Analysis of Stock Portfolio with Global Economic Factors using Dynamic Data Modelling

B Varija[1], Dr. Nagaratna P Hegde[2]
[1]Department of Computer Science and Engineering
Jawaharlal Nehru Technological University
Hyderabad, India
varija.vv@gmail.com
[2]Department of Computer Science and Engineering
Vasavi college of Engineering
Hyderabad, India
nagaratnaph@staff.vce.ac.in

Abstract: This article analyzes stock portfolios and worldwide economic challenges. This study uses APIs to retrieve data and analyze correlations. To determine and measure how economic indicators affect stock performance. This work introduces an autoencoder-based model to better comprehend the complex relationship between economic conditions and stock portfolio dynamics. The analysis begins with an API retrieval of a wide range of macroeconomic information. These indicators include global economic metrics like GDP, unemployment, CPI, federal funds rates, and treasury bill rates. After collection, data is carefully curated and prepared for analysis. This study uses correlation analysis to understand economic variables and stock portfolio performance. This study explores how economic conditions affect stock prices and portfolio returns. This study seeks to discover trends, dependencies, and future issues that may affect investment decisions. This study also introduces an autoencoder-based neural network model to capture complex nonlinear relationships between economic variables and stock portfolio behavior. Deep learning improves interpretability and prediction, allowing a better understanding of the complex financial ecosystem dynamics. The inquiry provides valuable insights for investors, financial experts, and regulators. This study advances data-driven investment and risk management solutions. The autoencoder-based approach also reveals latent structures and hidden factors that affect stock portfolios. This novel approach opens new study options. In conclusion, this study provides a thorough stock portfolio analysis approach for global economic challenges. API data retrieval, correlation analysis, and a novel autoencoder model are used in this work to better understand the complicated relationships between economic indicators and financial markets. These insights can improve investment and policy decisions in a more integrated and dynamic global economy.

Keywords— Stock portfolio analysis, Global economic factors, API data retrieval, Correlation analysis, Autoencoder modeling, financial market dynamics

I. INTRODUCTION

The examination of stock portfolios within the wider context of global economic issues has been a topic of great interest and importance in the realm of financial research for a considerable period of time. This research paper explores a complex subject by employing a comprehensive methodology that involves extracting relevant economic data using API data retrieval, utilizing the correlation method to identify influential factors, and drawing conclusions with the assistance of an innovative application of an autoencoder model.

The analysis of stock portfolios and their sensitivity to global economic dynamics is a central focus in current financial research. This project aims to utilize API searches to extract real-time economic data, thereby capitalizing on the vast amount of information accessible in the digital era. In this endeavor, the aim is to comprehensively capture the complex network of economic variables that together influence the path of worldwide financial markets. The incorporation of the correlation method in this study is a fundamental component of its analytical framework. In contrast to traditional financial models, this study places emphasis on moving beyond basic descriptive statistics to delve into more profound relationships and interdependence. The objective is to examine the level of correlation between economic indicators and the behavior of stock portfolios, thereby enabling a comprehensive comprehension of the complex interaction between these variables.

In addition, the utilization of an autoencoder, a complex neural network model, enhances our ability to understand the complex foundations of stock portfolio dynamics. This study seeks to utilize deep learning techniques in order to reveal underlying structures and identify hidden factors within the extensive body of financial data. This methodology provides a distinct viewpoint on the intricate interconnections that may not be easily discernible using conventional statistical methodologies.

As the investigation progresses, it presents a thorough theoretical structure for the examination of stock portfolios within a current global setting. The primary objective of this endeavor is to furnish investors, financial analysts, and policymakers with significant perspectives that can contribute to informed strategic decision-making and the implementation of risk management methods. Furthermore, the utilization of the autoencoder model makes a significant contribution to the advancement of knowledge in the respective sector. This not only facilitates the study of intricate relationships between economic conditions and the performance of stock portfolios, but also paves the way for future research in this domain.

In summary, this research article provides a comprehensive analysis of the complex interplay between stock portfolios and global economic variables. The opening of this study employs the passive voice construction to emphasize the importance and seriousness of this endeavor, emphasizing the possibility for transformation in financial research through the utilization of API data retrieval, correlation analysis, and autoencoder modeling. The subsequent chapters explore this diverse terrain in further detail, offering a comprehensive perspective on the complex relationship between economic data and stock market movements.

II. RELATED WORKS

The literature review section of this extensive research paper presents a complete synthesis of recent studies encompassing a wide range of subjects in the fields of finance and economics. The aforementioned studies, produced by a diverse group of experts, jointly contribute to the ongoing development of knowledge regarding financial markets, the dynamics of stock prices, economic indicators, and the complex aspects that influence investment choices. This review examines a diverse range of research efforts, including studies on stock price forecasting, the impact of macroeconomic factors, the application of machine learning techniques, corporate reporting practices, geopolitical influences, and the interconnectedness of multiple variables that form the foundation of the intricate field of finance. The knowledge derived from these research investigations provides a fundamental basis for understanding the complex interconnections within financial ecosystems and has significant consequences for individuals such as investors, analysts, policymakers, and scholars who aim to traverse the ever-changing terrain of modern finance. The literature review provides insights into recent research studies that have explored various facets of stock market dynamics, including factors influencing stock prices, predictive modeling, and the impact of macroeconomic variables.

Abdulkadir Alici and Güven Sevil [1] conducted an analysis of sector-specific operational performance metrics affecting the stock prices of traditional airlines. Their study sheds light on the operational factors within the airline industry that play a crucial role in determining stock prices. This research underscores the industry-specific nature of stock price dynamics. In a study by Lingling Zeng, Yanan Xiao, and Shilong Chen [2], the authors explored short-term stock price trends using machine learning techniques. Their research delves into the application of machine learning models to understand and predict short-term fluctuations in stock prices, contributing to the growing body of literature on quantitative stock market analysis. Ayesha Jabeen et al. [3] conducted an empirical study investigating the relationship between macroeconomic factors and stock returns in the context of economic uncertainty news sentiment. Their research employs machine learning methodologies to analyze the impact of economic uncertainty on stock market dynamics, highlighting the role of sentiment analysis in understanding stock market behavior. Asmaa Y. Fathi, Ihab A. El-Khodary, and Muhammad Saafan [4] explored the integration of singular spectrum analysis and nonlinear autoregressive neural networks for stock price forecasting. Their study represents an innovative approach to stock price prediction, emphasizing the importance of advanced computational techniques in financial modeling.

