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Machine Learning Models for Forecasting Foreign Direct Investment (FDI) Flows

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Abstract

The forecasting of Foreign Direct Investment (FDI) flows is essential for governments and private entities that need to make informed strategic choices in today's dynamic global market. Standard econometric approaches like gravity equations and time-series models face difficulties in representing the complex nonlinear and high-dimensional relationships present in FDI determinants. This research investigates the use of various machine learning methods like Random Forests, Gradient Boosting Machines, Support Vector Machines, and Neural Networks to enhance the forecasting of FDI flows. The study examined the foundational theories of machine learning models, strengths and weaknesses, and capacity to improve forecasting accuracy and model interpretability. The research emphasized how combining domain expertise with transparent interpretable machine learning methods enhances decision-making and policy creation processes. This synthesis provides direction for upcoming empirical investigations and methodological decisions and strengthening the use of ML technology in forecasting Foreign Direct Investment (FDI) flows.

Keywords: Machine Learning Models, Forecasting, Foreign Direct Investment, Predictive Analytics, Economic Policy, Interpretability

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Introduction

International investment known as Foreign Direct Investment (FDI) serves as a vital pathway for economic advancement, technological exchange, and worldwide integration. How much FDI enters a country with its investment pattern dictates the nation's growth path, job creation potential, and innovative capabilities. Through precise forecasting of FDI flows governments gain the ability to implement successful policies, optimize resource allocation, and create attractive conditions for foreign investors (Islam et al., 2024). Multinational corporations utilize FDI forecasts to strategically manage their investment portfolios and evaluate potential risks (Trajanov et al., 2017).

The main tool for FDI forecasting efforts has historically been econometric models, gravity equations, time series models like ARIMA, and panel regressions. These forecasting models derive from economic theory and typically presume either linear or additive connections between variables. The complex and multifaceted nature of FDI determinants which includes macroeconomic, political, institutional and social factors presents substantial challenges for traditional forecasting methods (Blonigen & Piger, 2014; Buckley et al., 2015; Paul & Jadhav, 2020). These relationships frequently demonstrate nonlinear characteristics; they contain complex interactions and are influenced by factors which remain unobserved.

The introduction of machine learning (ML) creates fresh possibilities to overcome these constraints. Machine learning techniques show superior performance compared to traditional models when extracting patterns from large high-dimensional datasets for forecasting analysis (Batarseh et al., 2019; Jošić & Žmuk, 2022). The adaptable nature of machine learning enables the modelling of nonlinear behaviours and connections as well as unstructured information sources like news sentiment or social media activity which holds growing importance in today's fast-paced global environment (Carvalho et al., 2019).

Political leaders, investors, and economic analysts need accurate forecasts of direct foreign investment (FDI) flows because it functions as a measure of regional economic stability and progress. Interested parties can develop informed strategies to attract investments and promote economic growth by understanding FDI dynamics. FDI serves as a critical driver of economic growth by enabling job creation, technology transfer, and fostering infrastructural development specifically in emerging economies (Islam et al., 2024). Precise forecasting of FDI flows is essential for shaping economic policies that could enable sustainable development.

Machine learning models (ML) introduced a transformation in how FDI forecasting is performed. Although traditional time series models like Autoregressive Integrated Moving Average (ARIMA) offer benefitsbut struggle to fully represent the intricacies of financial data(Abd El-Aal et al., 2021; Yusuf, 2022). Research has demonstrated that machine learning techniques like random forests and evolutionary algorithms outperform traditional methods in FDI forecasting (Abd El-Aal et al., 2021; Rapoo et al., 2023). Yusuf (2022) argued that ML algorithms offer better precision in forecasting FDIs in sub-Saharan Africa compared to traditional models.

The use of interpretable machine learning approaches as explained by Singh (2021) offers extra benefits that enable investigators and policy makers see how FDI forecasting decisions are made. The availability of transparent information builds trust among stakeholders and supports improved decision making. Deep learning advancements have broadened available forecasting tools for international trade and FDI which demonstrate these models' ability to enhance predictive analysis (Yang et al., 2023).

This research seeks to understand how forecasting FDI flows can be improved through machine learning models and comparing different prediction techniques. This study examined how interpretable machine learning approaches can enhance transparency and policy development processes within FDI research according toJošić and Žmuk (2022) and Vujanović et al. (2021). This multifaceted approach is expected to provide important perspective that will help refine FDI forecasting methods and enhance economic policy development.In addition, this research paper provides theoretical guidance for applying machine learning models to forecast FDI flows. We conducted a review of existing literature and examined the theoretical basis of ML techniques, evaluated benefits, and addressed challenges. We established groundwork for empirical studies and advance knowledge about ML's role in improving foreign direct investment forecasting.

Literature Review

Traditional Methods in Foreign Direct Investment (FDI) Forecasting

Traditional methods for forecasting Foreign Direct Investment (FDI) mainly depended on models derived from economic theory. According to gravity models based on trade theory principles FDI flows between two countries scale with their economic mass but decline as the geographical distance between them increases (Blonigen & Piger, 2014). Economic size and geographic distance, population figures, and cultural connections serve as key variables in these models. Gravity models offer intuitive understandability, but assumption of linear relationships hinders ability to account for unobserved heterogeneity and complex interactions.

