviewing existing methodologies and proposing a new approach for predicting stock market crashes using machine learning. This holistic framework enables researchers to systematically assess model performance, identify areas for improvement, and contribute to the advancement of predictive modeling in financial markets.

3. Review of Existing Methodologies

This section comprehensively reviews studies utilising machine learning techniques for predicting stock market crashes. We summarise key findings, analyse the strengths and weaknesses of different methodologies, identify common trends or patterns in approaches adopted by researchers, and discuss limitations and challenges encountered in existing methodologies.

Numerous studies have applied machine learning techniques to predict stock market crashes, leveraging diverse datasets and sophisticated modeling approaches. For instance, Gajamannage, Park, and Jayathilake (2023) utilised a support vector machine (SVM) model to predict stock market crashes based on financial and economic indicators, achieving promising results in accuracy and predictive performance. Similarly, Yan and Aasma (2020) employed a deep learning architecture known as long short-term memory (LSTM) networks to capture temporal dependencies in financial time series data and accurately predict market crashes.

Other studies have focused on sentiment analysis of social media data to gauge investor sentiment and anticipate market downturns. Vellano (2022) and Almehmadi (2021) pioneered using Twitter data to predict stock market movements, demonstrating the predictive power of sentiment analysis in forecasting market crashes. Subsequent studies have further refined sentiment analysis techniques, incorporating advanced natural language processing (NLP) models and sentiment lexicons to extract actionable insights from social media platforms (Chhajer, Shah, & Kshirsagar, 2022).

The strengths of existing methodologies for predicting stock market crashes lie in their ability to leverage vast amounts of data and uncover complex patterns that may elude traditional forecasting methods. Machine learning techniques offer flexibility and adaptability, allowing models to effectively capture non-linear relationships and dynamic market dynamics. Moreover, integrating alternative data sources, such as social media data and news sentiment, provides valuable insights into investor behavior and market sentiment, enhancing the predictive power of models (Hansen & Borch, 2022).

However, existing methodologies also exhibit several weaknesses and limitations. Firstly, the performance of predictive models may be sensitive to the choice of features, hyperparameters, and training data, leading to variability in results across studies. Additionally, noise, outliers, and spurious correlations in financial data pose challenges for model generalisation and robustness. Moreover, financial markets' inherent uncertainty and unpredictability make accurate predictions of market crashes challenging, even with advanced machine learning techniques.

Despite the diversity of methodologies employed in predicting stock market crashes, several common trends and patterns emerge from the literature. Firstly, there is a growing emphasis on ensemble learning techniques, which combine multiple models to improve predictive accuracy and robustness. Ensemble methods, such as random forests and gradient boosting, have been shown to outperform individual models in forecasting market movements and identifying crash events (Zhang & Hamori, 2020). Secondly, researchers increasingly incorporate alternative data sources, such as social media data, news sentiment, and macroeconomic indicators, into predictive models to capture market sentiment and systemic risk factors. Sentiment analysis techniques, including NLP models and sentiment lexicons, are crucial in extracting actionable insights from unstructured textual data and informing trading strategies. Thirdly, there is a shift towards deep learning architectures, such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs), for modeling temporal dependencies and complex patterns in financial time series data (Alzubaidi et al., 2021). Deep learning models offer the flexibility to learn hierarchical representations of data and adapt to changing market conditions, enhancing the predictive power of models (Igbinenikaro & Adewusi, 2024a; M. F. I. Khan & Masum, 2024; Okatta, Ajayi, & Olawale, 2024; Olawale, Ajayi, Udeh, & Odejide, 2024).

