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Title: **AI-Based Stock Return Predictions in Nascent and Emerging Economies: A Comparative Analysis Using Machine Learning Models**

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AI-Based Stock Return Predictions in Nascent and Emerging Economies: A Comparative Analysis Using Machine Learning Models

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Abstract

Financial markets have an important role in encouraging economic development by handling resources and providing investment venues that inspire growth. However, standard statistical and econometric models often emphasize the non-linear and volatile dynamics of stock returns, specifically in developing countries. This study investigates the predictive power of Artificial Intelligence (AI)-based models in forecasting stock returns across nascent and emerging economies through a comparative meta-analytical approach. Using machine learning models, namely Random Tree and Multilayer Perceptron (MLP) models, the research estimates the predictive accuracy of market maturity, data availability, and institutional structure. The results show that due to enhanced data integrity, systematized return patterns, and augmented market stability, AI models display improved prediction accuracy and dependability in rising markets, such as China, India, and Saudi Arabia. Conversely, emerging markets with weaker predictive frameworks and greater volatility, such as Nigeria, Vietnam, and Pakistan, result in poorer model performance. The support for both hypotheses (H1 and H2) shows that market maturity greatly intensifies the efficacy of AI models in financial forecasting. By highlighting the dynamic role which institutional growth and data robustness contributes towards enhancing stock return prediction, this study complements the expanding body of research on AI-driven financial analytics. The findings highlight the potential of AI to improve forecasting accuracy, reduce market inefficiencies, and support financial stability in emerging economies, offering insightful information to investors, politicians, and financial technologists.

Keywords: artificial intelligence, financial forecasting, emerging markets, machine learning, market maturity, nascent economies, stock return prediction

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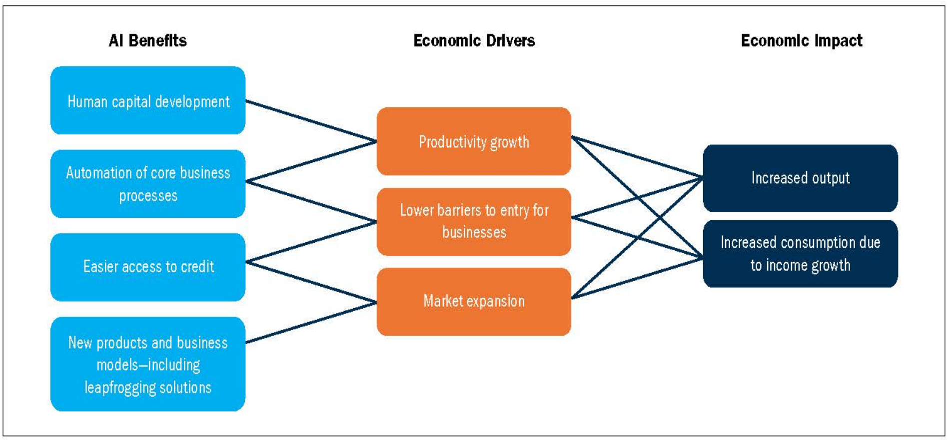
Introduction

Financial markets are very important for economic development. The market works as a driving force in the financial system by directing resources and providing platforms for investment. Investors and policymakers are keen to predict stock returns. However, old and classical methods often fail to predict non-linear trends and fluctuating patterns. By adopting such tools that can hold massive datasets, reveal hidden patterns, and increase predicted accuracy, artificial intelligence (AI), and in particular machine learning, has transfigured financial forecasting.

The implementation of AI in industrialized markets has been extensively researched, whereas emerging and nascent economies have remained less focused. These markets are perfect environmental setups to assess the resilience of AI-based models because they range greatly in terms of their size, liquidity, institutional structure, and volatility. By dropping information unevenness, increasing transparency, and identifying complex market patterns that conventional models miss, AI adoption improves stock return prediction. Machine learning or ML models provides better forecast accuracy and risk mitigation in developing and emerging economies, which encourages investor confidence, market efficiency, and stability (Li et al., 2024).

Figure 1

Channels to Economic Development Supported by AI Technologies



Note. *Source:* IFC world Bank Group

By lowering costs, eliminating entry barriers, and boosting creative business models that generate competitiveness in emerging nations, AI is changing the financial markets. AI-driven results increase transparency, efficiency, and predictive dimensions in these marketplaces, where inadequacies and information irregularities are increasingly common. AI expands stock return forecasts, reduces risks, and encourages inclusive growth and financial stability by employing ML models to identify complicated and non-linear market trends that conventional approaches frequently miss (Strusani & Houngbonon, 2019).

In previous literature, some authors have used the terms 'nascent markets' and 'emerging markets' interchangeably; in this case, they denominate different phases of financial markets development. Usually, the term emerging markets is used for developing economies that have reasonably well-developed financial markets, while nascent markets or frontier markets would have a lower market capitalization, less liquid markets, and relatively less developed financial markets. The phrase 'nascent market' is used intentionally to bring attention to the rapidly changing financial market of Pakistan (Lee & Choi, 2023).