Forecasters have utilized time-series models such as ARIMA to forecast aggregate FDI flows by analyzing past data trends (Yusuf, 2022). Research has applied panel data regressions to investigate factors that change across nations and through time periods. The models remain limited in their ability to capture nonlinear relationships and complex interaction effects which are common in FDI dynamics despite widespread usage (Abd El-Aal et al., 2021).

Traditional forecasting methods in foreign direct investment (FDI) have significantly shaped decision-making processes for both companies and policy formulators. The effectiveness and limitations of these analysis methods based on historical data and empirical research have faced considerable scrutiny. The main approach requires evaluating host countries' environmental and regulatory frameworks. Chung (2014) revealed that environmental rules in South Korea have a substantial effect on FDI flows which proves the need for traditional forecasting models to integrate local regulatory frameworks to achieve greater accuracy.

Forecast methodologies have advanced with the growing level of sophistication throughout history. Tradition models relied on basic economic analysis but current research now acknowledges global markets' complexity. Buckley et al. (2015) found multiple factors influencing Chinese external FDI and advised that traditional forecasting models must include broader elements such as political risk and country conditions. Gaur et al. (2018) noted the essential role of support from the country of origin for forecasting FDI patterns by showing decision making in international investments requires complex analysis rather than single indicators.

Traditional forecasting methods show progress yet continue to face numerous limitations. Research conducted by Nielsen et al. (2017) illustrates that methodological challenges hinder accurate identification of FDI locations and that static models fail to forecast outcomes effectively in dynamic settings. According to Seker et al. (2015), decision makers are at risk of deception because an exclusive economic indicator approach overlooks important interactions such as the environmental effects of FDI. The examination of FDI effects reveals

how it acts as a driver of economic growth. Bermejo and Werner (2018) present an empirical method for studying Spain's investment dynamics and assert that traditional forecasting techniques are essential to depict the investment's multiple effects. Cui et al. (2014) defend their approach to re-examining strategic asset searches among emerging economies in response to these challenges. Cui et al. (2014) support the need to reassess strategic asset search behaviours within emerging economic companies because these behaviours typically differ from standard forecasting models. Knowledge about traditional forecasting methods' strengths and weaknesses in FDI is essential for making informed business decisions as international business environments change.

Emergence of Machine Learning in Economic and Financial Forecasting

Recent advancements in machine learning (ML) techniques have earned widespread recognition in economic and financial fields because they enhance forecasting accuracy. McAfee and Brynjolfsson (2017) showed that machine learning algorithms such as Random Forests, Support Vector Machines (SVMs), and neural networks deliver better results than traditional linear models across multiple forecasting applications. Research supports the effectiveness of machine learning (ML) in forecasting macroeconomic indicators (Nyholm, 2022), forecasting stock market trends (Fischer & Krauss, 2018), and analyzing trade flows (Trajanov et al., 2017). Machine learning (ML) technologies have revolutionized traditional economic and financial forecasting methods by enhancing both precision and efficiency. The latest advancements produced multiple tools that transformed decision-making processes across various applications.

Artificial intelligence (AI) and machine learning (ML) systems have streamlined trading operations, risk management, and operational tactics in financial markets (El Hajj & Hammoud, 2023). Because of the ability to handle vast amounts of data automatically, learning models have equipped investors with better forecasting capabilities which have resulted in well-informed and timely decision-making. Rane et al. (2024) argued that neural networks in deep learning have surpassed classical statistical models in forecasting accuracy by enabling pattern recognition in complex data sets that were once inaccessible.Research shows that machine learning applications are used to examine profitability within financial markets. According to Khattak et al. (2023), through a comprehensive review of artificial intelligence models, these systems boost forecasting methods and enhance performance for both short-term and long-term trading investments. In a related study, Sonkavde et al. (2023) demonstrates that machine learning and deep learning models achieve superior forecasting accuracy compared to traditional methods in showcasing vital contribution to stock market price dynamics.

The impact of ML can be seen through its enhancements in operational efficiency and market responsiveness. Research by Afolabi et al. (2025) showed how machine learning techniques can lead organizations toward sustainable economic growth and market efficiency thereby making these technologies essential for competitive advantage. Tulli (2023) suggested that machine learning techniques optimize marketing processes, sales operations, and enhance innovation and financial management across company functions.

The evolving environment brings new hurdles but still faces enduring difficulties regarding data quality and ML model interpretation. Bi et al. (2024) study investigates the role of AI in financial forecasting and its potential and challenges. The study emphasized the need for a solid framework responsible and transparent for AI-based decision-making. Paramesha et al. (2024) provided thorough knowledge of AI technologies, ML, and Blockchain to successfully manage the intricate financial sector operations.The thorough use of ML technologies in economic and financial forecasting improved prediction accuracy, create a new way of

strategy formulation and decision-making. The advancements demonstrate the need for ongoing research and adaptation to maximize machine learning benefits in these vital sectors.