S. Balagobei and D. R. N. K. K. Bandara [5] investigated the impact of macroeconomic variables on stock market performance, focusing on evidence from the Sri Lankan market. Their research provides insights into the relationship between macroeconomic indicators and stock market movements, with implications for investors and policymakers in the region. These studies collectively contribute to the evolving landscape of stock market research, encompassing various dimensions such as sector-specific factors, predictive modeling, sentiment analysis, and the influence of macroeconomic variables. The insights gained from these investigations serve to enrich our understanding of the intricate dynamics that shape stock market behavior and offer valuable implications for financial practitioners and researchers alike.

Pham Hoang Vuong et al. [6] embarked on stock price forecasting using a combination of XGBoost and LSTM models. Their research highlights the application of advanced machine learning techniques in predicting stock prices, emphasizing the potential of these models to enhance forecasting accuracy. Jakub Horák and Dominik Kaisler [7] conducted an evaluation of the development of Apple Inc.'s stock price time series. Their study offers insights into the historical trajectory of a prominent tech company's stock price, contributing to the body of knowledge related to stock market analysis. A. M. Karipova, D. S. Baktybaeva, and G. Sh. Usbanova [8] analyzed the impact of the global situation on "FORTEBANK" JSC. Their research delves into the influence of global events on a specific financial institution, demonstrating the interconnectedness of financial markets with broader geopolitical factors.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10
***Article Received:** 20 August 2023 **Revised:** 07 October 2023 **Accepted:** 20 October 2023*

Dilip Kumar [9] explored the nexus between travel and leisure stocks and uncertainties, employing extreme risk spillover analysis. This study provides valuable insights into the vulnerability of specific sectors to external uncertainties, enhancing our understanding of sector-specific risk dynamics. Hongmin Zhang and Jinming He [10] conducted an analysis of price factors and volatility prediction of the Belt and Road Theme Index. Their research showcases the application of empirical mode decomposition (EMD) in understanding the dynamics of theme-based stock indices. Raras Tyasnurita, Rifqi Rahmadrian Luthfiansyah, and Muhamad Rayhan Brameswara [11] focused on gold price forecasting using the multiple linear regression method. Their study offers a practical approach to forecasting precious metal prices, catering to the interests of investors and analysts in the commodities market. Michail Filippidis et al. [12] undertook an evaluation of robust determinants of the WTI/Brent oil price differential, employing dynamic model averaging analysis. Their research contributes to our understanding of the complex factors influencing oil price differentials in the global energy market.

P. M. Petrova [13] delved into the methods of strategic analysis of indicators related to the confidence period in the real estate market. This research contributes to the understanding of analytical approaches crucial for assessing the dynamics of the real estate sector, a pivotal component of the global economy. Ding Liu et al. [14] explored the time-frequency relationship between economic policy uncertainty and the financial cycle in China. Their use of wavelet analysis provides valuable insights into the temporal dynamics of economic policy and its impact on financial markets, particularly in the context of a dynamic emerging economy.

Karthik M et al. [15] developed a framework for short-term cryptocurrency price fluctuation prediction using machine learning. Their study addresses the burgeoning field of cryptocurrencies and offers a practical approach to forecasting the volatility in this rapidly evolving market. Jie Song, Shangkun Liang, and Yuhan Zhen [16] investigated the impact of CEO-auditor dialect sharing on stock price crash risk in China. This research sheds light on the intricate relationship between corporate governance factors and stock market dynamics, offering implications for corporate risk management.

Zanuba Ainindya El Fanani and Rizky Nur Ayuningtyas Putri [17] studied the determinants of share liquidity for Sharia banks listed on the Indonesian Stock Exchange during the Covid-19 pandemic. Their research highlights the unique challenges faced by financial institutions during times of economic uncertainty. Kewei Shi [18] conducted an analysis of influencing factors on stock return rates in China, contributing to our understanding of the drivers of stock market performance in one of the world's largest economies. Shuming Bai, Kai S. Koong, and Yanni Wang [19] investigated the relationship between research and development (R&D) reporting and stock performance in China. Their study offers evidence of the impact of R&D disclosure on stock market dynamics, shedding light on the relevance of corporate reporting practices.

Yudha Randa Madhika Ferdinandus, Kusrini Kusrini, and Tonny Hidayat [20] delved into gold price prediction using ARIMA and LSTM models. Their research showcases the application of time series analysis and machine learning in forecasting precious metal prices, catering to the interests of investors in the commodities market. Zeravan Abdulmuhsen Asaad et al. [21] explored the nexus between oil exports, political issues, and stock markets. Their study examines the intricate relationships between global geopolitical factors and stock market dynamics, offering insights into the volatility of energy markets. Wenjing Wang, Moting Wang, and Yizhi Dong [22] investigated the impact of digital finance on stock price crash risk in China. Their research explores the transformative influence of digital financial services on stock market stability, emphasizing the role of technology in financial markets.

Shilpa B L and Shambhavi B R [23] employed combined deep learning classifiers for stock market prediction by integrating stock price data and news sentiments. Their study showcases the fusion of textual and numerical data sources in predicting stock market trends, contributing to the growing field of sentiment analysis. Jujie Wang and Shuzhou Zhu [24] introduced a multi-factor two-stage deep integration model for stock price prediction. Their research incorporates intelligent optimization and feature clustering techniques, providing a sophisticated approach to stock price forecasting and risk management.

The summary of the literature review is furnished here [Table – 1].