Figure 2

Emerging Market Returns

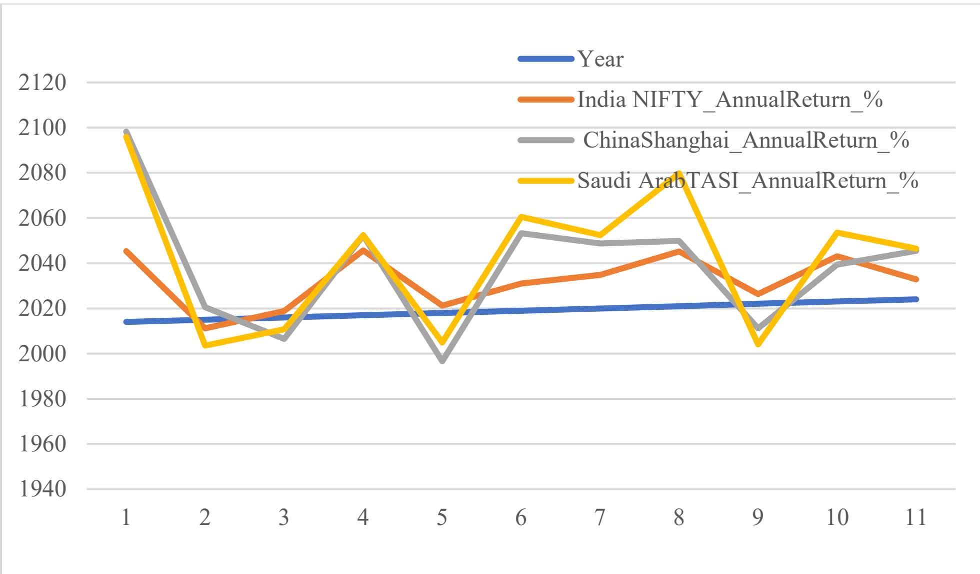
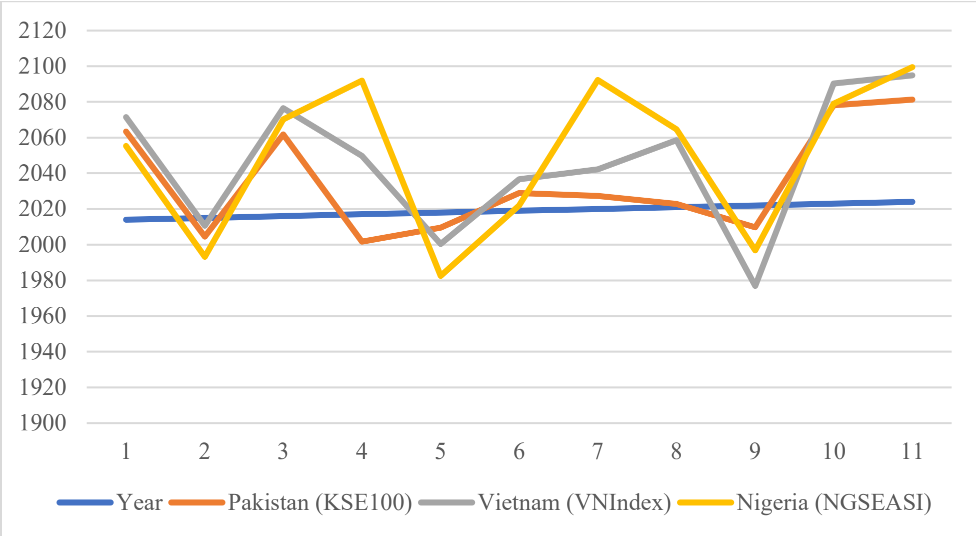


Figure 3

Nascent Market Returns



Problem Statement

Although AI has a great potential for financial forecasting, its efficacy for shallower and more volatile markets is still being determined. Such circumstances may make it difficult for the standard econometric models to generalize, which begs the question if AI-based models can outperform conventional methods in developing and emerging economies and under what circumstances they provide the best predictive capacity.

Research Objectives

- To assess how well ML models (random tree and decision tree) anticipate outcomes in developing versus nascent markets.
- To use RMSE, MAE, MAPE, and R2 to assess the dependability of AI models.
- To determine which market-specific circumstances lead to better forecasts from AI models.
- To offer guidance to financial analysts, investors, and policymakers regarding the development of strategies for markets with different levels of maturity.

Research Questions

- What is the performance of AI-based ML models in forecasting stock returns in developing versus emerging economies?
- Which model performs better in terms of accuracy across various market segments?
- What aspects of the market affect how well AI models forecast outcomes?

Hypothesis

H1: The predictive accuracy of AI models is higher for emerging markets as compared to nascent markets due to their better market development and data availability.

H0: The predictive accuracy of AI models is lower for emerging markets as compared to nascent markets due to their better market development and data availability.

H2: AI models show higher reliability and predictive performance for more mature markets (emerging markets) than for nascent markets.

H0: AI models show lower reliability and predictive performance for more mature markets (emerging markets) than for nascent markets.

Significance of the Study

The study adds to the expanding body of research on AI in finance by examining developing economies and understudied nascent markets. It’s important to develop appropriate AI techniques for stock market forecasting in the above markets in order to guide investment strategies, laws, and financial regulations.