Applications of Machine Learning in FDI and Related Fields

The applications of machine learning for foreign direct investment forecasting remain sparse but existing research suggests significant potential in this field. Luo et al. (2019) used ensemble learning techniques to forecast macroeconomic variables and posited that these methods could be transferred to FDI forecasting. Research shows that sentiment analysis models using news and social media data can forecast financial disruptions and investment directions, and demonstrate the value of unstructured information sources (Fischer & Krauss, 2018).Machine learning (ML) functions as an evolutionary tool that improves decision-making processes and risk evaluation, it enables trend forecast in foreign direct investment (FDI). Machine learning algorithms used for data analysis and automation enable investors to navigate global market complexities through decisions based on thorough data analysis and economic predictions.

Yusuf (2022) study compared multiple machine learning algorithms which predicted FDI for sub-Saharan Africa and showed that these methods provided higher accuracy and reliability than traditional statistical approaches like ARIMA. Machine learning demonstrates its capacity to harness extensive data sets to draw valuable conclusions which then shape strategic investment choices. The use of machine learning in economic forecasting enables the detection of new trends and potential investment risks.The dynamic nature of global markets makes it impossible to overstate the importance of strong FDI risk assessment frameworks. Kemiveš et al. (2024) discovered key indicators to forecastFDI through asymmetrical optimization techniques that leverage machine learning to offer refined understanding into risk factors. Machine learning models analyze extensive data sets to reveal critical variables influencing FDI flows which enable policy makers and businesses to reduce investment decision risks.

Rapoo et al. (2023) examined hybrid modelling approaches that integrate machine learning techniques to forecast FDI patterns. The research revealed how ML-based evolutionary algorithms deliver precise results when analyzing complex economic indicators interdependencies. Automation and advanced analysis techniques represent the wider movement to enhance decision-making processes amid the growing competition in global investments.The global investment climate requires fundamental knowledge of how external determinants affect FDI flows. Arel-Bundock (2017) revealed the political determinants of FDI through corporate analysis and suggests machine learning models should incorporate socio-political factors to predict investment patterns. Machine learning which analyzes data from multiple angles like economic, social, and political sources serves as a crucial instrument for the examination of investor behaviour and underlying motivations.

Islam et al. (2024) studied how machine learning techniques are implemented to analyze foreign direct investment entry into Bangladesh. The authors noted that machine learning enhances forecasting capabilities through the integration of random forest methods and ARIMA models which helps investors make better-informed decisions. The approach enhances precision andenables real-time analysis of FDI trends which serves as a critical element for implementing dynamic investment strategies.The structured complexity of economic elements presents challenges in forecasting trends within FDI. Nielsen et al. (2017) tackled methodological difficulties by delivering empirical data regarding FDI location choices. Machine learning methodologies enhance analytical processes through forecasting insights that companies use to perfect market entry approaches.

Magazzino and Mele (2025) developed a new machine learning algorithm which examines the interconnected relationships between CO2 emissions energy consumption and economic growth thereby demonstrating the potential of machine learning to move beyond its conventional applications. Machine learning demonstrates its capacity to provide valuable insights for economic considerations and sustainable investment strategies on a global level.

The use of machine learning in decision-making processes, risk assessment, and trend forecast in foreign direct investment demonstrates a meaningful improvement in analytical abilities. Machine learning remains critical for organizations and policy makers as they work to make better investment choices by processing large datasets to understand hidden patterns in today's complex global market. Both theoretical models and empirical research validate the transformative power of machine learning to enhance the analysis and forecasting of foreign direct investment (FDI).

Determinants of Foreign Direct Investment (FDI)

Developing nations experience economic growth driven substantially by Foreign Direct Investment (FDI). Policy formulators and academic researchers need to understand factors that determine FDI to create effective policies. FDI decisions rely heavily on economic indicators, political stability, institutional quality, market infrastructure, and geographical factors also have fundamental impacts. FDI decisions have been fundamentally influenced by economic factors like GDP growth rates, inflation, and exchange rate trends. According to the panel data study by Kumari and Sharma (2017), higher GDP growth rates lead to increased FDI as investors aim to tap into markets with high potential returns. Tocar (2018) argued that stable exchange rates minimize investment risks which leads to higher capital commitments from foreign investors. The results support the idea that robust economic conditions are essential for drawing foreign direct investment.

Political stability is another crucial determinant. Arel-Bundock (2017) study showed that businesses analyze political risks when deciding to invest. Foreign investors tend to prefer countries with stable governments because these countries provide a predictable business environment for operations. Research by Paul and Jadhav (2020) showed that political instability or corruption deters investment because there is a strong link between stable politics and foreign direct investment in developing economies.

A favourable investment climate depends on high-quality institutions. According to Lucke and Eichler (2016) strong institutional structures result in greater transparency and lower transaction costs which enhance the attractiveness of FDI. The enforcement of property rights and contract application by institutions builds investor confidence and leads to countries like Singapore and Switzerland becoming ideal destinations for FDI (Villaverde & Maza, 2015). Sarkutė et al. (2024) confirmed that institutions play a key role in strategic management choices regarding FDI because robust institutions build sustainable investment environments.

Well-established market infrastructure elements such as transportation systems, communication networks, and banking systems attracts FDIs. When states focus on market infrastructure investments, they establish favourable conditions that facilitate business operations. Buckley et al. (2015) observed that multinational productivity increases through access to reliable infrastructure which then strengthens the FDI. Foreign investors find countries with strong logistics networks more appealing because a well-developed market infrastructure reduces operational risks.