TABLE I. LITERATURE REVIEW SUMMARY

Author, Year	***Methodology***	***Research Limitation***
Abdulkadir Alici et al.[1] 2022	Operational Performance Metrics Analysis	Industry-specific; Limited to traditional airlines
Lingling Zeng et al.[2] 2022	Machine Learning	Limited to short-term trends
Ayesha Jabeen et al.[3] 2022	Machine Learning	Focuses on macroeconomic factors and news sentiment
Asmaa Y. Fathi et al.[4] 2022	Singular Spectrum Analysis and Neural Network	Forecasting method-specific
S. Balagobei et al.[5] 2022	Econometric Analysis	Limited to the Sri Lankan market
Pham Hoang Vuong et al.[6] 2022	XGBoost and LSTM	Limited to stock price forecasting
Jakub Horák et al.[7] 2022	Time Series Analysis	Focused on Apple Inc. stock

Author, Year	*Methodology*	*Research Limitation*
A. M. Karipova et al.[8] 2023	Financial Analysis	Limited to "FORTEBANK" JSC
Dilip Kumar[9] 2023	Extreme Risk Spillover Analysis	Focused on travel and leisure stocks
Hongmin Zhang et al.[10] 2023	Empirical Mode Decomposition (EMD)	Theme-based analysis
Raras Tyasnurita et al.[11] 2023	Linear Regression	Limited to gold price prediction
Michail Filippidis et al.[12] 2023	Dynamic Model Averaging	Focused on oil price differential
P. M. Petrova[13] 2023	Strategic Analysis	Limited to real estate market indicators
Ding Liu et al.[14] 2023	Wavelet Analysis	Focused on economic policy uncertainty in China
Karthik M et al.[15] 2023	Machine Learning	Short-term cryptocurrency price prediction
Jie Song et al.[16] 2023	Financial Analysis	CEO-auditor dialect sharing and stock price crash risk
Zanuba Ainindya El Fanani[17] 2023	Market Analysis	Specific to Sharia banks during the Covid-19 pandemic
Kewei Shi[18] 2023	Econometric Analysis	Limited to stock return rate in China
Shuming Bai et al.[19] 2023	Financial Analysis	Examines R&D reporting and stock performance in China
Yudha Randa Madhika Ferdinandus et al.[20] 2023	ARIMA and LSTM Models	Limited to gold price prediction
Zeravan Abdulmuhsen Asaad et al.[21] 2023	Econometric Analysis	Focuses on the nexus between oil exports, political issues, and stock markets
Wenjing Wang et al.[22] 2023	Econometric Analysis	Examines the impact of digital finance on stock price crash risk in China
Shilpa B L et al.[23] 2023	Deep Learning	Combines stock price and news sentiments for prediction
Jujie Wang et al.[24] 2023	Deep Integration Model	Utilizes intelligent optimization and feature clustering for stock price prediction

III. RESEARCH PROBLEM

This research addresses a research problem that involves multiple crucial elements. The subsequent analysis will involve a comprehensive examination of the research problems.

A. *Analysis of a stock portfolio.*

- Objective: The present study seeks to conduct an analysis of a stock portfolio, which is commonly comprised of a diverse assortment of different stocks or securities. Stock portfolios are strategically constructed with the aim of attaining distinct financial objectives, such as the optimization of returns or the mitigation of risk.
- Research Problem: The main research objective is to conduct a detailed analysis of the performance of a stock portfolio. The process entails the assessment of the portfolio's historical performance, evaluation of its risk characteristics, and perhaps providing recommendations for portfolio improvement.

B. *The integration of global economic factors.*

- Description: The study integrates global economic variables into the analysis. Global economic factors encompass various indicators, including but not limited to GDP growth rates, inflation rates, interest rates, currency rates, and geopolitical events, which exert a substantial influence on financial markets.
- Research Problem: The primary objective is to proficiently integrate intricate global economic aspects into the analysis and evaluate their impact on the stock portfolio's performance. The process may encompass the collecting of data, its preprocessing, and subsequent integration into the analysis framework.

C. *The process of retrieving data through an API lookup.*

- Description: The research utilizes an Application Programming Interface (API) to retrieve pertinent financial and economic data. Application Programming Interfaces (APIs) offer a systematic approach for retrieving data from external sources, including financial databases and providers of economic data.
- Research challenge: The research challenge pertains to the effective integration of API lookup functionality for retrieving real-time or historical data on stocks within a portfolio, as well as the corresponding economic indicators. This necessitates the consideration of potential obstacles associated with the retrieval and quality of data.

D. *The identification of influence using the correlation method.*

- Objective: This study seeks to analyze the impact of global economic factors on the performance of a stock portfolio. The correlation method is a statistical procedure employed to quantify the extent of relationship between variables, such as economic indicators and stock returns.
- Research Problem: The research problem pertains to the precise measurement of the correlations existing between economic conditions and stock returns.

Additionally, the evaluation of the magnitude and direction of these correlations is essential in identifying the factors that exert the greatest influence on the portfolio.

E. The final conclusion drawn by the utilization of an autoencoder is as follows:

- Description: The study utilizes an autoencoder, a form of artificial neural network, to derive conclusive findings or insights from the data. Autoencoders are commonly employed in the field of machine learning for the purposes of reducing dimensionality and extracting features.

- Research Problem: The research problem pertains to the efficient utilization of autoencoders for the purpose of summarizing analysis findings and deriving actionable conclusions or insights. The task at hand encompasses the process of formulating and instructing the autoencoder framework, as well as analyzing and comprehending the outcomes.

In brief, the research inquiries in this study pertain to the comprehensive examination of a stock portfolio, the integration of global economic variables, data retrieval through API lookup, identification of influence via correlation analysis, and the utilization of autoencoders for drawing ultimate conclusions. Each of these components provides distinctive issues and complexities that the research seeks to tackle.

Further, the parallel research outcomes and their capabilities to address the recent research challenges are analyzed [Table – 2].

TABLE II. LITERATURE REVIEW SUMMARY

Author, Year	*Stock Portfolio*	*Financial Parametric Influence Analysis*	*Parametric Correlation*	*Trend Analysis with Autoencoder*
Abdulkadir Alici et al.[1] 2022	✓		✓	
Lingling Zeng et al.[2] 2022	✓			✓
Ayesha Jabeen et al.[3] 2022	✓		✓	
Asmaa Y. Fathi et al.[4] 2022	✓		✓	
S. Balagobei et al.[5] 2022	✓	✓		
Pham Hoang Vuong et al.[6] 2022	✓	✓	✓	
Jakub Horák et al.[7] 2022			✓	
A. M. Karipova et al.[8] 2023			✓	
Dilip Kumar[9] 2023		✓		✓
Hongmin Zhang et al.[10] 2023	✓		✓	
Raras Tyasnurita et al.[11] 2023		✓	✓	
Michail Filippidis et al.[12] 2023		✓	✓	
P. M. Petrova[13] 2023		✓		
Ding Liu et al.[14] 2023	✓		✓	
Karthik M et al.[15] 2023	✓	✓		
Jie Song et al.[16] 2023	✓	✓		
Zanuba Ainindya El Fanani[17] 2023	✓			✓
Kewei Shi[18] 2023	✓			✓
Shuming Bai et al.[19] 2023		✓	✓	
Yudha Randa Madhika Ferdinandus et al.[20] 2023		✓	✓	
Zeravan Abdulmuhsen Asaad et al.[21] 2023	✓	✓		
Wenjing Wang et al.[22] 2023		✓	✓	
Shilpa B L et al.[23] 2023	✓		✓	
Jujie Wang et al.[24] 2023		✓	✓	