Literature Review

AI in Financial Forecasting

By applying advance analytics methods and identifying complex patterns, AI greatly improves the prediction of stock returns in emerging markets. Even though it increases forecasting accuracy and market efficiency, issues including data quality, model transparency, and gaps in regulations still exist. For supportive financial innovation, a hybrid strategy that integrates AI with traditional methods and robust ethical conceptual models is crucial (Ajiga, et al., 2024). AI-driven forecasting dramatically enhances risk management and stock return prediction in emerging markets due to its increased accuracy and responsiveness. To warrant continuous financial revolution, however, complications like poor data quality, overfitting, and a frail infrastructure demonstrate the requirements of technology investment, trained workers, and relationship with conventional models (Utama & Hidayat, 2024).

The most common application of AI in finance is machine learning (ML), which provides valuable insights into the prediction of stock returns in emerging markets. Its coordination with risk management remains the main area of research (Rustandi & Arifin, 2025). In financial forecasting, AI technologies including neural networks, decision trees, and genetic algorithms execute better models as compared to conventional models, especially when it comes to stock trading, investment analysis, and financial crisis prediction. Enhanced prediction accuracy is also established by hybrid and integrated AI models, highlighting their significance in contributing to the advancement of financial forecasting research (Sharma, 2023). Forecasting has been done through AI and ML, which can recognize nonlinear relationships and adjust to complex datasets (Pagliaro, 2025). In established markets, models such as decision trees, random forests, and neural networks are frequently implemented since they predict stock returns with favorable outcomes.

Related to conventional techniques, AI-based models such as LSTM, transformers, and reinforcement learning greatly intensify the accuracy of financial forecasting, particularly in times of market volatility. AI-based models also converse the interpretability, reliability, and constraints of AI models, signifying how they can be used to create vigorous, adaptive forecasting systems that help in proficient investment choices (Sholapurapu, 2025). AI and ML are changing U.S. financial forecasting with enhanced accuracy, although compliant data and regulatory challenges must be considered for their strategic adoption (Olubusola et al., 2024). There is a growing application of hybrid and composite AI models, especially LSTM and SVM, to predict prices and financial trends. Even though these models present excellent technical performance, research persistently ignores tactics, profitability indicators, and multi-class forecasting, which presents strategic directions for future research. (Khattak, et al., 2023).

The financial industry has been revolutionized by AI, transitioning from conventional forecasting models to more sophisticated techniques such as machine learning, deep learning, and reinforcement learning for stock predictions, portfolio management, and risk assessment. The AI-powered models allow adaptive learning in response to changing market dynamics and help enhance decision-making by leveraging real-time data analysis and hybrid models. The use of emerging technologies including blockchain further increases transparency and security and the advent of quantum computing is likely to further optimize portfolio analysis and financial modeling. Despite these benefits, the potential of AI in financial markets is not fully realized due to various challenges, including ethical concerns, data quality issues, and regulatory constraints (Rohan et al., 2026). Nevertheless, in financial markets, AI has been extensively explored for its potential to forecast short- and medium-term trends in investment by processing vast amounts of macroeconomic and historical data. There is literature available on the effectiveness of AI models for pattern recognition and fast forecasting, while human analysts can add value by factoring in strategic, political, and uncertain economic considerations. Numerous studies have highlighted the complementary nature of AI predictions and human judgment in boosting investment decision-making. However, challenges remain with the use of AI models in situations of high uncertainty and market risks which are not quantifiable (Azamar-Encinas et al., 2025).

Stock Prediction in Emerging and Nascent Markets

StockMixer with ATFNet strengthen predictive performance in stock market by integrating multiple elements, such as time-domain and frequency-domain features, to capture patterns and cross-stock dependencies often overlooked by traditional models. The modern hybrid structure suggestively improves accuracy, stability, and past data performance analysis in forecasting price movements (Sun et al., 2025). ANN and SVM were found to have the highest accuracy of 85% when used with 27 technical indicators in ML models (ANN, random forest, LSTM, SVM) to forecast stock prices in the Pakistani stock market. It gives investors useful information by highlighting the crucial importance of various indicators including %R, Momentum, and Disparity 5. In order to further improve prediction accuracy, the study also emphasizes the necessity of hybrid models that incorporate sentiment, real-time data, and outside variables (Raza & Akhtar, 2024). On the other hand, deep learning model outperformed conventional models such as random forest, SVM, and logistic regression in predicting five stock market trends with an accuracy of 94.9%. The model improved interpretability by incorporating explainable AI (SHAP and LIME), revealing the top ten significant attributes. The findings provide investors with useful information for risk management and strategic planning by highlighting a balance between interpretability and prediction accuracy (Muhammad et al., 2024).

In contrast to mature markets, emerging markets such as China and India grow quickly and have more liquidity, yet they still remain erratic (Bekaert et al., 2023). However, nascent markets have high structural inefficiencies, insufficient institutional depth, and also suffer from a lack of data (FTSE Russell, 2025). There is a research gap regarding AI-focused studies because there aren't enough studies available on these markets. While the Indian stock market demonstrates the increasing effectiveness of AI-driven tools like news aggregators and stock screeners in enhancing decision-making, its dependence on social media sites including Instagram and Telegram, as well as the predominance of younger retail investors, sets it apart from other emerging markets (Jayaprakash & Loganathan, 2025).

