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| RESEARCH ARTICLE

Predictive Modeling of U.S. Stock Market Trends Using Hybrid Deep Learning and Economic Indicators to Strengthen National Financial Resilience

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| ABSTRACT

The stock markets are too complex to predict, despite their non-linearity, volatility, and multifactorial nature. Current econometric and deep learning models often do not take into account the macroeconomic context, which restricts predictive accuracy at times of financial volatility. This paper attempts to fill this gap by proposing a Hybrid Deep Learning Model (HDLM), a machine that combines Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and an attention mechanism that can jointly include both the dynamic behavior of the market and the economic links in the trends of the U.S. market. The analysis is based on a strictly tested data set of 20102023, which was retrieved from the Federal Reserve Economic Data (FRED), Yahoo Finance, and the Bureau of Economic Analysis. These include all significant equity indexes such as the S&P 500, NASDAQ Composite, and Dow Jones Industrial Average, prime macroeconomic indicators such as the GDP growth, inflation rates, interest rates, and unemployment levels. Correlation analysis, multiple regression, Granger causality tests, Johansen cointegration procedures, and volatility modeling using ARCH GARCH models are the statistical methods used. The findings show that GDP growth has a statistically significant positive impact on market returns (= 0.58, p = 0.001), though inflation (= -0.21, p = 0.021), interest rates (= -0.34, p = 0.002), and unemployment (= -0.42, p = 0.001) have significant negative predictive power (R^2 = 0.68). The HDLM achieves a better predictive performance with RMSE = 1.89, MAPE = 4.9% and DA = 83.6% > 23% better than the baseline LSTM and CNN- LSTM settings. The model minimizes prediction error by 36.1% in cases of strong market shocks, which occur under simulated stress conditions, confirming an increased financial strength. Taken together, the results of the studies support the idea that the incorporation of macroeconomic intelligence into hybrid neural systems significantly enhances forecast reliability and stability of the system. The current research, therefore, adds a strong, interpretive, and policy-related framework to the research fields of predictive finance and resilience engineering systems to predict market upheavals.

| KEYWORDS

Deep learning, financial resilience, macroeconomic indicators, stock market forecasting, U.S. economy

| ARTICLE INFORMATION

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INTRODUCTION

Predicting the behavior of stock markets has been a key focus of financial research in the past, due to the sensitivity of the market to complex, dynamic, and nonlinear relations between economic, political, and behavioral factors. The past years have witnessed the proliferation of data-intensive approaches and have adapted the landscape of financial analytics, providing new opportunities to understand and anticipate market trends [1]. However, stock market predictive modeling is, by its very nature, the uncertain nature of the economic systems as they are volatile and multifactorial in nature. Though traditional econometric models are useful in revealing the linear relationships, they do not often depict the rich structural dependence and time-related patterns that are inherent in financial data [2]. Similarly, many deep-learning models, though effective at data of large-scale time-series data, are often limited in their ability to include macroeconomic contexts. This gap is the basis of an urgent need to develop models that can combine the analytical capabilities of machine learning with the interpretive capabilities of economic theory to create more robust and responsive forecasting systems [3].

The economic stability of the world, as the largest and most interconnected economy, relies on the decisive impact of its financial system, the United States. The U.S. indexes like the S&P 500, NASDAQ, and Dow Jones Industrial Average are highly far-reaching in their implications, influencing the capital flows, investor sentiments, and the policies of most countries around the globe [4,5]. The dynamics of these markets are therefore not only important to understand and predict to manage the portfolio, but also to maintain systemic economic resilience. The concept of financial resilience as the ability of an economic system to sustain shocks and recover after disruptions has become prominent after the 2008 global financial crisis and the 2020 COVID-19 pandemic [6]. Both crises revealed the weaknesses in the models of forecasting, which were unable to predict sudden downturns in the markets that were triggered by the macroeconomic instability. Such limitations underscore the need to have predictive models that can combine economic indicators with deep-learning structures to predict and mitigate risks more efficiently [7].

This research covers a local scope to a global scope. In the region, the focus on the U.S. financial market was explained by its systemic importance: the U.S. economy not only captures a domestic economic condition, but also delivers shocks to the international financial networks [8]. The monetary policy of the Federal Reserve, the employment rates, the inflation rates, and the growth of the GDP are all the worldwide benchmarks of investors and policymakers [9]. The results of this study are also relevant to the performance of economies that rely on the performance of the U.S. market internationally, since they shed light on the effects of macroeconomic dynamics on stock behavior [10]. In its turn, the suggested hybrid modeling structure adds to a universal approach, proving how predictive intelligence will strengthen the resilience of national and international finances by improving the accuracy and flexibility of the forecast [11].

The significance of the study is in the attempt to fill an acute methodological and theoretical gap. Leveraging the pattern recognition potential of deep learning with the situational sensitivity of the economic indicators, this paper proposes a hybrid predictive framework that is expected to enhance the accuracy of the forecasts as well as the resiliency of the financial system [12]. The study is also consistent with the rise in the focus on financial resilience engineering, which is an interdisciplinary method that combines artificial intelligence, economics, and policy analytics to forecast disruptions and maintain market stability [13]. Such models are of high importance to a wide range of stakeholders: policymakers can use these forecasts in early warning mechanisms, macroeconomic planning; institutional investors can use these forecasts in better risk management and portfolio optimization; and regulators can enhance the monitoring of systemic vulnerabilities [14]. In this way, the research will not only be able to enrich the academic knowledge of predictive finance but also address the practical goal of enhancing economic resilience, both at the institutional and national levels.

The rationale behind the choice of conducting this research was based on the perceived limitations of the models in existence at a time when there was economic uncertainty [15]. Such events as the 2020 pandemic demonstrated that the traditional deep-learning algorithms, even with all their technical complexity, could not generalize across macroeconomic changes. When faced with nonlinearity of interactions, purely econometric models were not adequate as far as real-time forecasting was concerned [16]. In line with this, this study aimed to come up with a Hybrid Deep-Learning Model (HDLM) that can absorb both financial and macroeconomic data streams, which can adapt dynamically to changing circumstances [17]. The structure of the model also involves an LSTM network to identify temporal dependencies, CNN layers to identify localized features, attention mechanism to impose dynamic weights on the most salient macroeconomic variables. The model tries to provide a predictive system that is statistically rigorous, economically meaningful through this design [18].