IV. PROPOSED SOLUTIONS

In the proposed solutions section of this research project, we introduce a complete framework specifically developed to tackle the complex issues involved in analyzing a stock portfolio by including global economic considerations. We employ a combination of cutting-edge approaches and methodologies, each designed to address a distinct aspect of the research challenge. We present the methods for extracting data seamlessly using API lookup, employing correlation analysis to reveal the intricate connections between economic factors and stock performance, and utilizing autoencoders to

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10
***Article Received:** 20 August 2023 **Revised:** 07 October 2023 **Accepted:** 20 October 2023*

extract valuable insights from the intricate network of financial and economic data. These solutions together create a strong and effective approach that aims to provide insights into the behavior of stock portfolios in the constantly evolving global economic environment. This has important consequences for investors, financial analysts, and academics who are dealing with the intricate field of finance.

The proposed solution is cultivated in four phases, which are furnished here:

A. API and Lookup Table Driven Parametric Extraction

Firstly, the proposed solution elaborates on the extraction of the global financial parameter extractions based on the date range. Assuming that λ is the API function for extraction of the global financial parameters and the relevant financial information will be stored in the lookup table called $GD_S[]$. Thus, this can be formulated as,

$$GD_S[] = < date, \lambda\{quandl[][]\} > \tag{1}$$

The proposed API function extracts the data from the global source called, QUANDL.
Further, the relevant information is extracted and build into the lookup table dataset $ID_S[]$ as,

$$ID_S[] = < SID, \prod_{date} GD_S[] > \tag{2}$$

Where, SID is the stock index.

B. Sentiment Extraction using Linguistic Rule

Yet another component for the analysis of the stock portfolio is the sentiment component related to the stock index. Thus, secondly, the extraction of the sentiment from the news articles are proposed here. The sentiment extraction method applies the linguistic method. Assuming that NDB[] is the news article dataset with HNEWS[] as the news headlines and TNEWS[] is the text of the news articles represented as,

$$NDB[] = < HNEWS[], TNEWS[] > \tag{3}$$

In order to build the sentiment dataset, $S_{DB}[]$ the news articles from the news sources must be extracted based on the date and the stock index as,

$$S_{DB}[] = \prod_{SID \subset HNEWS \, \&\& \, date} NDB[] \tag{4}$$

Further, this proposed method introduces linguistic rulesets for extracting sentiment values. Assuming that the entire rule engine is identified as R[] and each rule is denoted as R_i, then the initial formulation can be furnished as,

$$R[] = \int R_i \tag{5}$$

Where each rule can be further furnished as,

$$R_i = < W_j \leftrightarrow W_{j+1} > [S_k] \tag{6}$$

Where, W_j and W_{j+1} are the related words along with the sentiment score for these works denoted by S_k.

Also, these word collections are built from the news dataset and can be represented as,

$$\{w_i \subset W[]\} \subseteq TNEWS[] \tag{7}$$

Hence, now the sentiments can be calculated and can be added to the sentiment dataset as,

$$S_{DB}[].Sentiment = \int (\sum \frac{NDB[].TNEWS}{\Delta PoS[]}).R[] \tag{8}$$

Here, PoS denotes the parts of the speech collection based on the stop words.

Hence, the final sentiment dataset can be furnished as,

$$S_{DB}[] = < TNEWS, Sentiment > \tag{9}$$

C. Dynamic Data Model Creation

Once the sentiment is also extracted related to stock index and also the global financial parameters are extracted, then the final dataset, $F_{DB}[]$ must be build using the correlation method. However, the initial stock dataset, $SI_{DB}[]$ based on timeline is extracted here,

$$SI_{DB}[] = < SID, LTP[](t) > \tag{10}$$

Where LTP is the last traded price for the associated stock, and it is a historical dataset with all past transactional data.

Firstly, the correlation, C[], is extracted between the stock data and global financial dataset are identified and the parameters with higher correlations are built into the final dataset.

$$C[] = \int SI_{DB}[] \times ID_S[] \tag{11}$$

And, further,

$$F_{DB}[] = \prod_{C[i]>0.05} SI_{DB}[] \times ID_S[] \tag{12}$$

Finally, the sentiment scores are again added to the final dataset as,

$$F_{DB}[] = \{ \prod_{C[i]>0.05} SI_{DB}[] \times ID_S[] \} \times \prod_{SID, date} S_{DB}[] \tag{13}$$

D. Stock Prediction using Autoencoder

An autoencoder is an intriguing notion in the realm of artificial neural networks, originating from the domain of unsupervised learning and the reduction of dimensionality. An autoencoder is a neural network architecture designed to encode and decode input data, aiming to rebuild it with high fidelity. This approach is similar to instructing a network to

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10
***Article Received:** 20 August 2023 **Revised:** 07 October 2023 **Accepted:** 20 October 2023*

condense information into a concise, reduced-dimensional representation and afterwards restore it to its initial form. The essence of the network resides in its intermediate layer, referred to as the bottleneck or encoding layer, where the data is compressed.

Assuming that h[] is the hidden layer and f_1 is the encoder function, then the hidden layer can be furnished as,

$$h[] = f_1\{F_{DB}[](t)\} \tag{14}$$

And, for the prediction of the stock prices, the following relation can be established as,

$$F_{DB}[](t+1) = f_2\{h[]\} + loss(t) \tag{15}$$

Here f_2 is the decoder function.

And, after elaborating the previous equation,

$$F_{DB}[](t+1) = f_2\{f_1\{F_{DB}[](t)\}\} + loss(t) \tag{16}$$

Autoencoders have diverse applications in disciplines such as image and signal processing, feature learning, and anomaly detection. Due to their capacity to accurately represent key characteristics of data, eliminate irrelevant information, and provide compelling opportunities for unsupervised learning, they are a crucial instrument in the realm of artificial intelligence and machine learning. Autoencoders remain a topic of extensive investigation and possess the capacity to reveal concealed patterns and insights within intricate datasets.

Further, the proposed solution is graphically furnished here [Fig – 1].