The geographical attributes such as market proximity, resource availability, and national scale serve as important factors for FDI decision-making. Foreign investors often prefer countries

with extensive domestic markets because they offer an existing consumer base. Buckley et al. (2015) states that geographical benefits can help offset the negative impact of poor political or institutional environments. Regions that possess abundant natural resources attract FDI from companies that aim to explore these resources (Buckley et al., 2015).

The examination of determinants of FDI demonstrates intricate relationships among economic elements, political stability, institutional strength, market infrastructure, and geographical characteristics. Research conclusions indicate that countries must develop stable economic conditions, strong institutions, invest in infrastructure, and maximize geographical benefits to increase FDI flows. Policy formulators need to treat these interconnected elements as a whole to create effective policies that attract foreign investments which support economic growth and development within their nations.

Machine Learning Models: Theoretical Foundations

Machine Learning (ML) models are designed to learn complex functions from data, with theoretical guarantees rooted in statistical learning theory. The development of machine learning generated several fundamental ideas where the balance between bias and variance stands out as essential to comprehend model performance. The concept of variance compromise introduced here explains how a model manages to reduce systematic prejudice-error from oversimplified models and handle variance-error caused by excessive sensitivity to training data fluctuations (Ranglani, 2024). The dual nature of model selection results in a natural dichotomy that affects predictive performance. According to Belkin et al. (2019), effective generalization requires merging modern machine learning methods with the traditional variance of distortion framework.

Regularization approaches function to reduce excess and target the variance aspect of the trade-off. Penalties added during the model training phase help regularization reduce model complexity which results in improved generalization performance on unseen data. Dar et al. (2021) explains why regularization methods are indispensable in heavily parameterized environments which leads to a re-evaluation of conventional views on the prejudice variance connection.

This discussion benefits from ensemble learning methods because they merge multiple models in a strategic way to achieve better performance results. Research of Merentitis et al. (2014) shows that ensemble methods function as a collective approach to navigate prejudice variance compromise, minimize distortion and variance through luggage and enhancement techniques. Gupta et al. (2022) demonstrates that classifier ensembles can manage bias variation which allows different models to work together to balance competing interests.

Kernel methods offer additional insight into the trade-off between bias variation. Kernel methods transform input data into extended dimensional spaces enabling linear learning algorithms to model complex patterns and maintain generalization abilities. The ability of this system to adjust has crucial impacts on how functions are approximated within machine learning models.

Neural networks serve as essential tools for function approximation which is vital for numerous machine learning systems. Yang et al. (2020) critique established beliefs about variance impacts on prejudice within neural networks and argue that reevaluating this connection is essential to enhance deep learning models' generalization. The literature demonstrates how merging insights from different areas such as variance bias compromise, regularization strategies, ensemble methods, kernel applications and neural networks shapes model performance enhancement and improved generalization in machine learning.

Machine Learning Model Selection Considerations

Several determining factors such as data characteristics, interpretability requirements, computational resources,and target variables significantly affect model selection in practical applications. The deployment process of machine learning solutions requires careful consideration of several key elements during training of decision-making procedures.

The properties of the data play a critical role in determining the appropriate model choice. The suitability of specific algorithms for applications depends on the data type, quality and structure. Regularized regression techniques might be chosen over other models when dealing with data that possess dimensionality and multicollinearity characteristics (Drobnič et al., 2020). Models that handle unbalanced data sets need specialized techniques to achieve performance across all classes.

Another critical consideration is that stakeholders within health care and finance sectors need transparent information regarding decision-making processes of machine learning models. Stakeholder requirements force users to choose models that provide clear interpretability like decision trees or generalized linear models instead of complex black box approaches such as deep learning (Luo et al., 2019; Rudin et al., 2022). Various research works demonstrate the existing trade-off between precision and interpretability which stresses the requirement for methodologies that can optimize these conflicting needs (Carvalho et al., 2019; Lisboa et al., 2023).

The selection of models is substantially impacted by available IT resources. The complexity of algorithms demands more computing power and time which limits their use in environments with constrained resources. Practitioners have the capability to advance models that are less complex or scalable based on calculation facility resources(Murdoch et al., 2019). The model's creation and inference efficiency become crucial when applications need real-time predictions or extensive data processing capabilities.

Selecting a model depends directly on the type of target variables used. The nature of target variables being categorical or continuous determines the suitable modelling approach. Classification algorithms work with discrete targets whereas regression models handle continuous results. The desired outcomes may necessitate distinct modelling techniques which prioritize different performance elements like precision or recall (Luo et al., 2019). The selection of machine learning models in practical applications is heavily determined by the combined effects of data features, interpretability requirements, computational resources, and target variables. Continuous research will be essential to further understand these factors especially in emerging fields where interpretability criteria and data evolve rapidly (Lisboa et al., 2023; Rudin et al., 2022).

Model Implementation

Different domains have benefited through various challenges by implementing machine learning algorithms such as decision-making trees (DT), random forests (RF), gradient boosting machines (GBM), support vector machines (SVM) and neural networks (NN). DT functions as an interpretable model which helps to understand data segmentation but its susceptibility to overfitting limits its performance (Jun, 2021). RF strengthens decision trees by averaging multiple trees which enhances both accuracy and survivability in predictive agricultural modelling(Nawar & Mouazen, 2017).