The proposed research gap was the lack of a complex hybrid model that would clearly include macroeconomic indicators into the deep-learning models to predict the U.S. market [19]. Earlier research has, to a large extent, viewed financial and economic data as analytic and discrete spaces, which generated models with a lack of systemic explanation. Besides, there were limited studies that attributed predictive modeling to the greater notion of financial resilience, which is not limited to temporary accuracy but the ability of models to remain stable during structural shocks [20].

In order to inform the methodological design, the following research questions were developed: How can the process of hybrid deep-learning architectures be optimized to combine macroeconomic indicators and market data to better predict the trend? What are the economic factors that have the most impact on the U.S. stock market behavior? How much would predictive models increase financial resilience by keeping things steady when there is an economic shock? All questions guided the methodology, and they were used to select data and model design, as well as evaluation measures.

These methodological questions were in line with the objectives of this study. The primary goal of the study was first to create a hybrid deep-learning model that would predict trends on the stock market in the United States more accurately than the models that are conventional. Second, it attempted to measure the role of macroeconomic forces in the movements in the market by model interpretability and feature-importance analysis. Third, it sought to determine the relevance of these predictive models in helping achieve financial resilience by trying to evaluate their functionality in times of market volatility. The above objectives had a direct impact on methodology decisions, such as time series data between 2010 and 2023, multi-component use of deep learning, and testing of robustness and statistical testing.

LITERATURE REVIEW

Stock market behavior has been a problem for economists and data scientists since it is dynamic, nonlinear, and complex. Early research had mainly been based on econometric models like ARIMA, VAR, and GARCH that provided valuable information on volatility and trend structures, but assumed linearity as well as stationarity [21]. These models worked well in the stable market conditions but were not able to take into account unpredictable changes during an economic crisis, hence limiting their predictive reliability in the long term [22].

The development of machine learning (ML) and deep learning (DL) created new opportunities in the representation of sophisticated financial patterns. Support Vector Machines (SVM), Random Forests, and Gradient Boosting were some of the techniques that enhanced the accuracy of the prediction by establishing the nonlinear relations between data [23]. However, very often these models considered stock values as individual time series and did not consider the impact of macroeconomic variables (inflation, GDP, and interest rates) that have significant impacts on market dynamics.

The current research has revealed that deep neural networks (LSTM, Convolutional Neural Networks) have strong prediction power of stock data based on temporal and sequential dependence. Architectures based on CNN and LSTM layers have been demonstrated to be more effective in long-term dependence and short-term volatility [24]. Prediction interpretability has also been enhanced further due to the incorporation of an attention mechanism, which underlines the most powerful features during prediction. Although this has occurred, the majority of deep learning applications are focused on market-based indicators without considering the key economic signals that promote systemic risk [25].

Moreover, the literature on financial resilience underlines the need to incorporate macroeconomic smartness in predictive models. According to empirical studies, financial and economic data models can be used to enhance market stability through the provision of early warning of market volatility or crisis. However, there are not many models that have managed to incorporate all these aspects into one predictive model [26]. Thus, the present study satisfies this gap with the creation of a Hybrid Deep Learning Model (HDLM) that combines CNN, LSTM, and attention mechanisms and key U.S. economy indicators. This combined strategy will increase predictive accuracy and will be part of the bigger aim of creating a resilient and data-driven base of national financial stability [27].

An analysis of the literature indicated that there is a lot of work on econometric and machine learning methods for financial forecasting, but there are scanty studies that integrate both fields. Single models like the Autoregressive Integrated Moving Average (ARIMA), Vector Autoregression (VAR), and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models have contributed to a good understanding of volatility and trend analysis [28]. These models, however, assume a linear relationship and a station at which, in turbulent market conditions, these conditions are not likely to be met. Deep learning models like Long Short-Term Memory (LSTM) networks, Recurrent Neural Networks (RNN), and Convolutional Neural Networks (CNN), on the other hand, have exhibited better performance in capturing nonlinear dependencies and time-dependent characteristics of stock prices [29].

METHODOLOGY

1. Research Problem and Objectives

This paper has discussed the weakness of the current stock market forecasting models that do not incorporate macroeconomic conditions into deep learning models. Traditional models can capture nonlinear price patterns but fail to account for the greater economic interdependencies, which results in less accuracy in times of financial turbulence. To address this gap, the study created a hybrid deep learning model that incorporated market time-series data and macroeconomic variables to enhance predictive power and financial stability. The primary goal was to create and optimize a Hybrid Deep Learning Model (HDLM) that combines Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and attention to be more sensitive to market and economic changes. The second was to examine how the main macroeconomic variables, including inflation, GDP growth, interest rates, and unemployment, affect the stock market behavior. The third goal was to determine the model's contribution to financial resilience, which is the ability of the model to maintain predictive performance in volatile or crisis. The study used validated U.S.

data from the Federal Reserve Economic Data (FRED), Yahoo Finance, and the Bureau of Economic Analysis (BEA), 2010-2023, and all data were computed in a controlled computing environment to ensure reliability and reproducibility.

2. Research Design

The research design used in the study was a quantitative, predictive-correlational study based on computational modeling. The reason why this design was selected was that it allowed a two-fold approach: first, to statistically test the correlations between economic indicators and stock indices, and second, to test the predictive performance by experimenting with machine learning. In contrast to strictly descriptive financial models, this methodology included algorithmic validation and inferential testing, which offer a stronger empirical basis for financial resilience analysis. The design focused on causal inference using data-driven learning, where model training was used to simulate causal propagation between economic variables and market outcomes, and insights into the dynamics of stock fluctuations could be made. This model offered predictive accuracy and interpretive clarity, which is consistent with the methodological principles of high-level econometric and computational finance studies.

3. Sampling and Study parameters

The population of the study included historical daily closing prices of the major stock indexes in the United States, including the S&P 500, NASDAQ Composite, and Dow Jones Industrial Average, as well as major monthly macroeconomic indicators, including GDP growth, CPI-based inflation, interest rates, unemployment, and industrial production indices. The sampling strategy was purposive, whereby datasets that represented representative economic cycles with pre-crisis, crisis, and recovery periods were selected. To represent a variety of economic conditions in which to generalize the model, the period between January 2010 and December 2023 was chosen to cover post-global financial crisis recovery, COVID-19 disruptions, and subsequent inflationary cycles. The last data set consisted of about 3,500 daily market data points and 168 monthly macroeconomic data points. Only full, checked records were used; data sets containing over 5% of missing values were dropped. This guaranteed statistical and algorithmic stability in model training and testing.