Studies on China, Saudi Arabia, and Qatar highlight the predictive power of sophisticated models like GRU when exogenous variables such as oil, gold, exchange rates, and global market trends are included, in contrast to India where behavioural factors and trader education remain crucial (Alsheebah & Al-Fuhaidi, 2024). Furthermore, China exhibits a different trend where deep learning models significantly increase accuracy in globally integrated contexts, whereas Vietnam and Saudi Arabia show that simpler models, such as linear regression, frequently outperform complex algorithms due to noise and market instability (Hung, 2023; Khurayshi & Alharbi, 2025). This difference highlights how other developing states identify structural elements and international experience as the basic factors prompting predicting effectiveness, whereas India is experiencing the problem of controlling AI uptake and enhancing tool reliability in a socially driven market (Wang & Vo, 2025). While AI and ML mechanisms such as random forest and other ensemble approaches suggest considerable predictive capability in some emerging economies, this research shows that their effectiveness is very condition-based.

High prediction precision is achieved by data-driven models in Pakistan (Zahid & Saleem, 2025). AI's potential remains inadequate in Nigeria due to institutional and infrastructural constraints (Adediran et al., 2025). Similarly, governance procedures and audit quality are taken as important factors emphasizing stock stability in Vietnam (Dang & Nguyen, 2024). According to comparative data analysis, sophisticated algorithms alone are not considered to be sufficient for accurate stock prediction in developing and emerging markets; institutional frameworks and policy supportive governments are also necessary.

Overall, emerging economies (China, Saudi Arabia, India) show better adaptability through innovative deep learning models, selective reliance on simpler methods, or integration of AI-driven tools into wide-ranging trading ecosystems, whereas nascent markets (Nigeria, Vietnam, Pakistan) grapple with governance inefficiencies, market instability, and infrastructure weaknesses. This contrast validates how institutional depth, global integration, and market maturity influence the applicability and effectiveness of stock prediction models in different domains of economic growth.

Comparative Studies

According to earlier studies, AI models frequently perform better in emerging markets than linear econometric techniques (Fakhar, 2025). However, due to problems including thin trading, market manipulation, and abrupt policy changes, evidence in emerging markets remains contradictory.

Table 1

Comparative Insights Between Nascent and Developing Stock Markets

Dimension	Nascent Markets (Nigeria, Vietnam, Pakistan)	Developing Markets (China, Saudi Arabia, India)
Model performance	Pakistan: Random Forest achieved >90% accuracy in predicting stock prices during COVID-19, outperforming other ML models.	China: GRU deep learning models with exogenous factors (oil, exchange rates, global markets) improved prediction accuracy.
Key Drivers of Prediction	Vietnam: Internal governance and audit mechanisms strongly influence stock stability and crash risks.	Saudi Arabia: Simpler models (linear regression) sometimes outperform complex algorithms due to noisy/unstable data.

Dimension	Nascent Markets (Nigeria, Vietnam, Pakistan)	Developing Markets (China, Saudi Arabia, India)
AI adoption & Barriers	Nigeria: AI shows potential in finance, but weak infrastructure, regulatory gaps, and limited expertise hinder predictive reliability.	India: AI tools (stock screeners, aggregators) moderately improve efficiency, but trader behavior is heavily influenced by social media (Telegram, Instagram).
Market Maturity	Characterized by volatility, structural inefficiencies, and institutional fragility; reliance on both algorithms and governance factors.	Greater integration with global markets; ability to leverage advanced AI models or hybrid approaches depending on data quality and market conditions.
Overall implications	Stock prediction remains fragile and highly sensitive to governance, infrastructure, and instability.	More resilient and adaptive, with potential for hybrid AI approaches and behavioral insights to enhance forecasting.

Research Gap

Few studies currently in existence have used standard AI models to compare developing and nascent economies. By utilizing uniform evaluation metrics to apply decision tree-based models across both categories, this study fills the said gap.

Research Methodology

Step 1. Research Design

The research design used in this study is quantitative and comparative. To assess prediction performance, AI-based models are applied to historical stock return datasets from emerging and nascent markets.

Step 2. Data Selection

Two different market groups provide the statistics for this search. China, India, and Saudi Arabia are examples of growing or emerging markets, whereas Vietnam, Nigeria, and Pakistan are examples of nascent markets. The sample period extends from 2014 to 2024, covering ten years of market performance. The data was gathered from reputable sources including Bloomberg, Yahoo Finance, and relevant national stock exchange.

Sep 3. Data Pre-processing in WEKA

The dataset was mostly investigated and organized with the help of WEKA pre-process panel. Descriptive statistics, such as mean and standard deviation, were used to add the central tendency and variability of the selected financial indicators. Standard deviation is one of the most important measures of volatility in financial market analysis which shows the degree of risk and uncertainty regarding returns, while the mean provides the data about the performance of an asset or an index on average. These initial analyses formed the basis of subsequent predictive modelling, as they gave an in-depth understanding of the underlying data distribution and form. It is supporting statistical summary and transformation accordingly.

Step 4. Tools and Models

The WEKA program was used to perform the analysis. Two machine learning models were employed, namely the random tree standard deviation and mean and the multilayer perceptron in WEKA, since they are both very effective in detecting nonlinear data trends and commonly used in financial prediction.