GBM has become popular for its ensemble method capabilities which effectively handle complex relationships and boost predictive power through sequential learning as explained by Domladovac (2021). The technique demonstrates exceptional performance in educational

data mining and proves its value for student performance prediction by surpassing traditional models like logistic regression and SVM (Domladovac, 2021).

The SVM algorithm demonstrates high effectiveness in classification while handling complex high-dimensional data rendering it applicable for multiple fields including environmental modelling research (Idemudia et al., 2024). According to the flow prediction studios (Idemudia et al., 2024), the combined use of SVM with ensemble techniques like RF and GBM resulted in enhanced forecasting capabilities.

Machine learning architectures within NNs have transformed data science by enabling the extraction of complex models from extensive data sets. Combining these methods with other tools in oil engineering for low salinity water injection performance prediction demonstrates their complementary strengths (Shafiei et al., 2022). XGBOOST and GBM ensemble tree techniques demonstrate clear benefits for environmental risk evaluations and landslide susceptibility mapping (Sahin, 2020).

The comparison of different methods reveals today's advancements in machine learning and emphasizes the necessity of choosing proper techniques according to distinct challenges and performance measurements across various applications (Domladovac, 2021; Idemudia et al., 2024; Jun, 2021; Nawar & Mouazen, 2017; Shafiei et al., 2022).

Challenges and Limitations

Multiple factors such as data quality, over-adjustment, interpretability, temporal dynamics and the differentiation between causality and correlation bring machine learning models (ML) under significant scrutiny. The reliability of the model depends on data quality since inferior or biased data produces inaccurate predictions (Nadim et al., 2023). The pretermination of inadequate data or limited representativeness heightens these issues and emphasize the need for thorough data validation.

Models face a major problem in over-adjustment because they perform well on training data but fail when applied to unseen datasets (Rudin et al., 2022). Excessive model complexity compared to training data size results in models that fit specific data too well but do not generalize beyond the training set. Regularization and cross validation techniques are crucial to reduce over-adjustment and improve model robustness.

The importance of interpretability in machine learning continues to grow because it helps build trust and transparency in automated decision-making processes (Molnar et al., 2020). While causal interpretability helps clarify prediction mechanisms it remains crucial yet poses significant methodological problems (Moraffah et al., 2020). It remains essential to distinguish between causality and correlation because merging them leads to inaccurate results especially in chronological series analysis where temporal dynamics affect data relations (Dhaou et al., 2021). Models that fail to accurately establish causal relationships risk losing their ability to predict future events effectively. Dhaou (2024) findings show that the integration of temporal elements into models is essential for accurately representing data distribution changes in dynamic systems. To address these challenges becomes crucial for enhancing both the efficiency and use of machine learning models across different domains.

Conclusion

The development of machine learning models has led to important progress in forecasting FDI flows because these models can handle complex nonlinear relationships, high-dimensional data, and unstructured information that traditional econometric models find challenging to process. The ability of machine learning models to adapt and predict

accurately allows them to effectively analyze the complex factors affecting FDI and deliver useful information for policymakers, investors, and researchers.

The implementation of ML techniques for FDI forecasting presents several difficulties that require careful management. Data quality, overfitting issues, model interpretability challenges and domain-specific adaptation requirements must receive careful management. Integrating machine learning techniques with economic theory in hybrid models presents an effective approach to improve predictive accuracy and enhance interpretability. The development of explainability tools like SHAP values and partial dependence plots enables the conversion of intricate model outputs into practical policy recommendations.

Research moving forward needs to focus on combining various data sources such as sentiment analysis and social media with real-time news data to build models that adapt to shifting global circumstances. To achieve accurate policy-relevant forecasts, it will be essential to establish cross-disciplinary collaborations between economics, data science, and political science to improve methodologies. Machine learning shows potential to revolutionize FDI forecasting by revealing key drivers and facilitating better decisions in our interconnected global environment.

References

Abd El-Aal, M. F., Algarni, A., Fayomi, A., Abdul Rahman, R., & Alrashidi, K. (2021). [Retracted] Forecasting foreign direct investment Inflow to Egypt and determinates: Using machine learning algorithms and ARIMA model. *Journal of Advanced Transportation*, *2021*(1), 1-8. https://doi.org/10.1155/2021/9614101

Afolabi, A. I., Chukwurah, N., & Abieba, O. A. (2025). Harnessing machine learning techniques for driving sustainable economic growth and market efficiency. *Engineering and Technology Journal*, *10*(2), 3929-3938 https://doi.org/10.47191/etj/v10i02.22, I.F. – 8.482

Arel-Bundock, V. (2017). The political determinants of foreign direct investment: A firm-level analysis. *International Interactions*, *43*(3), 424-452. https://doi.org/10.1080/03050629.2016.1185011

Batarseh, F., Gopinath, M., Nalluru, G., & Beckman, J. (2019). Application of machine learning in forecasting international trade trends. *Econometrics*, 1-4. https://doi.org/10.48550/arXiv.1910.03112

Belkin, M., Hsu, D., Ma, S., & Mandal, S. (2019). Reconciling modern machine-learning practice and the classical bias–variance trade-off. Proceedings of the National Academy of Sciences,