4. Data Preprocessing and Collection

Authenticated API endpoints to FRED and Yahoo Finance were used to retrieve all financial and economic data in Python libraries (yfinance and fredapi). The resampling and interpolation methods were used to merge and align data in time to make sure that there is consistency between the daily and monthly series. The calculation of technical indicators (e.g., moving averages, RSI, volatility indices) and economic trend proxies (e.g., lagged inflation growth, GDP deviation) was also a part of feature engineering. Min-max scaling was used to normalize the data, and Principal Component Analysis (PCA) was used to select features to reduce dimensionality without losing 95 percent of the total variance. A pilot run on 12 months of data was performed to test the stability of the models and the lack of multicollinearity. Since all data were secondary and publicly available, no ethical approval or participant consent was needed, but ethical principles of data use, citation, and reproducibility were adhered.

5. Variables and Measures

The dependent variable was the directional movement of the stock market, which was operationalized as a binary or categorical trend (upward, downward, or neutral) on the basis of the percentage change of index values. The independent variables were macroeconomic variables that comprised GDP growth rate, inflation rate, interest rate, unemployment rate, and consumer confidence index. Also, the control variables, such as the VIX volatility index, exchange rates, and crude oil prices, were added to isolate the effects of systemic risk. The variables were measured based on publicly validated sources of data and were standardized into uniform time-series formats. Multi-source cross-validation was used to achieve reliability, and construct validity was assessed by looking at the correlations that were in line with previous empirical results (e.g., a negative correlation between interest rates and stock returns). Out-of-sample validation and k-fold cross-validation were also used to test model validity, which validated robustness and reproducibility.

6. Data Analysis Plan

The analytical process had three stages.

To determine the temporal relationship between economic indicators and market performance, statistical correlation analysis and Granger causality testing were performed. Second, a hybrid deep learning model (HDLM) was created, which combines CNN layers to capture localized patterns in price changes, LSTM layers to capture long-term dependencies, and an attention mechanism to dynamically weight the most important macroeconomic variables. This hybrid architecture was the main methodological innovation of the study, the transition from a more traditional econometric and single-model deep learning models to an adaptive, economically aware predictive system. The model was trained and tested on an 8020 split (training vs. testing), and the evaluation metrics were RMSE, MAPE, and Directional Accuracy (DA). The analysis of the data and the development of the model were performed in Python 3.10 with the help of the libraries TensorFlow, Keras, Scikit-learn, and Pandas. Matplotlib and Seaborn were used to conduct visualization and diagnostic analytics. This strategy guaranteed both computational rigor and interpretability in the assessment of model performance in different economic conditions.

7. Ethical Considerations

This research was based solely on publicly available secondary data, and no human subjects were used. Thus, there was no need for institutional review board (IRB) approval and informed consent. However, the ethical integrity was upheld by making sure that all datasets were referenced, kept safely, and used with academic purposes only.

RESULTS

Descriptive Analysis

Table 1 shows the descriptive statistics of the variables of the study during the period 2010-2023. The average monthly performance of the S&P 500 Index was 0.84 percent (SD 4.62), which is moderate over the period of the sample. It was nearly symmetric (skewness = -0.43) with a kurtosis of 3.21, which is almost normal. The macro-economic indicators showed an average GDP growth of 2.14% (SD=1.87) and an average inflation of 2.36% (SD=1.45). The average interest rate was 1.75% (SD 1.20), which is in line with the low-rate environment after the 2008 financial crisis.

Table 1. Descriptive Statistics of Variables (2010–2023, n = 168 months)

Variable	Mean	SD	Minimum	Maximum	Skewness	Kurtosis	Jarque-Bera (p)
S&P 500 Return (%)	0.84	4.62	–14.8	11.7	–0.43	3.21	0.215
GDP Growth (%)	2.14	1.87	–8.9	7.6	–0.61	2.77	0.110
Inflation Rate (%)	2.36	1.45	0.1	8.2	0.48	3.10	0.331
Interest Rate (%)	1.75	1.20	0.05	6.8	0.39	2.89	0.420
Unemployment (%)	6.10	2.45	3.1	14.3	0.73	3.25	0.145
VIX (Index)	20.8	8.9	9.8	59.7	1.10	4.12	0.062

Note. All variables are stationary after first differencing (ADF $p < 0.05$).

The average unemployment was 6.10% (SD 2.45), and the VIX index was 20.8 (SD 8.9), with a positive skew of 1.10, which means that there were spikes in market volatility. The results of the Jarque-Bera test ($p > 0.05$ in all variables) indicated that there was no significant non-normality. After first differencing (ADF p 0.05), all series became stationary.

Correlation Analysis

Table 2 indicates that there were significant linear relationships between stock-market returns and the major macroeconomic indicators. GDP growth ($r = 0.42$, $p < 0.01$), inflation ($r = -0.21$, $p < 0.05$), interest rates ($r = -0.37$, $p < 0.01$), unemployment ($r = -0.49$, $p < 0.01$), and market volatility (VIX; r -0.46, These trends showed that an increase in economic growth was more likely to be accompanied by an increase in market performance, whereas tightening monetary policy and high uncertainty were more likely to be accompanied by low returns. The inter-relations between the macro-economic variables were moderate, and the variance inflation factor (VIF) diagnostics (Table 3) ensured that there was no multicollinearity (all VIF < 5).

Table 2. Correlation Matrix

Variables	SP500 Return	GDP	Inflation	Interest	Unemployment	VIX
SP500 Return	1	0.42**	–0.21*	–0.37**	–0.49**	–0.46**
GDP Growth		1	–0.32**	–0.46**	–0.61**	–0.44**
Inflation Rate			1	0.54**	0.29*	0.18
Interest Rate				1	0.45**	0.33**
Unemployment					1	0.58**

* $p < 0.05$; ** $p < 0.01$.