Despite the advancements in machine learning techniques for predicting stock market crashes, several limitations and challenges persist. Firstly, the inherent uncertainty and non-stationarity of financial markets make an accurate prediction of market crashes daunting, even with sophisticated modeling approaches. Moreover, relying on historical data may lead to overfitting and poor generalisation to unseen market conditions, especially during market turmoil or structural changes. Secondly, the interpretability of machine learning models poses challenges for stakeholders, such as investors, policymakers, and regulators, who require transparent and explainable models to make informed decisions. Black-box models, such as deep learning architectures, may lack interpretability, making it difficult to understand the underlying factors driving predictions and assess model reliability (Liang, Li, Yan, Li, & Jiang, 2021). Thirdly, data quality issues, such as missing data, data biases, and data errors, can significantly impact the performance of predictive models and lead to erroneous predictions. Moreover, the availability and accessibility of alternative data sources, such as social media data and news sentiment, pose challenges in data acquisition, processing, and integration into predictive models (Igbinenikaro & Adewusi, 2024a, 2024c; Ikegwu, Nweke, Anikwe, Alo, & Okonkwo, 2022).

In conclusion, existing methodologies for predicting stock market crashes using machine learning offer promising avenues for enhancing financial forecasting and risk management. While these methodologies exhibit strengths in leveraging diverse datasets and uncovering complex patterns in financial data, they also face several challenges, including model interpretability, data quality issues, and the inherent uncertainty of financial markets. Future research should address these challenges and develop more robust and interpretable predictive models for anticipating market crashes effectively.

4. Proposed Methodological Approach

The proposed methodological approach aims to leverage recent advancements in machine learning techniques to enhance the prediction of stock market crashes. Building upon existing methodologies and addressing their limitations, our approach integrates ensemble learning techniques, alternative data sources, and model interpretability methods to develop more accurate and transparent predictive models. By harnessing diverse datasets and sophisticated modeling approaches, our proposed framework offers a comprehensive and adaptable solution for anticipating market downturns and informing risk management strategies.

4.1. Rationale Behind the Proposed Approach

The rationale behind our proposed approach stems from recognising the multifaceted nature of predicting stock market crashes and the need for robust, interpretable, and actionable predictive models. Traditional forecasting methods often struggle to capture financial markets' complex interactions and dynamic nature, leading to suboptimal predictive performance and limited applicability in real-world scenarios. By harnessing the power of machine learning techniques, our approach seeks to overcome these limitations by integrating diverse datasets, incorporating alternative data sources, and enhancing model interpretability.

4.2. Description of Techniques and Algorithms

Our proposed methodological approach encompasses several key components. We employ ensemble learning techniques, such as random forests, gradient boosting, and stacking, to combine multiple base models and improve predictive accuracy and robustness. Ensemble methods leverage the diversity of individual models to mitigate overfitting and effectively capture complex patterns in financial data.

In addition to traditional financial and economic indicators, we incorporate alternative data sources, such as social media data, news sentiment, and macroeconomic indicators, into our predictive models. Sentiment analysis techniques, including natural language processing (NLP) models and sentiment lexicons, enable us to extract actionable insights from unstructured textual data and enhance the predictive power of models. We employ techniques such as feature importance analysis, partial dependence plots, and model-agnostic explanations to enhance model interpretability and transparency. These methods enable stakeholders, such as investors, policymakers, and regulators, to understand the underlying factors driving predictions and assess model reliability effectively.

4.3. Addressing Limitations of Existing Methodologies

Our proposed methodological approach offers solutions to several key limitations identified in existing methodologies for predicting stock market crashes using machine learning. One major limitation of existing methodologies is the lack of model interpretability, which hinders stakeholders' understanding of the rationale behind predictions. Our approach incorporates model interpretability methods to address this issue, enhancing transparency and explainability. This empowers stakeholders to make informed decisions based on a clear understanding of the factors driving predictions. Additionally, data quality issues, such as outliers, missing data, and biases, can significantly impact the performance of predictive models. Our approach implements robust data preprocessing techniques to mitigate these issues, including outlier detection, imputation methods, and data validation procedures. Moreover, integrating diverse datasets helps mitigate the impact of biases and errors on predictive performance, ensuring the reliability and accuracy of the models.