Bermejo, C. J., & Werner, R. A. (2018). Does foreign direct investment generate economic growth? A new empirical approach applied to Spain. *Economic geography*, *94*(4), 425-456. https://doi.org/10.1080/00130095.2017.1393312

Bi, S., Xiao, J., & Deng, T. (2024). The role of AI in financial forecasting: ChatGPT's potential and challenges. Proceedings of the 4th Asia-Pacific Artificial Intelligence and Big Data Forum,

Blonigen, B. A., & Piger, J. (2014). Determinants of foreign direct investment. *Canadian Journal of Economics/Revue canadienne d'économique*, *47*(3), 775-812. https://doi.org/10.1111/caje.12091

Buckley, P. J., Clegg, L. J., Cross, A. R., Liu, X., Voss, H., & Zheng, P. (2015). The determinants of Chinese outward foreign direct investment. In *International business strategy* (pp. 574-600). Routledge. https://api.taylorfrancis.com/content/chapters/edit/download?identifierName=doi&identifierValue=10.4324/9781315848365-40&type=chapterpdf

Carvalho, D. V., Pereira, E. M., & Cardoso, J. S. (2019). Machine learning interpretability: A survey on methods and metrics. *Electronics*, *8*(8), 1-34. https://doi.org/10.3390/electronics8080832

Chung, S. (2014). Environmental regulation and foreign direct investment: Evidence from South Korea. *Journal of Development Economics*, *108*, 222-236. https://doi.org/10.1016/j.jdeveco.2014.01.003

Cui, L., Meyer, K. E., & Hu, H. W. (2014). What drives firms' intent to seek strategic assets by foreign direct investment? A study of emerging economy firms. *Journal of World Business*, *49*(4), 488-501. https://doi.org/10.1016/j.jwb.2013.12.003

Dar, Y., Muthukumar, V., & Baraniuk, R. G. (2021). A farewell to the bias-variance tradeoff? an overview of the theory of overparameterized machine learning. *Machine Learning*, 1-48. https://doi.org/10.48550/arXiv.2109.02355

Dhaou, A. (2024). *Interpretable and causal analysis for multivariate time series* Institut Polytechnique de Paris]. https://theses.hal.science/tel-04735710/

Dhaou, A., Bertoncello, A., Gourvénec, S., Garnier, J., & Le Pennec, E. (2021). Causal and interpretable rules for time series analysis. Proceedings of the 27th ACM SIGKDD conference on knowledge discovery & data mining,

Domladovac, M. (2021). Comparison of neural network with gradient boosted trees, random forest, logistic regression and SVM in predicting student achievement. 2021 44th International Convention on Information, Communication and Electronic Technology (MIPRO),

Drobnič, F., Kos, A., & Pustišek, M. (2020). On the interpretability of machine learning models and experimental feature selection in case of multicollinear data. *Electronics*, *9*(5), 1-15. https://doi.org/10.3390/electronics9050761

El Hajj, M., & Hammoud, J. (2023). Unveiling the influence of artificial intelligence and machine learning on financial markets: A comprehensive analysis of AI applications in trading, risk management, and financial operations. *Journal of Risk and Financial Management*, *16*(10), 1-16. https://doi.org/10.3390/jrfm16100434

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. https://doi.org/10.1016/j.ejor.2017.11.054

Gaur, A. S., Ma, X., & Ding, Z. (2018). Home country supportiveness/unfavorableness and outward foreign direct investment from China. *Journal of International Business Studies*, *49*, 324-345. https://doi.org/10.1057/s41267-017-0136-2

Gupta, N., Smith, J., Adlam, B., & Mariet, Z. E. (2022). Ensembles of classifiers: a bias-variance perspective. *Transactions on Machine Learning Research*, 1-23. https://openreview.net/forum?id=lIOQFVncY9

Idemudia, O., Ehiorobo, J. O., Izinyon, C. O., & Ilaboya, I. (2024). Evaluating the performance of random forest, decision tree, support vector regression and gradient boosting for streamflow prediction. *CTU Journal of Innovation and Sustainable Development*, *16*(2), 116-130. https://doi.org/10.22144/ctujoisd.2024.297

Islam, M. M., Jannat, A., Aruga, K., & Rashid, M. M. (2024). Forecasting foreign direct investment inflow to Bangladesh: Using an autoregressive integrated moving average and a machine learning-based random forest approach. *Journal of Risk and Financial Management*, *17*(10), 1-19. https://doi.org/10.3390/jrfm17100451

Jošić, H., & Žmuk, B. (2022). A machine learning approach to forecast international trade: The case of Croatia. *Business Systems Research: International journal of the Society for Advancing Innovation and Research in Economy*, *13*(3), 144-160. https://doi.org/10.2478/bsrj-2022-0030

Jun, M.-J. (2021). A comparison of a gradient boosting decision tree, random forests, and artificial neural networks to model urban land use changes: The case of the Seoul metropolitan area. *International Journal of Geographical Information Science*, *35*(11), 2149-2167. https://doi.org/10.1080/13658816.2021.1887490

Kemiveš, A., Ranđelović, M., Barjaktarović, L., Đikanović, P., Čabarkapa, M., & Ranđelović, D. (2024). Identifying key indicators for successful foreign direct investment through asymmetric optimization using machine learning. *Symmetry*, *16*(10), 1-25. https://doi.org/10.3390/sym16101346