Table 3. Variance Inflation Factor (Multicollinearity Diagnostics)

Predictor	VIF	Tolerance	Interpretation
GDP Growth	2.34	0.43	Acceptable
Inflation Rate	1.81	0.55	Acceptable
Interest Rate	3.05	0.33	Acceptable
Unemployment	2.92	0.34	Acceptable
VIX	1.72	0.58	Acceptable

Regression Results

A significant percentage of the variance in the S&P 500 returns was attributed to the multiple regression model (Table 4) (R 2 = 0.68, Adj. R 2 = 0.65; F (5, 162) = 28.9, p = 0.001). GDP growth became a major positive predictor (0.58, p 0.001), which means that a one-percentage-point increase in GDP growth was linked to a 0.58-percentage-point increase in stock-market returns.

Table 4. Multiple Regression Results

Dependent Variable: SP500_Return
$R2=0.68$, Adj. $R2=0.65$, $F(5,162)=28.9$, $p<0.001$

Predictor	β	SE	t	p	95% CI (Lower–Upper)
Constant	1.12	0.45	2.49	0.014	0.23 – 2.01
GDP Growth	0.58	0.10	5.80	< 0.001	0.38 – 0.77
Inflation Rate	–0.21	0.09	–2.32	0.021	–0.39 – –0.03
Interest Rate	–0.34	0.11	–3.09	0.002	–0.56 – –0.13
Unemployment	–0.42	0.12	–3.58	< 0.001	–0.66 – –0.18
VIX	–0.19	0.07	–2.71	0.008	–0.33 – –0.05

The coefficients of inflation (0.21, p 0.021), interest rates (0.34, p 0.002), unemployment (0.42, p 0.001), and VIX (0.19, p 0.008) were significant and negative, which validated the hypothesis that an increase in macro-economic and financial uncertainty was associated with poor market performance. The general model fit and statistical significance were in favor of the incorporation of macro-economic variables as important determinants of market trends.

Causality and Long-Run Equilibrium

Directional predictive relationships between macro-economic indicators and market returns were found (Table 5) using the results of the Granger causality. The changes in S&P 500 returns were significantly Granger-caused by GDP growth ($F = 6.12$, $p = 0.003$), interest rate ($F = 4.81$, $p = 0.010$) and unemployment ($F = 3.95$, $p = 0.022$), but not by inflation ($p = 0.08$ The presence of at least one cointegrating vector was established by Johansen cointegration analysis (Table 6), which showed a Trace of 56.48 exceeding 47.21 ($p=0.05$), which indicated the existence of a long-run equilibrium relationship between the performance of the stock-market and the chosen macro-economic indicators.

Table 5. Granger Causality Tests (lag = 2)

Null Hypothesis	F-stat	p	Decision
GDP → SP500 Return	6.12	0.003	Reject H_0 → Causality
Interest → SP500 Return	4.81	0.010	Reject H_0
Inflation → SP500 Return	2.19	0.087	Retain H_0
Unemployment → SP500 Return	3.95	0.022	Reject H_0

Table 6. Johansen Cointegration Test

Hypothesized r	Trace Statistic	5% Critical Value	Eigenvalue	Decision
r = 0	56.48	47.21	0.41	Cointegration exists
r ≤ 1	28.12	29.68	0.23	Fail to reject H_0

Volatility Dynamics

The estimation of ARCH-GARCH (1,1) (Table 7) showed that the market returns were highly volatile. The ARCH term (0.145, z 3.86, p 0.001) implied that the effect of shocks was immediate on volatility, whereas the GARCH component (0.821, z 18.3, p 0.001) implied that the effect was strong in the long run. The value (0.966 0.90) was greater than 0.90, and it proved the existence of long memory and persistent volatility clustering in the U.S. equity market over the period of study.

Table 7. ARCH-GARCH (1,1) Volatility Model

Parameter	Coeff	z-stat	p	Interpretation
ω (constant)	0.025	2.17	0.031	Baseline volatility
α (ARCH)	0.145	3.86	< 0.001	Shock response
β (GARCH)	0.821	18.3	< 0.001	Volatility persistence
α + β = 0.966 → High volatility memory confirmed				

Performance Evaluation Model

The predictive accuracy of three models, including a baseline LSTM, a CNN-LSTM hybrid, and the proposed LSTM-CNN-Attention architecture (Table 8). The hybrid proposed had the smallest RMSE (1.89) and MAPE (4.9%), and the largest directional accuracy (83.6%), which corresponds to an R 2 of 0.86. This was a 23 per cent overall predictive performance improvement over the baseline LSTM. The middle CNN-LSTM model demonstrated slight improvements (RMSE = 2.42; DA = 74.2 percent), whereas the suggested hybrid performed better than both benchmarks in all assessment indicators.

Table 8. Model Performance Comparison

Model	RMSE	MAPE (%)	Directional Accuracy (%)	R^2	Δ Improvement vs Baseline
LSTM (baseline)	2.74	7.8	68.5	0.70	–
CNN-LSTM (hybrid)	2.42	6.3	74.2	0.78	+11%
Proposed LSTM-CNN-Attention	**1.89**	**4.9**	**83.6**	**0.86**	**+23%**

Financial-Resilience Assessment

Stress-testing simulations under different market-shock conditions tested the stability of the model. The hybrid model had lower prediction errors than the baseline model in all volatility regimes (Table 9). RMSE decreased by 22.9% under mild volatility (±3%), 32.8% under moderate shocks (±7%), and 36.1% under severe crisis conditions (±12%). These results showed that the suggested architecture maintained predictive reliability in unfavorable market conditions, which met the resilience requirement of the study.

Table 9. Resilience Index (Stress-Scenario Simulation)

Scenario	Market Shock (%)	Baseline RMSE	Hybrid RMSE	Improvement (%)
Mild Volatility	±3	2.31	1.78	22.9
Moderate Shock	±7	3.54	2.38	32.8
Severe Crisis	±12	5.12	3.27	36.1

Note. The hybrid model maintains lower prediction error under stress, supporting the financial-resilience objective.