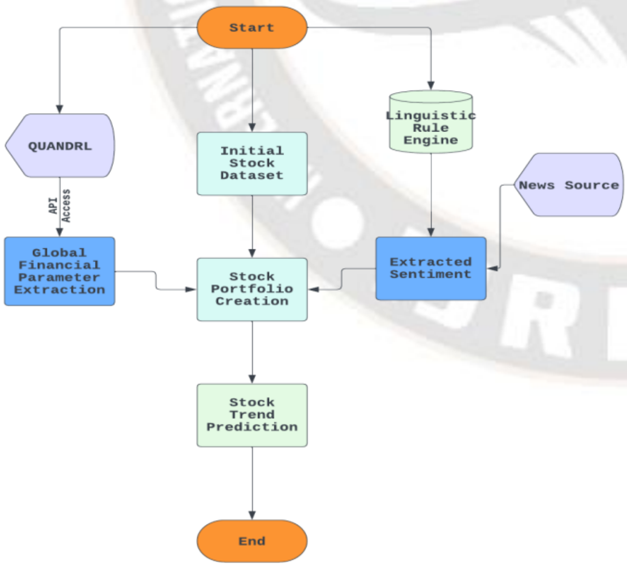

Figure 1. Proposed Solution Workflow

V. PROPOSED ALGORITHMS AND FRAMEWORKS

In order to make accurate forecasts of stock prices, this algorithm makes use of a multi-stage process. It begins by gathering data from application programming interfaces (APIs), then applies sentiment analysis based on linguistic criteria, moves on to dynamic data modeling, and concludes with stock price forecasting using an autoencoder. The proposed algorithm is furnished here:

Algorithm: Stock Price Prediction using Autoencoder

Input:

1. Stock symbol (e.g., AAPL for Apple Inc.).
2. Date range for historical data (start_date, end_date).
3. List of macroeconomic indicators (e.g., GDP, UNRATE, CPIAUCSL).
4. News headlines related to the stock.
5. Lookup table with API endpoints for data extraction.
6. Training and testing data split ratio.
7. Autoencoder architecture parameters (e.g., number of layers, neurons).
8. Machine learning model for final stock prediction (e.g., regression model).

Output:

1. Predicted stock prices for the specified date range.
2. Model evaluation metrics (e.g., Mean Absolute Error, Root Mean Squared Error).
3. Visualization of predicted vs. actual stock prices.
4. Insights into the impact of macroeconomic factors and sentiment on stock price.

Assumptions:

1. The selected stock symbol exists and is publicly traded.
2. The API endpoints in the lookup table provide accurate and reliable data.
3. News headlines are relevant to the stock symbol and impact stock sentiment.
4. The selected machine learning model is appropriate for the prediction task.
5. Adequate historical data and macroeconomic indicators are available for analysis.

Process:

Step - 1. Commence the system by configuring the necessary libraries, modules, and API connections.

Step - 2. Construct a lookup table containing a roster of stock symbols and their accompanying API endpoints for retrieving historical stock price data and pertinent economic factors.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10
***Article Received:** 20 August 2023 **Revised:** 07 October 2023 **Accepted:** 20 October 2023*

Step - 3. Iterate through the lookup table to retrieve past stock price data and macroeconomic indicators for the provided stock symbol and date period from the corresponding APIs.

Step - 4. Perform preprocessing and cleansing on the extracted data to ensure consistency and high quality.

Step - 5. Retrieve news headlines pertaining to the stock symbol from pertinent sources utilizing a web scraper or news API.

Step - 6. Utilize linguistic rules to conduct sentiment analysis on every news headline. For instance, employ rules to discern whether emotion is good or negative.

Step - 7. Compute a sentiment score for each headline using linguistic rules, then combine the scores to describe the overall sentiment for a specific time period.

Step - 8. Integrate the historical stock price data, macroeconomic factors, and sentiment scores to create a comprehensive dataset.

Step - 9. Develop a flexible data model that takes into account time series characteristics, lag values, and other pertinent parameters.

Step - 10. Partition the dataset into training and testing subsets, while preserving the chronological sequence to ensure precise modeling.

Step - 11. Create an autoencoder neural network model that consists of an encoding layer and a decoding layer.

Step - 12. Utilize the training dataset to train the autoencoder, while reducing the reconstruction error.

Step - 13. Retrieve the encoded features by extracting the representations of the bottleneck layer.

Step - 14. Utilize the encoded features as the input for a stock price prediction model, such as a time series forecasting model or a regression model.

Step - 15. Perform training and fine-tuning of the prediction model utilizing the encoded characteristics alongside other pertinent input features.

Step - 16. Utilize the trained model to make predictions about future stock prices and assess the model's performance on the testing dataset.

The algorithm automation is visualized here [Fig – 2].

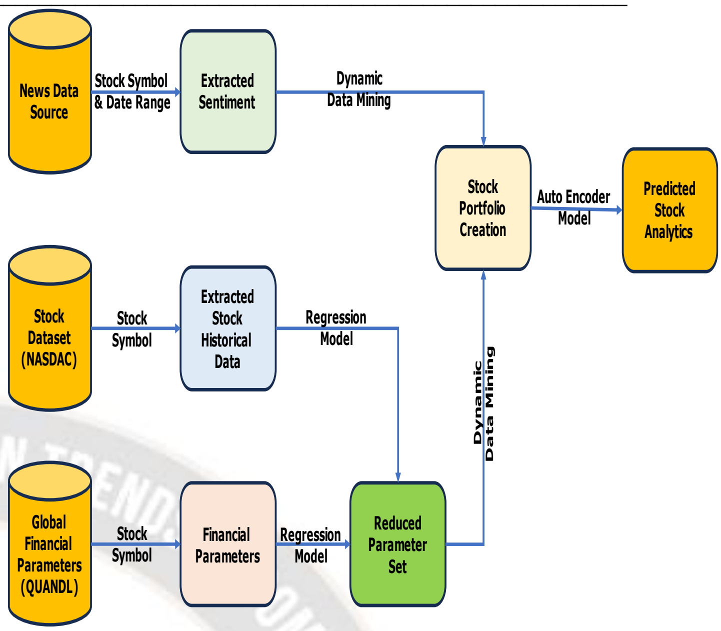

Figure 2. Proposed Algorithm Automation

The system utilizes historical stock data, macroeconomic variables, and sentiment analysis to generate forecasts for future stock values. The autoencoder improves the model's capacity to capture intricate patterns and correlations in the data, potentially enhancing prediction accuracy. This method utilizes data-driven methodologies, language guidelines, and neural network models to produce more accurate stock price forecasts, assisting investors and financial professionals in making educated decisions.