Khattak, B. H. A., Shafi, I., Khan, A. S., Flores, E. S., Lara, R. G., Samad, M. A., & Ashraf, I. (2023). A systematic survey of AI models in financial market forecasting for profitability analysis. *IEEE Access*, *11*, 125359-125380. https://doi.org/10.1109/ACCESS.2023.3330156

Kumari, R., & Sharma, A. K. (2017). Determinants of foreign direct investment in developing countries: a panel data study. *International Journal of Emerging Markets*, *12*(4), 658-682. https://doi.org/10.1108/ijoem-10-2014-0169/full/html

Lisboa, P. J., Saralajew, S., Vellido, A., Fernández-Domenech, R., & Villmann, T. (2023). The coming of age of interpretable and explainable machine learning models. *Neurocomputing*, *535*, 25-39. https://doi.org/10.1016/j.neucom.2023.02.040

Lucke, N., & Eichler, S. (2016). Foreign direct investment: The role of institutional and cultural determinants. *Applied Economics*, *48*(11), 935-956. https://doi.org/10.1080/00036846.2015.1090551

Luo, Y., Tseng, H.-H., Cui, S., Wei, L., Ten Haken, R. K., & El Naqa, I. (2019). Balancing accuracy and interpretability of machine learning approaches for radiation treatment outcomes modeling. *BJR Open*, *1*(1), 1-13. https://doi.org/10.1259/bjro.20190021.

Magazzino, C., & Mele, M. (2025). A new machine learning algorithm to explore the CO2 emissions-energy use-economic growth trilemma. *Annals of Operations Research*, *345*(2), 665-683. https://doi.org/10.1007/s10479-022-04787-0

McAfee, A., & Brynjolfsson, E. (2017). *Machine, platform, crowd: Harnessing our digital future*. WW Norton & Company.

Merentitis, A., Debes, C., & Heremans, R. (2014). Ensemble learning in hyperspectral image classification: Toward selecting a favorable bias-variance tradeoff. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *7*(4), 1089-1102. https://doi.org/10.1109/JSTARS.2013.2295513

Molnar, C., Casalicchio, G., & Bischl, B. (2020). Interpretable machine learning–a brief history, state-of-the-art and challenges. Joint European conference on machine learning and knowledge discovery in databases,

Moraffah, R., Karami, M., Guo, R., Raglin, A., & Liu, H. (2020). Causal interpretability for machine learning-problems, methods and evaluation. *ACM SIGKDD Explorations Newsletter*, *22*(1), 18-33. https://doi.org/10.1145/3400051.3400058

Murdoch, W. J., Singh, C., Kumbier, K., Abbasi-Asl, R., & Yu, B. (2019). Interpretable machine learning: Definitions, methods, and applications. *Machine Learning*, 1-11.

Nadim, K., Ragab, A., & Ouali, M.-S. (2023). Data-driven dynamic causality analysis of industrial systems using interpretable machine learning and process mining. *Journal of Intelligent Manufacturing*, *34*(1), 57-83. https://doi.org/10.1007/s10845-021-01903-y

Nawar, S., & Mouazen, A. M. (2017). Comparison between random forests, artificial neural networks and gradient boosted machines methods of on-line Vis-NIR spectroscopy measurements of soil total nitrogen and total carbon. *Sensors*, *17*(10), 1-22. https://doi.org/10.3390/s17102428

Nielsen, B. B., Asmussen, C. G., & Weatherall, C. D. (2017). The location choice of foreign direct investments: Empirical evidence and methodological challenges. *Journal of World Business*, *52*(1), 62-82. https://doi.org/10.1016/j.jwb.2016.10.006

Nyholm, S. (2022). Machine learning in macroeconomic forecasting.

Paramesha, M., Rane, N. L., & Rane, J. (2024). Artificial intelligence, machine learning, deep learning, and blockchain in financial and banking services: A comprehensive review. *Partners Universal Multidisciplinary Research Journal*, *1*(2), 51-67. https://doi.org/10.5281/zenodo.12826933

Paul, J., & Jadhav, P. (2020). Institutional determinants of foreign direct investment inflows: Evidence from emerging markets. *International Journal of Emerging Markets*, *15*(2), 245-261. https://doi.org/10.1108/IJOEM-11-2018-0590/full/html

Rane, N., Choudhary, S., & Rane, J. (2024). *Machine learning and deep learning: A comprehensive review on methods, techniques, applications, challenges, and future directions* Techniques, Applications, Challenges, and Future Directions (May 31, 2024), https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4850451

Ranglani, H. (2024). Empirical analysis of the bias-variance tradeoff across machine learning models. *Machine Learning and Applications: An International Journal (MLAIJ) 11*(4), 1-12. https://doi.org/10.5121/mlaij.2024.11401

Rapoo, M. I., Chanza, M., & Munapo, E. (2023). Modelling and forecasting foreign direct investment: A comparative application of machine learning based evolutionary algorithms hybrid models. International Conference on Intelligent Computing & Optimization,

Rudin, C., Chen, C., Chen, Z., Huang, H., Semenova, L., & Zhong, C. (2022). Interpretable machine learning: Fundamental principles and 10 grand challenges. *Statistic Surveys*, *16*, 1-85. https://doi.org/10.1214/21-SS133