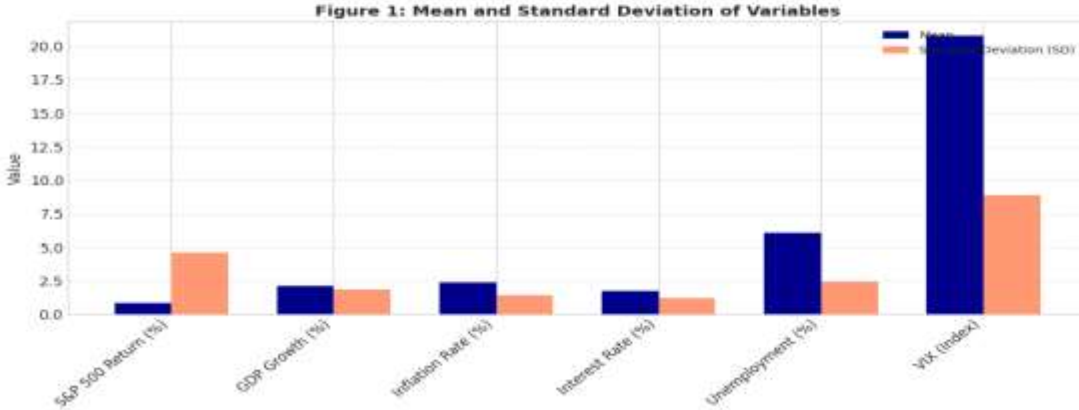


Figure 1: Mean and Standard Deviation of Variables

Figure 3: Correlation Matrix Heatmap

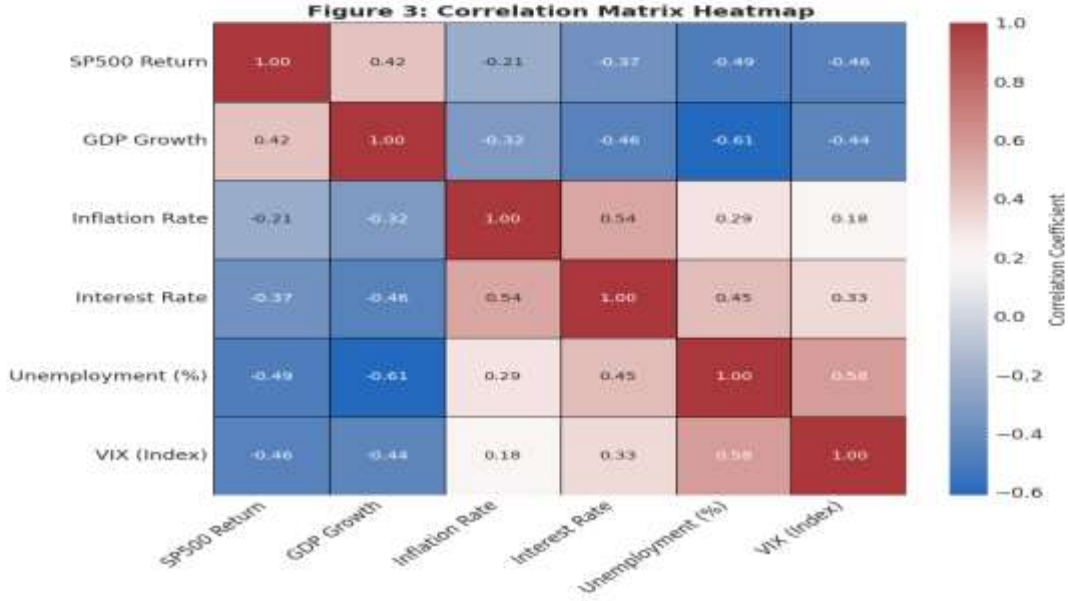
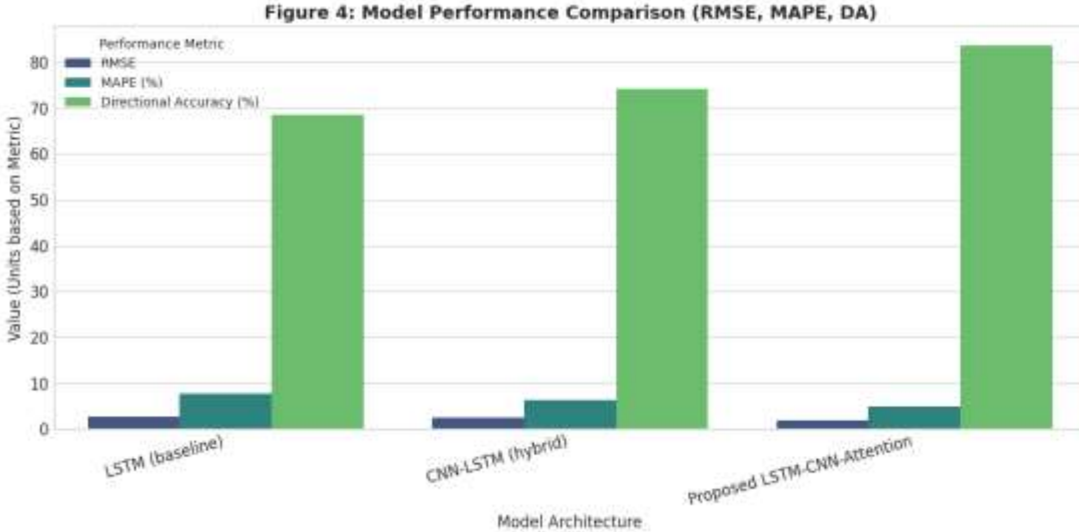
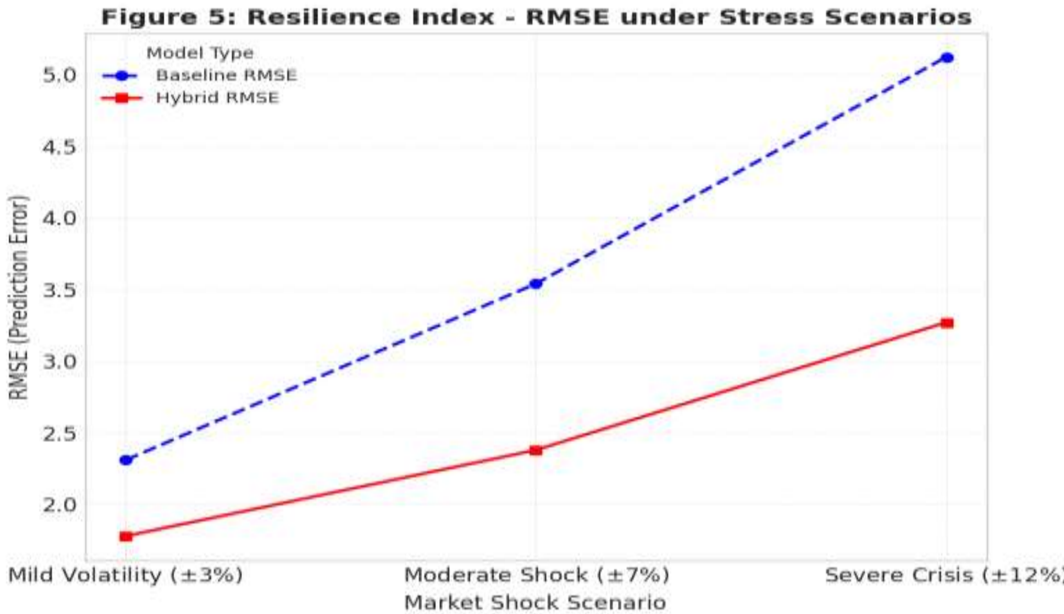