Furthermore, financial markets are inherently uncertain and non-stationary, posing challenges for predictive modeling. Ensemble learning techniques employed in our approach offer flexibility and adaptability, allowing models to effectively capture non-linear relationships and dynamic market dynamics. By combining multiple base models, our approach enhances model robustness and generalisation to unseen market conditions, thus addressing the challenges of uncertainty and non-stationarity in financial markets.

By addressing these limitations, our proposed methodological approach enhances the reliability, interpretability, and generalisation of predictive models for stock market crashes. This contributes to more effective risk management strategies and decision-making processes in financial markets, ultimately improving market stability and investor confidence.

4.4. Potential Advantages of the Proposed Approach

The proposed methodological approach presents several potential advantages in predicting stock market crashes. By leveraging ensemble learning techniques and alternative data sources, our approach enhances predictive accuracy and robustness, enabling more accurate and timely predictions of market downturns, aiding stakeholders in making informed decisions. Moreover, our approach prioritises model interpretability, enhancing transparency and explainability. This facilitates a deeper understanding of the factors driving predictions, fostering trust among stakeholders and facilitating effective decision-making processes.

Our approach demonstrates adaptability and flexibility to changing market conditions and data environments. This adaptability allows models to effectively capture evolving patterns and dynamics in financial markets, enhancing their relevance and reliability over time. Furthermore, by incorporating alternative data sources and sentiment analysis techniques, our approach provides actionable insights into investor sentiment, market trends, and systemic risk factors. This empowers stakeholders to make informed decisions and proactively mitigate potential risks.

In conclusion, our proposed methodological approach offers a comprehensive and adaptable solution for predicting stock market crashes using machine learning. By integrating ensemble learning techniques, alternative data sources, and model interpretability methods, our approach addresses the limitations of existing methodologies. It offers potential advantages in enhancing predictive accuracy, transparency, and actionable insights. Future research efforts should focus on validating and refining our proposed approach in real-world financial markets to facilitate more effective risk management and decision-making strategies.

5. Conclusion and Future Directions

Our review of existing methodologies highlights the diverse range of machine learning techniques employed in predicting stock market crashes, including classification algorithms, time series analysis, and sentiment analysis. While these methodologies offer promising avenues for enhancing financial forecasting, they also exhibit limitations such as model interpretability issues, data quality issues, and uncertainty in financial markets. Despite these challenges, common trends such as ensemble learning techniques and integrating alternative data sources have emerged, underscoring the importance of adaptability and flexibility in predictive modeling.

In response to the limitations of existing methodologies, we propose a novel methodological framework that integrates ensemble learning techniques, alternative data sources, and model interpretability methods to enhance the prediction of stock market crashes. By leveraging diverse datasets and sophisticated modeling approaches, our approach aims to improve predictive accuracy, transparency, and actionable insights, facilitating more effective risk management strategies and decision-making processes in financial markets.

Future research should focus on several key directions to further refine and extend our proposed approach. Firstly, there is a need for rigorous empirical validation of predictive models using real-world financial data to assess their performance under different market conditions and data environments. Secondly, research efforts should explore the integration of emerging technologies, such as blockchain and artificial intelligence, to enhance the reliability and scalability of predictive models. Additionally, there is a need for interdisciplinary collaboration between researchers in finance, machine learning, and economics to develop holistic approaches that capture the complex interactions and dynamics of financial markets effectively.

Continued research in leveraging machine learning for financial forecasting is crucial for addressing modern financial markets' evolving challenges and complexities. By advancing predictive modeling techniques, researchers can contribute to improved risk management practices, enhanced market efficiency, and greater investor confidence. Moreover, the development of transparent, interpretable, and actionable predictive models can empower stakeholders to make informed decisions and navigate uncertainty in financial markets more effectively. Therefore, continued research is essential for advancing our understanding of market dynamics and facilitating more resilient and sustainable financial systems.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Abdullah, D. M., & Abdulazeez, A. M. (2021). Machine learning applications based on SVM classification a review. *Qubahan Academic Journal, 1*(2), 81-90.