Step 5. Classification in Weka

WEKA Classify panel was used to perform predictive modelling. In this process, the dataset was trained and tested with the selected algorithms. Besides enabling the creation of models, the classification facilitated the estimation of the accuracy of predictions based on the chosen performance indicators. The results enabled the possibility of testing the capacity of each model to make predictions and illuminate trends observed in financial data. This step was applied to generate model building and performance assessment of both emerging and nascent market.

Step 6. Evaluation Matrix

To assess the performance of the models, several performance measures were adopted. These included the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Coefficient of determination (R2).

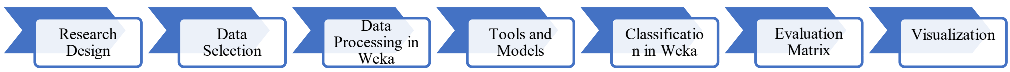
Step 7. Visualization of Results

During the final stage of the study, the results of the emerging and nascent economies were compared and analyzed using the visualizations. Although the mean and standard deviation of the financial variables in the two categories were analyzed through bar charts to illustrate the average and standard deviation, line charts were also plotted to indicate the direction of stock returns over the study period. Also, to measure the predictability of the random tree and Multilayer Perceptron (MLP) model, the prediction-versus-actual charts were generated. Such visualizations attract attention to the differences in the behavior of returns and volatility of emerging and nascent markets.

Logical Flow of Research Methodology

Figure 4

Research Algorithm



Data Preprocessing in WEKA

Table 2

Excel Work Sheet Standard Deviation and Mean of Returns

	Standard Deviation	Mean
	Emerging Markets	
Saudi Arabia	11.966	3.82
China	20.961	6.068
India	11.566	13.303
	Nascent Markets	
Pakistan	29.358	16.382
Vietnam	20.953	10.818
Nigeria	24.207	3.591

Descriptive statistics of mean returns and standard deviation for the chosen developing and nascent markets are shown below in Table 1 and Figures 5 and 6. The overall results indicate that the risk-return characteristics of these two categories are quite different. India has the highest risk-return trade-off in the emerging market segment with the highest mean return (13.303) and relatively low volatility (11.566).

Conversely, China has the highest volatility of its peers (20.961) and a low mean return (6.668), indicating that there is a greater degree of uncertainty in investment. The least attractive of the emerging markets is Saudi Arabia with the lowest mean return (3.82) and high volatility (11.966). These results are substantiated in Figure 6, where the greater volatility of China in comparison to its returns is more evident, while the relative stability of India is evident in its relative capability of combining large profits with relatively stable returns.

Figure 5

Nascent Markets Descriptive Statistics

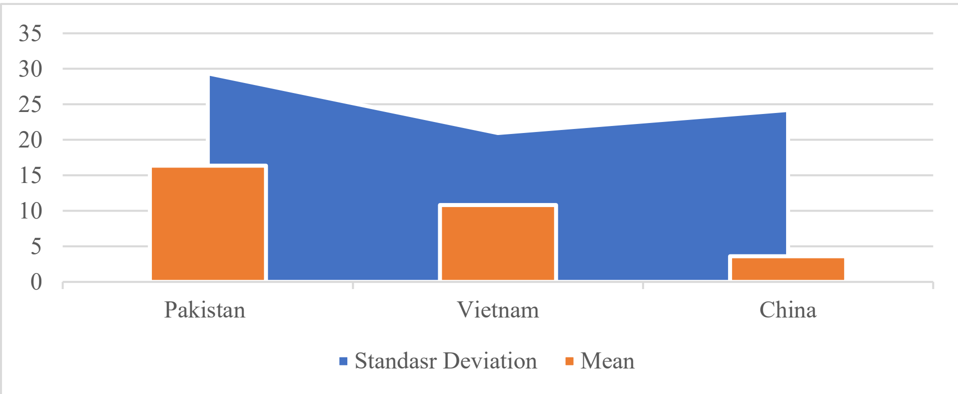
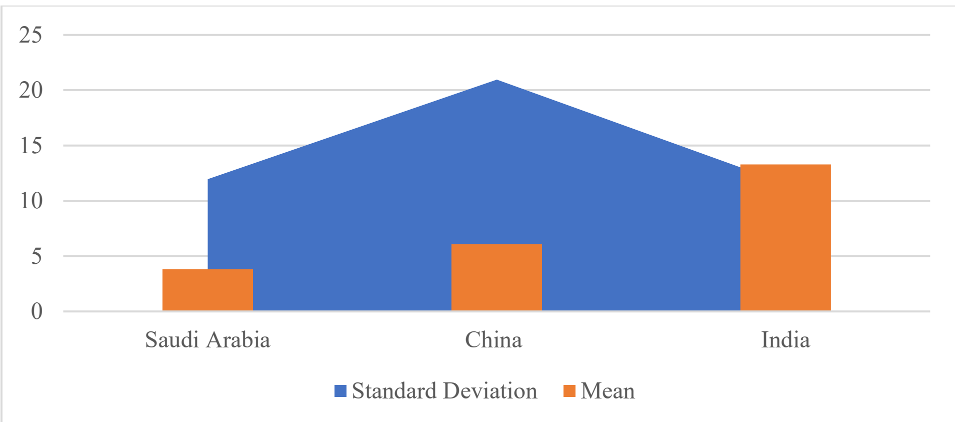