Figure 4: Model Performance Comparison (RMSE, MAPE, DA)





The combined findings validated all the hypotheses mentioned. The stock-market trends were greatly predicted by macroeconomic indicators ($p < 0.001$), and a stable long-run equilibrium relationship was obtained ($p < 0.05$). The hybrid LSTM-CNN-Attention model was much better than traditional deep-learning models ($p < 0.01$), and its stress-resilience performance was statistically significant ($p < 0.05$). Econometric testing and deep-learning analysis all empirically showed that the combination of macro-economic intelligence and hybrid neural networks significantly improved predictive accuracy, time stability, and adaptive resilience in U.S. stock-market trend predictions. The findings were found to be within all the analytical and statistical standards established in the research objectives and confirmed the methodological framework presented in this study.

DISCUSSION

This paper has shown that the combination of the macroeconomic indicators and hybrid deep learning models can greatly enhance the forecasting of the U.S. stock market patterns between the years 2010 and 2023. The hybrid structure that included Long Short-Term Memory (LSTM) Convolutional Neural Networks (CNN) and a predictive attention mechanism had better predictive performance compared to traditional econometric models, and when using these deep-learning initiatives alone [30]. It had the smallest Root Mean Square Error (RMSE = 1.89), the highest directional accuracy (83.6%), and the greatest coefficient of determination (R 2 = 0.86). These findings support the main hypothesis according to which the integration of financial time-series data with macroeconomic indicators can improve the performance of the model and its resistance [31]. Additionally, the results indicate that the behavior of the market is not only controlled by the dynamic aspects of intrinsic prices but also by the external macroeconomic settings that determine the investment expectation and risk perception [32].

GDP growth was a strong positive predictor of equity returns, and inflation, interest rates, unemployment, and market volatility (VIX) were negative predictors, according to the econometric perspective. The regression model (R 2 = 0.68) suggested that about 68 percent of the fluctuation in S and P 500 performance could be explained by these variables, and this indicates that the U.S equity markets were sensitive to the economy [33]. This is in view of the efficient market hypothesis, which assumes that macroeconomic information is quickly reflected in the prices of the asset. Both the short-term predictive relationships and long-term equilibrium relationships between the market performance and the economic fundamentals were found to be true using the Granger cause and the Johansen cointegration tests, which showed that the structural associations hold despite the market volatility [34]. The findings can be used to justify the goal of uniting deep-learning methods with economic interpretability such that the forecasts become more reliable and resilient in different conditions.

The correlations that were found between macroeconomic variables and stock performance were generally in line with the existing empirical research. The works of [35] confirmed that industrial production, inflation, and interest rates have a considerable effect on U.S market returns, which agrees with the current results that inflation and interest rates have a negative impact. On the same note, studies [35] have also demonstrated the predictive characteristics of GDP growth and unemployment and pointed out that the actual increase in the economy has been a factor in boosting corporate profits and, thus, the market confidence [36]. This paper reiterates these classical findings in a modern machine-learning context and affirms that the use of algorithms in market direction cannot replace the important role played by basic economics in the market [37].

The volatility persistence was strong in the ARCH (1,1) model (1 +2 =0.966), which showed that market shocks are long-memoried, as also proposed by [38], the first who discussed volatility clustering as a structural phenomenon of the financial time series. This continuity is a manifestation of behavioral feedback in investor sentiment: increased uncertainty generates increased volatility over time, especially in times of crisis, like the COVID-19 pandemic. The strength of the hybrid model over the volatility regimes illustrates the ability of the hybrid model to learn and adjust to these nonlinear temporal dependencies [39]. LSTM layers reflected sequential dependencies on long horizons, CNN layers reflected localized trend patterns, and the attention mechanism dynamically emphasized influential macroeconomic variables, which led to an adaptable, context-sensitive model that has been able to remain predictive in stressful economic conditions [40].

The development of the hybrid model enabled a substantial performance improvement compared to those of previous machine-learning models. Baseline LSTM models, though useful when the time-series to predict is a time one, typically failed to perform well in the identification of cross-variable interaction, as well as the impact of external economic factors [41]. The CNN-LSTM hybrid had a moderate improvement, but was still limited to the static feature weighting. The inclusion of attention allowed the model to give variable weights to the input of the economy over time, which increases its interpretability and reactivity. A comparable set of architectural benefits has been documented by other researchers, including [42], who report that hybrid deep networks made better predictions on stock indices and volatility forecasting. In contrast to such models, the proposed study incorporated both macroeconomic variables and market data, which enhanced accuracy and created a theoretical connection between computational learning and economic reasoning.

The better modeling capability of the hybrid deep-learning model to approximate complex nonlinear mappings between inputs and outputs, and also maintain temporal causality, can be explained scientifically. CNN layers act as spatial filters, finding short-term variability in financial data, but LSTM networks remember over time, finding cyclical relationships and structural trends [43]. The attention layer is a dynamic adaptor that is used to establish the relevance of macroeconomic features like GDP or fluctuations in interest rates. This combination is also useful to reflect the real-life financial systems where markets are in a constant response to the internal momentum and external macroeconomic indicators [44]. This means that the hybrid structure is a form of computational analog of economic adaptivity, the ability of a system to reweight the inputs to react to new information and shocks [45].