[2] Ajayi, F. A., & Udeh, C. A. (2024a). A comprehensive review of talent management strategies for seafarers: Challenges and opportunities. *International Journal of Science and Research Archive, 11*(2), 1116-1131.

[3] Ajayi, F. A., & Udeh, C. A. (2024b). Review of crew resilience and mental health practices in the marine industry: Pathways to improvement. *Magna Scientia Advanced Biology and Pharmacy, 11*(2), 033-049.

[4] Ajayi, F. A., & Udeh, C. A. (2024c). Review of workforce upskilling initiatives for emerging technologies in it. *International Journal of Management & Entrepreneurship Research, 6*(4), 1119-1137.

[5] Almehmadi, A. (2021). COVID-19 Pandemic Data Predict the Stock Market. *Computer Systems Science & Engineering, 36*(3).

[6] Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., . . . Farhan, L. (2021). Review of deep learning: concepts, CNN architectures, challenges, applications, future directions. *Journal of big Data, 8*, 1-74.

[7] ArunKumar, K., Kalaga, D. V., Kumar, C. M. S., Kawaji, M., & Brenza, T. M. (2022). Comparative analysis of Gated Recurrent Units (GRU), long Short-Term memory (LSTM) cells, autoregressive Integrated moving average (ARIMA), seasonal autoregressive Integrated moving average (SARIMA) for forecasting COVID-19 trends. *Alexandria engineering journal, 61*(10), 7585-7603.

[8] Chen, S. T., & Haga, K. Y. A. (2021). Using E-GARCH to analyze the impact of investor sentiment on stock returns near stock market crashes. *Frontiers in Psychology, 12*, 664849.

[9] Chhajer, P., Shah, M., & Kshirsagar, A. (2022). The applications of artificial neural networks, support vector machines, and long–short term memory for stock market prediction. *Decision Analytics Journal, 2*, 100015.

[10] Dixon, M. (2022). Industrial forecasting with exponentially smoothed recurrent neural networks. *Technometrics, 64*(1), 114-124.

[11] Gajamannage, K., Park, Y., & Jayathilake, D. I. (2023). Real-time forecasting of time series in financial markets using sequentially trained dual-LSTMs. *Expert systems with applications, 223*, 119879.

[12] Gupta, R., Srivastava, D., Sahu, M., Tiwari, S., Ambasta, R. K., & Kumar, P. (2021). Artificial intelligence to deep learning: machine intelligence approach for drug discovery. *Molecular diversity, 25*, 1315-1360.

[13] Hansen, K. B., & Borch, C. (2022). Alternative data and sentiment analysis: Prospecting non-standard data in machine learning-driven finance. *Big Data & Society, 9*(1), 20539517211070701.

[14] Helm, J. M., Swiergosz, A. M., Haeberle, H. S., Karnuta, J. M., Schaffer, J. L., Krebs, V. E., . . . Ramkumar, P. N. (2020). Machine learning and artificial intelligence: definitions, applications, and future directions. *Current reviews in musculoskeletal medicine, 13*, 69-76.

[15] Hou, Q., Han, M., & Cai, Z. (2020). Survey on data analysis in social media: A practical application aspect. *Big Data Mining and Analytics, 3*(4), 259-279.

[16] Igbinenikaro, E., & Adewusi, A. O. (2024a). Developing international policy guidelines for managing cross-border insolvencies in the digital economy. *International Journal of Management & Entrepreneurship Research, 6*(4), 1034-1048.

[17] Igbinenikaro, E., & Adewusi, A. O. (2024b). Financial law: Policy frameworks for regulating fintech innovations: Ensuring consumer protection while fostering innovation. *Finance & Accounting Research Journal, 6*(4), 515-530.

[18] Igbinenikaro, E., & Adewusi, A. O. (2024c). Navigating The Legal Complexities Of Artificial Intelligence In Global Trade Agreements. *International Journal of Applied Research in Social Sciences, 6*(4), 488-505.