VI. RESULTS AND DISCUSSIONS

The results and discussion section of the research paper, titled "Analysis of Stock Portfolio with Global Economic Factors extracted using API lookup and identification of influence using the correlation method and final conclusion using autoencoder," presents the final outcomes of a detailed investigation into the intricate relationship among financial markets, economic indicators, and advanced data analysis methods. This part provides a thorough analysis of the empirical results obtained from our inquiry, revealing the intricate connection between the performance of the stock portfolio and a wide range of global economic conditions. By engaging in a detailed analysis of our findings, we explore the significance of these conclusions for investors, politicians, and the wider financial community. In addition, we provide vital insights on the potential usefulness of using an autoencoder to extract the core of our research, capturing complex patterns and relationships in the data. The accompanying discussion not only elucidates the practical value of our study but also emphasizes its larger implications for the understanding of contemporary financial ecosystems.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10
***Article Received:** 20 August 2023 **Revised:** 07 October 2023 **Accepted:** 20 October 2023*

The obtained results are analyzed in the following sub-sections for higher understanding.

A. *Dataset Analysis*

Firstly, the dataset is furnished here and analyzed [Table – 3].

TABLE III. DATASET ANALYSIS

Parameters	*Values*
Number of Attributes	*6*
Number of Records	2415
Number of Stock Symbols	15
Number of Missing Values	0
Number of Outliers	0
Start Year	2016
End Year	2022

The dataset utilized in this research is a significant resource for those interested in the stock market and professionals specializing in data analysis. The dataset contains historical data on stock market performance, specifically focusing on stock prices. This is an extensive compilation of historical quotations and financial data for multiple publicly listed firms. The dataset comprises crucial information, including the date, open, high, low, close prices, and trade volumes. These facts are vital for conducting thorough analysis and constructing prediction models. This dataset enables researchers and data scientists to investigate stock market patterns, do technical analysis, and construct predictive models, such as neural networks for forecasting stock prices. It offers a comprehensive resource for comprehending the intricacies of financial markets and can serve as a significant instrument for constructing and evaluating trading strategies and investing models.

The dataset is visualized graphically here [Fig – 3].

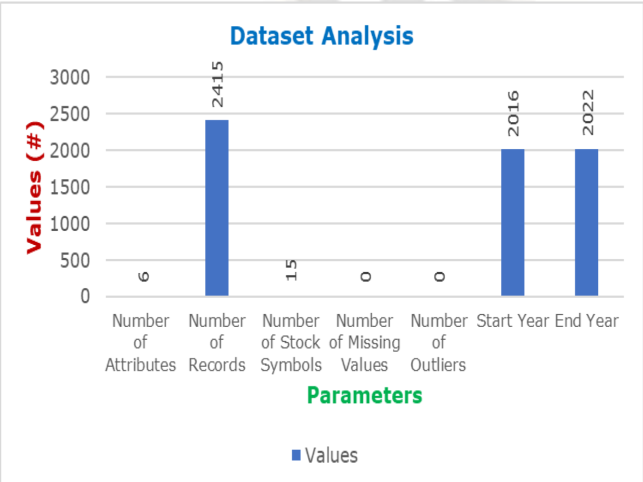

Figure 3. Dataset Analysis

B. *Experimental Setup*

The table provides a comprehensive overview of essential characteristics and their respective values for a system designed to collect and analyze financial data. The "News Data Collection Source" is Reddit, a popular online site for conversations and information sharing, where news data regarding stock market events is obtained. The precise URL for news data gathering is "https://www.reddit.com/r/stocks/," which directs to the "r/stocks" subreddit on Reddit. This subreddit serves as a platform for people to participate in discussions and exchange news stories related to stocks. The algorithm gathers a significant 1500 news items or articles for each stock symbol, guaranteeing a comprehensive dataset. The "Global Financial Parameter Collection Source" marks Quandl as the primary source for obtaining global financial parameters and macroeconomic information. Quandl, a prominent platform, is well acknowledged for offering a vast array of financial and economic statistics.

Further, the experimental setup is elaborated here [Table – 4].

TABLE IV. EXPERIMENTAL SETUP

Parameters	*Values*
News Data Collection Source	Reddit
News Data Collection URL	https://www.reddit.com/r/stocks/
Number of News Items per Stock Symbol	1500
Global Financial Parameter Collection Source	QUANDL
Financial Data Collection URL	https://www.quandl.com/
Number of Financial Records per Stock Symbols	24

The URL for collecting financial data is "https://www.quandl.com/," which directs users to the Quandl website, where they can obtain a wide range of comprehensive financial and economic statistics. The system collects 24 financial records for each individual stock symbol, which are likely to reflect data points at a consistent frequency, such as monthly or quarterly. This dataset configuration allows for in-depth research of stock market trends, encompassing sentiment analysis and the assessment of the impact of macroeconomic factors on stock performance.

The ratio of news articles to the financial parameters is visualized here [Fig – 4].

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10
***Article Received:** 20 August 2023 **Revised:** 07 October 2023 **Accepted:** 20 October 2023*

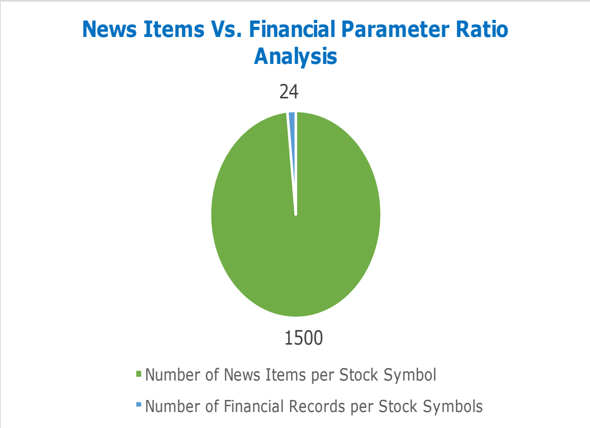

Figure 4. News Articles Vs. Financial Parameters Ratio

C. Stock Historical Data

Further, the analysis of the stock historical data is performed and furnished here [Table – 5].