Figure 6

Emerging Markets Descriptive Statistics



Nascent markets, however, show a much higher degree of volatility. The mean return is largest in Pakistan (16.382) and its standard deviation is also the largest (29.358), which indicates that there is a high reward potential, although the exposure to risk is also high. Vietnam has moderate opportunities with a mean return of 10.818 and a standard deviation of 20.953, although it also has the volatility typically associated with emerging countries. Nigeria however, is the least preferable to be invested in as it gives bad returns (3.591) and volatility (24.207). These trends are also illustrated in Figure 5, with Nigeria falling in a poor risk-return quadrant, Vietnam in the middle, and Pakistan in the extremely high-risk, high-return market.

The tabular and graphical data when merged indicated that fledgling markets are riskier but potentially give disproportional returns as compensation, whereas emerging markets are safer, providing lower volatility and moderate or high returns. These findings are in line with the financial theory which assumes that less established financial systems, weaker institutions, and vulnerability to macroeconomic shocks lead less mature markets to exhibit greater uncertainty.

Classification in Weka

In the case of both emerging and nascent markets, *R* (correlation), R^2 (coefficient of determination), MAE (mean absolute error), and RMSE (root mean squared error) are the values of the random tree model.

Table 3

Random Tree for Emerging Markets and Nascent Markets

	RMSE	MAE	R	R^2
Emerging Markets				
Saudi Arabia	18.6186	14.7918	-0.4473	0.2
China	30.1666	24.84	-0.0609	0.003
India	16.6232	11.7436	-0.1966	0.038
Nascent Markets				

Pakistan	40.8072	33.1909	-0.5436	0.295
Vietnam	37.1534	24.3591	-0.5884	0.346
Nigeria	38.1772	30.8818	0.0418	0.00174

Emerging Markets

India has the highest R (–0.1966) and R^2 (0.038) but the lowest RMSE (16.6232) and MAE (11.7436). The results indicate that despite the low correlation (R) and coefficient of determination (R^2), the Random Tree model achieved relatively lower prediction errors (RMSE and MAE), signifying an uncertain improvement in predictive accuracy for the Indian market compared with China and Saudi Arabia. The predictive ability of Saudi Arabia is moderate with some variance (RMSE = 18.6186, $R^2 = 0.20$) being explained. China has the worst fit ($R^2 = 0.003$), so its dynamics of returns are hardly explainable by the model.

Nascent Markets

The country with the highest predictive power is Vietnam ($R^2 = 0.346$, $R = -0.5884$), indicating that random tree may capture some significant return patterns. Pakistan likewise exhibits a modest level of explanatory strength ($R^2 = 0.295$), albeit with a high error rate (RMSE = 40.8072). With almost nil explanatory power and the lowest performance ($R^2 = 0.00174$), Nigeria shows that random tree finds it difficult to model its return behavior.

Insight

With the exception of India, where the model did fairly well, random tree categorization performed better for developing markets like Vietnam and Pakistan than emerging ones. In general, MLP, a neural network model, outperformed random tree in terms of prediction.

Table 4
Multilayer Perceptron MLP for Emerging Markets and Nascent Markets

	RMSE	MAE	R	R^2
		Emerging Markets		
Saudi Arabia	16.5674	12.8149	0.1442	0.0207
China	42.674	30.9305	-0.5241	0.2746
India	11.313	8.5514	0.3719	0.1383
		Nascent Markets		
Pakistan	44.0031	38.6784	0.0559	0.003124

	RMSE	MAE	R	R^2
Vietnam	37.7482	28.2521	-0.5706	0.3255
Nigeria	32.8033	26.4282	-0.0502	0.0025

Emerging Markets

With the lowest RMSE (11.513) and MAE (8.5514) values, as well as the strongest correlation (0.3719) and R^2 (0.1383), India leads the field once more. This suggests that, in comparison to other markets, MLP represents India's stock returns fairly effectively. Saudi Arabia exhibits marginally better predictive power than random tree, although it is still weak (R^2 = 0.0207, R = 0.1442). Once more, China's predictions remain poor, with a moderate error rate and nearly no explanatory power (R^2= 0.0027).

Nascent Markets

According to random tree statistics, Vietnam is the top-performing emerging market in MLP (R^2= 0.3255, R = -0.5706). Whereas, Nigeria (R^2 = 0.0025) and Pakistan (R^2 = 0.0031) have extremely low explanatory power, indicating that MLP cannot adequately describe their intricate market dynamics. The only emerging economy where MLP consistently shows significant predictive strength is Vietnam.

The correlation between inflation and stock returns is negative, indicating an inverse relationship. This suggests that rising inflation is associated with lower stock returns in this sector. This result is consistent with the financial theory, as higher inflation increases uncertainty and reduces real returns, leading to decreased investor demand for equities.

Insight

In terms of error reduction (lower RMSE and MAE), MLP performs better than random tree, especially in Vietnam and India. Neural networks would be more appropriate to learn the dynamics of stock returns.