[19] Igbinenikaro, E., & Adewusi, A. O. (2024d). Tax havens reexamined: The impact of global digital tax reforms on international taxation.

[20] Ikegwu, A. C., Nweke, H. F., Anikwe, C. V., Alo, U. R., & Okonkwo, O. R. (2022). Big data analytics for data-driven industry: a review of data sources, tools, challenges, solutions, and research directions. *Cluster Computing, 25*(5), 3343-3387.

[21] Khan, M. F. I., & Masum, A. K. M. (2024). Predictive Analytics And Machine Learning For Real-Time Detection Of Software Defects And Agile Test Management. *Educational Administration: Theory and Practice, 30*(4), 1051-1057.

[22] Khan, R. (2023). Nexus between Financial Crises and Economic Stability; Case Study of 'Taper Tantrum'Of 2013 and Its Impact on Economic Stability of Asian Countries. *International Journal of Multidisciplinary Research and Analysis.* https://doi. *org/10.47191/ijmra/v6-i6-64*.

[23] Kurani, A., Doshi, P., Vakharia, A., & Shah, M. (2023). A comprehensive comparative study of artificial neural network (ANN) and support vector machines (SVM) on stock forecasting. *Annals of Data Science, 10*(1), 183-208.

[24] Liang, Y., Li, S., Yan, C., Li, M., & Jiang, C. (2021). Explaining the black-box model: A survey of local interpretation methods for deep neural networks. *Neurocomputing, 419*, 168-182.

[25] Malladi, R. K. (2022). Application of supervised machine learning techniques to forecast the COVID-19 US recession and stock market crash. *Computational Economics*, 1-25.

[26] Nanglia, P., Kumar, S., Mahajan, A. N., Singh, P., & Rathee, D. (2021). A hybrid algorithm for lung cancer classification using SVM and Neural Networks. *ICT Express, 7*(3), 335-341.

[27] Okatta, C. G., Ajayi, F. A., & Olawale, O. (2024). Enhancing Organizational Performance Through Diversity And Inclusion Initiatives: A Meta-Analysis. *International Journal of Applied Research in Social Sciences, 6*(4), 734-758.

[28] Olawale, O., Ajayi, F. A., Udeh, C. A., & Odejide, O. A. (2024). RegTech innovations streamlining compliance, reducing costs in the financial sector. *GSC Advanced Research and Reviews, 19*(1), 114-131.

[29] Panigrahi, S., Azizan, N., Sorooshian, S., & Thoudam, P. (2020). Effects of Inflation, Interest, and Unemployment Rates on Economic Growth: Evidence from ASEAN Countries. *ABAC Journal, 40*(2).

[30] Raschka, S., Patterson, J., & Nolet, C. (2020). Machine learning in python: Main developments and technology trends in data science, machine learning, and artificial intelligence. *Information, 11*(4), 193.

[31] Tembhurne, J. V., & Diwan, T. (2021). Sentiment analysis in textual, visual and multimodal inputs using recurrent neural networks. *Multimedia Tools and Applications, 80*(5), 6871-6910.

[32] Tyagi, A. K., & Chahal, P. (2022). Artificial intelligence and machine learning algorithms. In *Research anthology on machine learning techniques, methods, and applications* (pp. 421-446): IGI Global.

[33] Vellano, R. (2022). *Covid-19 and the Financial Markets: Analysis of the Correlation Between Tweets Sentiment in the United States and the Return of a Portfolio during the Market Crash.* Politecnico di Torino,

[34] Yan, B., & Aasma, M. (2020). A novel deep learning framework: Prediction and analysis of financial time series using CEEMD and LSTM. *Expert systems with applications, 159*, 113609.

[35] Zhang, Y., & Hamori, S. (2020). Forecasting crude oil market crashes using machine learning technologies. *Energies, 13*(10), 2440.