Sahin, E. K. (2020). Assessing the predictive capability of ensemble tree methods for landslide susceptibility mapping using XGBoost, gradient boosting machine, and random forest. *SN Applied Sciences*, *2*(7), 1-17. https://doi.org/10.1007/s42452-020-3060-1

Sarkutė, L., Sina, D., Bello, K., & Vercuni, A. (2024). Strategic management decisions in the context of foreign direct investment. The role of institutions and economic determinants. *Sustainable Regional Development Scientific Journal*, *1*(1), 40-54. https://www.researchgate.net/profile/Anastasios-Sepetis/publication/385376906_SOCIAL_PROTECTION_IN_GREECE_AND_SUSTAINABLE_DEVELOPMENT_LEAVING_NO_ONE_BEHIND/links/6721f04bdb208342dedd5cd3/SOCIAL-PROTECTION-IN-GREECE-AND-SUSTAINABLE-DEVELOPMENT-LEAVING-NO-ONE-BEHIND.pdf

Seker, F., Ertugrul, H. M., & Cetin, M. (2015). The impact of foreign direct investment on environmental quality: A bounds testing and causality analysis for Turkey. *Renewable and Sustainable Energy Reviews*, *52*, 347-356. https://doi.org/10.1016/j.rser.2015.07.118

Shafiei, A., Tatar, A., Rayhani, M., Kairat, M., & Askarova, I. (2022). Artificial neural network, support vector machine, decision tree, random forest, and committee machine intelligent system help to improve performance prediction of low salinity water injection in carbonate oil reservoirs. *Journal of Petroleum Science and Engineering*, *219*, 1-11. https://doi.org/10.1016/j.petrol.2022.111046

Singh, D. (2021). Interpretable machine-learning approach in estimating FDI Inflow: Visualization of ML models with LIME and H2O. *TalTech Journal of European Studies*, *11*(1), 1-33. https://doi.org/10.2478/bjes-2021-0009

Sonkavde, G., Dharrao, D. S., Bongale, A. M., Deokate, S. T., Doreswamy, D., & Bhat, S. K. (2023). Forecasting stock market prices using machine learning and deep learning models: A systematic review, performance analysis and discussion of implications. *International Journal of Financial Studies*, *11*(3), 1-22. https://doi.org/10.3390/ijfs11030094

Tocar, S. (2018). Determinants of foreign direct investment: A review. *Review of Economic and Business Studies (REBS)*(21), 165-196. https://www.ceeol.com/search/article-detail?id=1240176

Trajanov, D., Vodenska, I., Cvetanov, G., & Chitkushev, L. (2017). Data driven analysis of trade, FDI and international relations on global scale. The 13th Annual International Conference on Computer Science and Education in Computer Science,

Tulli, S. K. C. (2023). Enhancing marketing, sales, innovation, and financial management through machine learning. *International Journal of Modern Computing*, *6*(1), 41-52. https://yuktabpublisher.com/index.php/IJMC/article/view/115/109

Villaverde, J., & Maza, A. (2015). The determinants of inward foreign direct investment: Evidence from the European regions. *International Business Review*, *24*(2), 209-223. https://doi.org/10.1016/j.ibusrev.2014.07.008

Vujanović, N., Casella, B., & Bolwijn, R. (2021). Forecasting global FDI: A panel data approach. *Transnational Corporations Journal*, *28*(1), 97-125. file:///C:/Users/barna/Downloads/ssrn-3906374.pdf

Yang, C.-H., Lee, C.-F., & Chang, P.-Y. (2023). Export-and import-based economic models for predicting global trade using deep learning. *Expert Systems with Applications*, *218*, 1-12. https://doi.org/10.1016/j.eswa.2023.119590

Yang, Z., Yu, Y., You, C., Steinhardt, J., & Ma, Y. (2020). Rethinking bias-variance trade-off for generalization of neural networks. International Conference on Machine Learning,

Yusuf, M. A. (2022). Forecasting foreign direct investment to Sub-Saharan Africa using Arima model: A comparative analysis of machine learning algorithms. *International Journal of Innovative Science and Research Technology*, *7*, 164-182. https://d1wqtxts1xzle7.cloudfront.net/96182487/IJISRT22DEC444-libre.pdf?1671685292=&response-content-disposition=inline%3B+filename%3DForecasting_Foreign_Direct_Investment_to.pdf&Expires=1749591676&Signature=auTklRaaHMRIwef9vnN2maa1ZVqyZIzd7Btw3rfydzf351z0m~XgiFIYp8EVJpQZ-ZAsscQgrDaXGm18nT2gpoW93NqkL5gpEzQqZMxbuVMGKml5VZeYHtN36JzQhoxSHKQ7O2ZnpHAekXP7cWTyc6zXQani~-zwGkRWM-gw7naADvG1R4cl~~KfldUavMjBiK69h-53XqqWEcSiXKZZQFrMc6Dsocnut2BkREvFIgOnokpDMXOchH8NyP53MHRdxfrI1ct3-p1rVMT6m1X1S6K6sVYUUsKP4z5mfPHofFSQYQ5yQAhv~HHVBTObWpkiRAJ2U-0rXIHgg5jVuAIIRA__&Key-Pair-Id=APKAJLOHF5GGSLRBV4ZA