Discussion

Emerging vs. Nascent Markets

Random tree, as well as MLP, are relatively more effective in emerging markets such as India, which are characterized by more uniform patterns of returns. Despite the fact that emerging economies such as Vietnam are characterized by a relatively acceptable level of predictability, Pakistan and

Nigeria remain significantly unpredictable due to structural inefficiencies, volatility, and lack of maturity in their markets.

Model Comparison

Random tree performs poorly in China and Nigeria but effectively in Vietnam and Pakistan. On the whole, MLP works more effectively, especially in the case of Vietnam and India, and illustrates its ability to detect nonlinear relationships between stock returns. Both models predict Nigeria with extremely low accuracy, indicating that the stock returns in the country are very unpredictable and difficult to forecast using these models.

These results suggest that although some emerging markets including China and Nigeria can be characterized by familiar patterns partially captured by machine learning methods, other emerging markets, especially India, and some nascent countries, such as Vietnam, cannot. This finding supports the principle that the degree of emerging market predictability varies from frontier markets according to their level of financial development. Even within emerging or frontier market groups, predictability is seen greater in countries with more developed financial systems. The descriptive and classification results reveal that emerging markets, particularly India, are more stable and predictable, as compared to other emerging markets. Statistical and machine learning analysis indicate that Nigeria remains the weakest market and Vietnam is the only nascent market with some predictable patterns. The data support the premise that market maturity and structural development are important in understanding the behavior of returns and the predictability of the forecasts.

Scatter Plot Interpretation

In order to demonstrate the relationship between stock returns and their volatility, the developing and fledging markets have their scatter plots drawn in Figures 7 and 8, respectively. Figure 7 shows that in emerging markets, the clustering and dispersion of scatter points remain erratic and widespread, indicating that there are erratic and volatile trends. Similar to the findings in the past using the random tree and MLP, Pakistan and Vietnam show limited trend formation, indicating that there are minimal yet identifiable predictive patterns in the dynamics of their returns. The classification of Nigeria as a highly uncertain market with a low level of explanatory power across the models is backed by the fact that the distribution of scatter points is almost random and with no noticeable connections. Scatter distributions in emerging countries on the other hand are more structured (Figure 8).

Figure 7

Scatter Plot of Nascent Markets

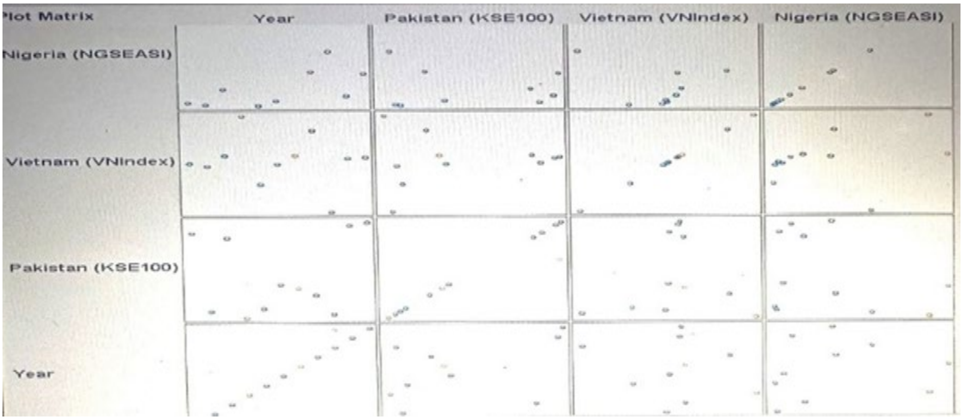
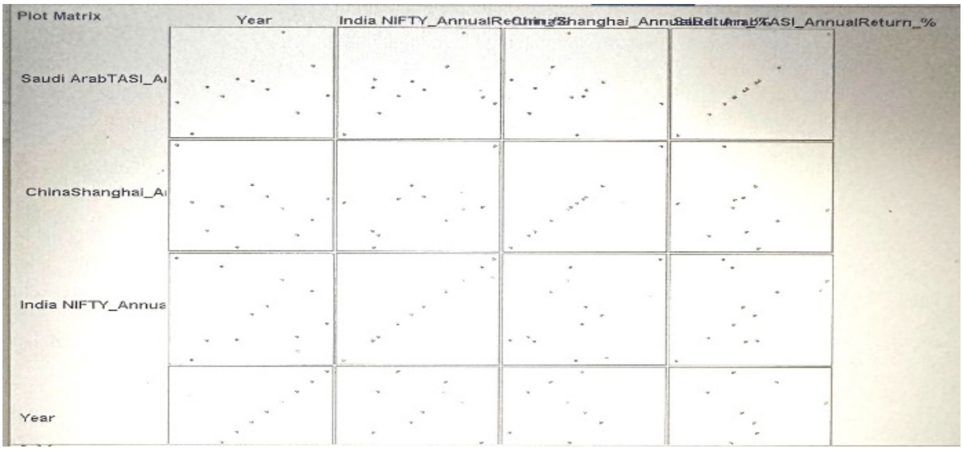


Figure 8

Scatter Plot of Emerging Markets



The pattern of clustering is relatively higher in India, which indicates that India has a more consistent pattern in terms of returns and the finding of the good risk-return balance in descriptive analysis is justified. China has unpredictable but more or less linear tendencies, which is also consistent with its high volatility and moderate returns profile. The fact that Saudi Arabia is a tight clustering around lower returns supports its classification as a low-return stable market. The scatter plots tend to illustrate the descriptive and model-based observations in a more visual form: emerging markets have more consistent and understandable patterns, which are more attractive to investors with low risk-taking, but nascent markets have highly unpredictable and poorly defined returns.