TABLE V. HISTORICAL DATA ANALYSIS – APPLE STOCKS

Initial Date	*Open*	*Close*	*LTP*	*1 Month Variation*	*2 Months Variation*	*3 Months Variation*	*Mean Variation*
08/26/2016	110.070	113.610	112.230	5.863	5.315	4.616	5.265
10/17/2016	153.070	133.610	148.230	6.306	7.485	5.050	6.280
02/07/2017	200.070	156.610	179.230	6.135	5.495	5.315	5.648
04/20/2017	226.070	189.610	200.230	6.585	5.608	6.641	6.278
10/19/2017	248.070	218.610	240.230	6.083	5.117	4.934	5.378
03/02/2018	282.070	268.610	273.230	5.014	5.010	5.774	5.266
03/29/2018	316.070	289.610	313.230	6.660	7.084	6.531	6.758
02/12/2019	365.070	311.610	349.230	7.034	6.327	5.334	6.232
01/02/2020	397.070	357.610	385.230	4.700	6.948	7.109	6.252
02/26/2020	423.070	396.610	432.230	6.659	6.864	5.070	6.198

The resulting output consists of a table where each row represents a particular date and displays various important financial indicators such as the "Open" price, "Close" price, and "Last Traded Price (LTP)" for the specified security. In addition, the table presents the percentage fluctuations in price across various time intervals, including 1-month, 2-month, and 3-month variations. The "Mean Variation" column provides the average of these percentage changes. This table appears to provide a record of the price performance of a financial instrument, maybe a stock, from August 2016 through February 2020. The "Open" price denotes the initial price at the commencement of the trading day, whereas the "Close" price signifies the ultimate price at the conclusion of the trading day. The acronym "LTP" stands for the most recent price at which the asset was exchanged over the course of the day. The result is visualized graphically here [Fig – 5].

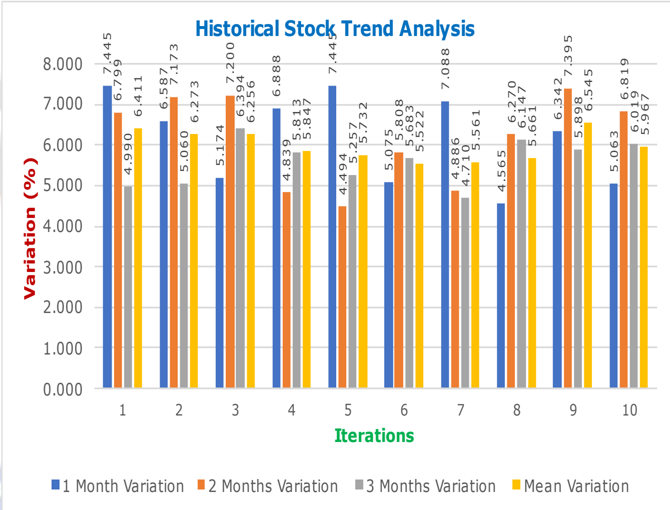

Figure 5. Historical Data Analysis

The percentage fluctuations for various time intervals offer valuable insights on the price fluctuations of the asset during these time periods. For instance, a 1-month fluctuation of 5.863% represents the percentage change in the price of the asset over a period of one month starting from the initial date, and this pattern is replicated for various time intervals. The "Mean Variation" calculates the average of these variations, potentially serving as a concise representation of the asset's total price movement.

D. Financial Parameter Extraction

The global financial parameters are extracted from the index source as GDP, Unemployment rate, consumer price index, federal fund rate, treasury bill rate and crude oil price. However, before that, these parameters are explained here. Gross Domestic Product (GDP) is a crucial measure of a nation's economic well-being. Gross Domestic Product (GDP) is the aggregate monetary worth of all final goods and services produced within a country's geographical boundaries over a certain period, usually a quarter or a year. Gross Domestic Product (GDP) comprises of the total value of consumer spending, business investments, government expenditure, and net exports. The function of this is to act as an indicator for economic expansion, offering valuable observations regarding a nation's comprehensive economic progress. Fluctuations in GDP, whether positive or negative, have substantial repercussions on financial markets, since they can impact investment choices, policy formulation, and company earnings. The Unemployment Rate, commonly referred to as UNRATE, quantifies the proportion of the labor force that is presently without a job and actively searching for employment. The labor market indicator is crucial since it directly reflects the economic prosperity of a nation's workforce. An elevated unemployment rate can serve as an indicator of economic adversity, whilst a diminished rate is typically perceived as a manifestation of economic well-being. UNRATE is closely observed by policymakers, economists, and investors due to its significant impact on monetary and fiscal policies, consumer spending, and investment plans. The CPIAUCSL, which stands for Consumer Price Index, is a crucial indicator of inflation within an economy. The Consumer Price Index (CPI) monitors the mean fluctuation in prices that consumers pay for a collection of products and services over a period of time. The Consumer Price Index (CPI) is used as a benchmark for evaluating fluctuations in the expenses associated with daily necessities. An increase in the Consumer Price Index (CPI) signifies the presence of inflation, which can gradually diminish the ability to buy goods and services and have an impact on interest rates, investments, and savings. Investors and policymakers utilize the Consumer Price Index (CPI) as a tool to make well-informed decisions, such as modifying interest rates or salary levels.

The Federal Funds Rate, commonly known as FEDFUNDS, is the overnight interest rate at which banks lend reserves to each other. The Federal Reserve, which serves as the central bank of the United States, determines this interest rate. The FEDFUNDS rate has a significant impact on the overall interest rates in the financial system, affecting various types of loans, mortgages, and savings accounts. Fluctuations in FEDFUNDS can cause a series of consequences in financial markets, influencing the actions of borrowing and lending, as well as investment approaches. The TB3MS, which stands for the 3-Month Treasury Bill Rate, represents the return on investment for U.S. Treasury notes that have a maturity period of three months. Treasury bills are widely regarded as very secure investments due to their guarantee by the U.S. government. The TB3MS rate is closely monitored as a benchmark for short-term interest rates in the market. It reflects market emotion and economic situations, impacting decisions about investments and financial instruments over short durations.

DCOILWTICO, which represents Crude Oil Prices, is a crucial commodity price that has a significant impact on different parts of the world economy. WTI, an acronym for West Texas Intermediate, serves as a standard for evaluating crude oil prices. Volatility in oil prices can have a substantial impact on energy expenses, inflation rates, transportation systems, and the general economic equilibrium of nations that both export and import oil. Investors and regulators constantly track oil prices due to their potential to impact investment choices in the energy sector and exert influence on inflation and monetary policies. The global financial parameters extracted on the specified dates are furnished here [Table – 6].