These implications of these results are far-reaching. To the policymakers, the model provides an early-warning mechanism of systemic financial risk analysis, which allows the mitigation of economic crises. As an institutional investor, it gives them a data-based portfolio optimization and risk management tool that changes with a changing macroeconomic environment [46]. What is more, the interpretative level of the model gives greater transparency and accountability in terms of market surveillance to financial regulators. The framework is consistent with the emerging field of financial resilience engineering that incorporates artificial intelligence, macroeconomic analysis, and regulatory foresight in order to maintain economic stability. Using quantitative measures of resilience in quantifiable predictive metrics, the hybrid deep-learning model is shown to have lower forecast error even in crises [47].

Moreover, the research adds to the current discussion in the field by bridging two historical paradigms of modeling econometrics and deep learning. The classic econometric models are valued in their ability to be understood, but are limited by being linear, and the deep-learning models are great at recognizing nonlinear patterns, but do not necessarily place them in an economic perspective. Combining these two paradigms, this paper provides a ground in between that lowers the predictive accuracy and simultaneously increases the theoretical transparency. This method provides a platform upon which to conduct future research of explainable AI in finance, in which the ability to explain the reasoning supporting the predictions of the model is as important as the model prediction itself.

CONCLUSION

The empirical results of this study show that the suggested hybrid deep learning model successfully forecasts the trends of the U.S. stock market with the help of financial and macroeconomic indicators. The findings substantiate that the effects of GDP growth, interest rates, unemployment, and market volatility have strong impacts on stock returns, and the model has good predictive ability and is resilient in changing market conditions. These deliverables show that the study has effectively achieved its goals of improving forecasting accuracy, determining the effect of the major economic factors, and strengthening financial resilience by using adaptive modeling. The scientific value of the study lies in the fact that a hybrid LSTM-CNN-Attention framework is developed to combine the benefits of deep learning with the benefits of economic analysis, thus providing a more reliable and explainable prediction system. In general, the research provides a factual basis to guide policy decision-making, risk reduction, and surveillance of the market. Future studies must build on this framework to include the international markets, combine real-time news and sentiment data, and explore explainable artificial intelligence techniques to further support transparency and global financial resilience.

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REFERENCES

[1] Maja, M. M., & Letaba, P. (2022). Towards a data-driven technology roadmap for the bank of the future: Exploring big data analytics to support technology roadmapping. *Social Sciences & Humanities Open*, *6*(1), 100270.

[2] Goldani, M. (2023). Comparative analysis on forecasting methods and how to choose a suitable one: case study in financial time series. Journal of Mathematics and Modeling in Finance, 3(2), 37-61.

[3] Sharma, A., Zhang, Z., & Rai, R. (2021). The interpretive model of manufacturing: a theoretical framework and research agenda for machine learning in manufacturing. *International Journal of Production Research*, *59*(16), 4960-4994.

[4] Cheffins, B. R. (2009). Did Corporate Governance" Fail" During the 2008 Stock Market Meltdown? The Case of the S&P 500. *The Business Lawyer*, 1-65.

[5] Abramov, A. E., Radygin, A., Chernova, M., & Kosyrev, A. (2020). Snapshot review of financial markets. Monitoring of Russian Economic Outlook. Moscow. IEP, (7), 34-46.

[6] Hynes, W., Trump, B., Love, P., & Linkov, I. (2020). Bouncing forward: a resilience approach to dealing with COVID-19 and future systemic shocks. *Environment Systems and Decisions*, *40*(2), 174-184.

[7] Apu, K. U., Rahman, M. M., Hoque, A. B., & Bhuiyan, M. (2022). FORECASTING FUTURE INVESTMENT VALUE WITH MACHINE LEARNING, NEURAL NETWORKS, AND ENSEMBLE LEARNING: A META-ANALYTIC STUDY. *Review of Applied Science and Technology*, *1*(02), 01-25.

[8] Omopariola, B. J., & Aboaba, V. (2019). Comparative analysis of financial models: Assessing efficiency, risk, and sustainability. *Int J Comput Appl Technol Res*, *8*(5), 217-231.

[9] Carney, M. (2019, August). The growing challenges for monetary policy in the current international monetary and financial system. In *Remarks at the Jackson Hole symposium* (Vol. 23, pp. 377-411).

[10] Mohammed, M., & Zheng, M. (2023). The impact of macroeconomic factorson the propensity of risk: How macroeconomic factors influence the level of risk in different stock market.

[11] Vudugula, S., Chebrolu, S. K., Bhuiyan, M., & Rozony, F. Z. (2023). Integrating artificial intelligence in strategic business decision-making: A systematic review of predictive models. International Journal of Scientific Interdisciplinary Research, 4(1), 01-26.

[12] Hussain, K. (2023). Harnessing AI for Predictive Accuracy in Financial Forecasting and Risk Assessment.

[13] Ahmad, A. S. (2023). Application of big data and artificial intelligence in strengthening fraud analytics and cybersecurity resilience in global financial markets. *International Journal of Advanced Cybersecurity Systems, Technologies, and Applications*, *7*(12), 11-23.

[14] Omopariola, B., & Aboaba, V. (2021). Advancing financial stability: The role of AI-driven risk assessments in mitigating market uncertainty. *Int J Sci Res Arch*, *3*(2), 254-270.

[15] Duarte, F., & Jiménez-Molina, Á. (2021). Psychological distress during the COVID-19 epidemic in Chile: The role of economic uncertainty. *PloS one*, *16*(11), e0251683.

[16] Gourieroux, C., & Jasiak, J. (2018). Financial econometrics: Problems, models, and methods.

[17] Chen, W., Hussain, W., Cauteruccio, F., & Zhang, X. (2023). Deep learning for financial time series prediction: A state-of-the-art review of standalone and hybrid models. *CMES-Computer Modeling in Engineering and Sciences*.

[18] Zheng, Y., Xu, Z., & Xiao, A. (2023). Deep learning in economics: a systematic and critical review. *Artificial Intelligence Review*, *56*(9), 9497-9539.

[19] Weng, B., Martinez, W., Tsai, Y. T., Li, C., Lu, L., Barth, J. R., & Megahed, F. M. (2018). Macroeconomic indicators alone can predict the monthly closing price of major US indices: Insights from artificial intelligence, time-series analysis and hybrid models. *Applied Soft Computing*, *71*, 685-697.

[20] Guimaraes, R. R. (2022). Deep learning macroeconomics. *arXiv preprint arXiv:2201.13380*.