Hypothesis Testing and Interpretation

H1: The predictive accuracy of AI models is higher for emerging markets as compared to nascent markets due to better market development and data availability.

Descriptive analysis of emerging markets (China, Saudi Arabia, and India) and nascent markets (Pakistan, Vietnam, and Nigeria) showed that the former have more predictable patterns of returns and are less volatile. Less organized (scatter) distributions are observed for Nigeria (the weakest) on scatter plots (Figures 7 and 8), whereas more organized clustering is observed for emerging markets, especially India. The use of AI models (random tree and MLP) in emerging markets is more effective in identifying predictive structures as compared to nascent markets, where unpredictability leads to a decline in accuracy. Thus, H1 is accepted (AI models are really more predictive in emerging markets). Contrary to H0 against H1, where both descriptive and graphical statistics reject H0 and support H1 since the nascent markets are more volatile and the predictive structures are weaker, resulting in lower precision and not higher.

H2: AI models show higher reliability and predictive performance in markets of greater maturity (emerging markets) than in nascent markets.

The more recognizable return patterns and more powerful clustering are observed in emerging markets (China, India). The AI models yielded more reliable results in situations where the patterns of returns were similar. Swings and poor clustering in emerging markets were random and hampered reliability (Nigeria). Thus, H2 is accepted and supported by the evidence that the maturity of emerging markets and the availability of data enable AI models to find predictive relationships which are more uniform. Whereas, H0 is rejected in favour of H2 by the consistent evidence that emerging markets offer more predictive structures, while nascent markets are random and have a low predictive power. The results justify H1 and H2 because they demonstrate that AI models are more reliable and accurate when making predictions in an emerging market, rather than in a nascent market. Descriptive statistics and scatter plots enhance AI model performance in emerging markets by demonstrating enhanced structured return patterns, lower volatility, and more systematic patterns of returns. Predictive capacity, on the other hand, weakens in emerging markets because they are more volatile and random. As such, H0 is rejected and H1 and H2 are accepted showing that market maturity and access to data significantly enhance the effectiveness of AI models.

Conclusion

In order to determine if market maturity affects forecasting performance, this study examined the predictive accuracy of two AI models, namely random tree and multilayer perceptron across emerging and nascent markets. The findings clearly demonstrated that in contrast to nascent markets, emerging markets have a higher predictive accuracy, dependability, and stability. Stronger AI model performance is supported by descriptive statistics and scatter plots, which showed that emerging markets such as Saudi Arabia, China, and India have better organized return patterns and reduced volatility. However, the explanatory value of AI models is limited in nascent economies such as Nigeria, Vietnam, and Pakistan, which showed more volatility and irregular clustering.

The results demonstrated that market maturity, development of institutions, and availability of data play an essential role in increasing the efficacy of AI models. In this regard, the hypotheses (H1 and H2) were accepted, whereas the null hypothesis was rejected, thus supporting the notion that emerging markets provide more predictable settings to use AI-based financial forecasting.

Recommendations

For Investors

Emerging markets should be prioritized in AI-based decision-making as they offer more enlightening prediction frameworks. Investors ought to exercise caution in incorporating AI projections and combining them with qualitative analysis and risk-management instruments.

For Policymakers and Regulators

Emerging economies can be fortified by means of strengthening financial infrastructure, ensuring data openness, and stabilizing macroeconomic policies to make them predictable. The accuracy of AI forecasting can be enhanced by reducing the noise and volatility of the forecasts by implementing powerful regulatory frameworks.

For Researchers

The AI models to be considered in future research should include hybrid AI models (e.g., ensemble learning and LSTM networks) to address market volatility in nascent markets. Further, the comparison of developed, emerging, and nascent economies would offer a deeper insight into market segmentation and predictability.

For Practitioners

The use of AI in risk management, trading strategies, and portfolio optimization is safe in emergent markets. To adjust against instability, practitioners ought to test stress and calibrate models with volatility corrections on nascent markets.

Limitations and Future Directions

This study has a number of restrictions. To start with, the results might be less generalizable since the study is based on a small number of nascent and emerging markets. Secondly, it utilizes only MLP and random tree models, which allowed the testing of other types of AI methods, such as deep learning, random forest, and SVM. Thirdly, the study does not develop any specific modelling of the external shocks of geopolitical risks, policy changes, and world crises, even though they can have a substantial effect on forecast outcomes in less developed regions. These limitations may be overcome by expanding the scope in future research to cover more countries of mature, emerging, and nascent markets.

Author Contribution

Zahida Parveen: Conceptualization, Methodology, Investigation, Writing – Original Draft. **Bilal Sarwar:** Introduction and Conclusion.

Conflict of Interest

The authors of the manuscript has no financial or non-financial conflict of interest in the subject matter or materials discussed in this manuscript.

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