[21] Rubio, L., Palacio Pinedo, A., Mejía Castaño, A., & Ramos, F. (2023). Forecasting volatility by using wavelet transform, ARIMA and GARCH models. *Eurasian Economic Review*, *13*(3), 803-830.

[22] Pahlavani, M., & Roshan, R. (2015). The comparison among ARIMA and hybrid ARIMA-GARCH models in forecasting the exchange rate of Iran. *International Journal of Business and Development Studies*, *7*(1), 31-50.

[23] Shanmugasundar, G., Vanitha, M., Čep, R., Kumar, V., Kalita, K., & Ramachandran, M. (2021). A comparative study of linear, random forest and adaboost regressions for modeling non-traditional machining. *Processes*, *9*(11), 2015.

[24] Zaheer, S., Anjum, N., Hussain, S., Algarni, A. D., Iqbal, J., Bourouis, S., & Ullah, S. S. (2023). A multi parameter forecasting for stock time series data using LSTM and deep learning model. *Mathematics*, *11*(3), 590.

[25] Verma, S., Sahu, S. P., & Sahu, T. P. (2023). Stock Market Forecasting with Different Input Indicators using Machine Learning and Deep Learning Techniques: A Review. *Engineering Letters*, *31*(1).

[26] Padhan, R., & Prabheesh, K. P. (2019). Effectiveness of early warning models: A critical review and new agenda for future direction. *Bulletin of Monetary Economics and Banking*, *22*(4), 457-484.

[27] Shah, J., Vaidya, D., & Shah, M. (2022). A comprehensive review on multiple hybrid deep learning approaches for stock prediction. *Intelligent Systems with Applications*, *16*, 200111.

[28] Muşetescu, R. C., Grigore, G. E., & Nicolae, S. (2022). The use of GARCH autoregressive models in estimating and forecasting the crude oil volatility. *European Journal of Interdisciplinary Studies*, *14*(1), 13-38.

[29] Muşetescu, R. C., Grigore, G. E., & Nicolae, S. (2022). The use of GARCH autoregressive models in estimating and forecasting the crude oil volatility. *European Journal of Interdisciplinary Studies*, *14*(1), 13-38.

[30] Chen, W., Hussain, W., Cauteruccio, F., & Zhang, X. (2023). Deep learning for financial time series prediction: A state-of-the-art review of standalone and hybrid models. *CMES-Computer Modeling in Engineering and Sciences*.

[31] Gricar, S., Šugar, V., & Starc, J. (2023). Interrelationships among Tourism, Economic, and Environmental Time Series—The Case of Slovenia. *Sustainability*, *15*(19), 14488.

[32] Pflueger, C., Siriwardane, E., & Sunderam, A. (2020). Financial market risk perceptions and the macroeconomy. *The Quarterly Journal of Economics*, *135*(3), 1443-1491.

[33] Rounaghi, M. M., & Zadeh, F. N. (2016). Investigation of market efficiency and financial stability between S&P 500 and London stock exchange: monthly and yearly forecasting of time series stock returns using ARMA model. *Physica A: Statistical Mechanics and its Applications*, *456*, 10-21.

[34] Ahmad, A. U., Abdullah, A., Sulong, Z., & Abdullahi, A. T. (2015). Causal relationship between stock market returns and macroeconomic variables in Nigeria. *IOSR Journal of Humanities and Social Science*, *20*(5), 74-96.

[35] Ernest, W. C., Jnr, S. D., & Kofi, S. A. (2016). Macroeconomic variables and stock market performance of emerging countries. *Journal of Economics and International Finance*, *8*(7), 106-126.

[36] Guerard, J., Thomakos, D., & Kyriazi, F. (2020). Automatic time series modeling and forecasting: A replication case study of forecasting real GDP, the unemployment rate and the impact of leading economic indicators. *Cogent Economics & Finance*, *8*(1), 1759483.

[37] Doloc, C. (2019). *Applications of Computational Intelligence in Data-Driven Trading*. John Wiley & Sons.

[38] Gunnarsson, E. S., & Isern, H. R. (2023). *Volatility Prediction and Uncertainty Quantification using Bayesian Neural Networks* (Master's thesis, NTNU).

[39] Apu, K. U., Rahman, M. M., Hoque, A. B., & Bhuiyan, M. (2022). FORECASTING FUTURE INVESTMENT VALUE WITH MACHINE LEARNING, NEURAL NETWORKS, AND ENSEMBLE LEARNING: A META-ANALYTIC STUDY. *Review of Applied Science and Technology*, *1*(02), 01-25.

[40] Lim, B., & Zohren, S. (2021). Time-series forecasting with deep learning: a survey. *Philosophical Transactions of the Royal Society A*, *379*(2194), 20200209.

[41] Toubeau, J. F., Bottieau, J., Wang, Y., & Vallée, F. (2021). Interpretable probabilistic forecasting of imbalances in renewable-dominated electricity systems. *IEEE Transactions on Sustainable Energy*, *13*(2), 1267-1277.

[42] Fan, C., Xiao, F., Yan, C., Liu, C., Li, Z., & Wang, J. (2019). A novel methodology to explain and evaluate data-driven building energy performance models based on interpretable machine learning. *Applied Energy*, *235*, 1551-1560.

[43] Freeborough, W. (2022). *Investigating explainablity methods in recurrent neural network architectures for financial time-series data* (Master's thesis, University of the Witwatersrand, Johannesburg (South Africa)).

[44] Huang, A., Qiu, L., & Li, Z. (2021). Applying deep learning method in TVP-VAR model under systematic financial risk monitoring and early warning. *Journal of Computational and Applied Mathematics*, *382*, 113065.

[45] Koohborfardhaghighi, S. (2017). *Analyzing Socio-Economic Complex Adaptive Networks: A Hybrid Approach* (Doctoral dissertation, 서울대학교 대학원).

[46] Montes, C. P., Galán, J. E., Bru, M., Gálvez, J., García, A., González, C., ... & Roibás, I. (2023). *Systemic analysis framework for the impact of economic and financial risks*. Banco de España.

[47] Olukoya, O. (2023). Time series-based quantitative risk models: enhancing accuracy in forecasting and risk assessment. *International Journal of Computer Applications Technology and Research*, *12*(11), 29-41.