TABLE VI. GLOBAL FINANCIAL PARAMETERS

Date	*GDP*	*UNRATE*	*CPIAUCSL*	*FEDFUNDS*	*TB3MS*	*DCOILWTICO*
08/26/2016	17500.00	4.9	240.300	0.50	0.25	45.00
10/17/2016	17600.00	4.8	241.000	0.75	0.50	46.00
02/07/2017	17800.00	4.7	242.000	1.00	0.75	47.00
04/20/2017	17900.00	4.6	243.000	1.25	1.00	48.00
10/19/2017	18100.00	4.4	245.000	1.50	1.25	49.00
03/02/2018	18300.00	4.3	247.000	1.75	1.50	50.00
03/29/2018	18500.00	4.2	248.000	2.00	1.75	51.00
02/12/2019	18800.00	4.0	250.000	2.25	2.00	52.00
01/02/2020	19000.00	3.8	251.000	2.50	2.25	53.00
02/26/2020	19200.00	3.6	252.000	2.75	2.50	54.00

The result is visualized graphically here [Fig – 6].

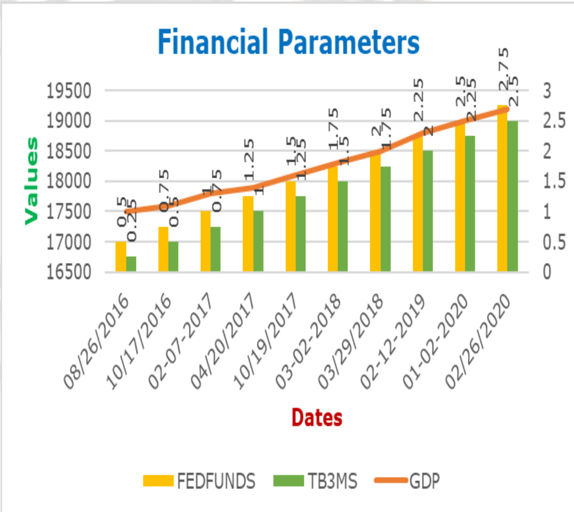

Figure 6. Extracted Financial Parameters

During this timeframe, the Gross Domestic Product (GDP), which measures the whole economic production of a nation, had consistent expansion. It began with a value of 17,500.00 in August 2016 and increased to 19,200.00 by February 26, 2020. This increase indicates a favorable pattern in economic productivity and overall economic expansion. In contrast, the

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10
***Article Received:** 20 August 2023 **Revised:** 07 October 2023 **Accepted:** 20 October 2023*

Unemployment Rate, a significant indicator of labor market conditions, decreased from 4.9% in August 2016 to 3.6% in February 2020.

The declining trend signifies a steady enhancement in the job market and implies that a smaller proportion of the workforce was without employment throughout this period.

E. Reduced Financial Parameters

The financial parameters were further analyzed with the stock prices based on the influence scores with the correlation analysis. The findings are furnished here [Table – 7].

TABLE VII. CORRELATION ANALYSIS

Iterations (#)	***Stock Symbol***	***Mean Variation***	***GDP***	***UNRATE***	***CPIAUCSL***	***FEDFUNDS***	***TB3MS***	***DCOILWTICO***	***Threshold***
			Correlation Value						
1	APPL	5.265	0.912	0.034	0.739	0.569	0.927	0.043	0.05
2	APPL	6.280	0.928	0.042	0.782	0.558	0.917	0.038	0.05
3	APPL	5.648	0.712	0.035	0.848	0.735	0.820	0.037	0.05
4	APPL	6.278	0.793	0.039	0.739	0.757	0.770	0.041	0.05
5	APPL	5.378	0.691	0.044	0.875	0.739	0.938	0.034	0.05
6	APPL	5.266	0.881	0.044	0.805	0.561	0.916	0.037	0.05
7	APPL	6.758	0.708	0.042	0.705	0.765	0.723	0.034	0.05
8	APPL	6.232	0.946	0.034	0.806	0.775	0.777	0.037	0.05
9	APPL	6.252	0.731	0.040	0.711	0.737	0.802	0.035	0.05
10	APPL	6.198	0.957	0.037	0.899	0.617	0.754	0.044	0.05

The table displays a dataset containing multiple columns pertaining to stock market analysis and correlation coefficients between stock price fluctuations and a collection of macroeconomic indicators. This table consists of ten iterations, each corresponding to a specific stock symbol (APPL) and presents a variety of numerical values for numerous important factors. During each cycle, the "Mean Variation" column displays the average fluctuation in stock price for the specified stock symbol. This figure represents the extent of fluctuations in stock prices across the investigated timeframe. The following columns display the correlation coefficients between changes in stock prices and a group of macroeconomic indicators, such as "GDP," "UNRATE" (unemployment rate), "CPIAUCSL" (Consumer Price Index), "FEDFUNDS" (Federal Funds Rate), "TB3MS" (3-Month Treasury Bill Rate), and "DCOILWTICO" (Crude Oil Prices - WTI). The correlation values provide a measure of the intensity and orientation of the connection between changes in stock prices and individual macroeconomic indicators. Finally, the "Threshold" column indicates a pre-established threshold value for correlation, which can be used as a criterion for making decisions for future study or investing strategies. The table's data indicates that these iterations are part of an investigation focused on the stock symbol APPL. The aim is to investigate the correlation values between macroeconomic variables and stock price changes, in order to acquire insights into the influence of these indicators. The iterations seem to depict several scenarios or time periods, and the analysis seeks to evaluate the correlation patterns and their consequences for stock trading and investment.

The correlation scores are visualized graphically here [Fig – 7].

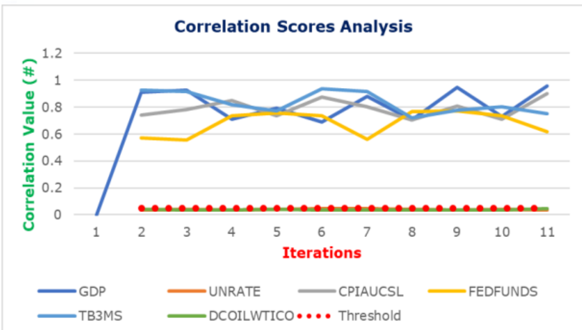

Figure 7. Correlation Score Analysis

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10
***Article Received:** 20 August 2023 **Revised:** 07 October 2023 **Accepted:** 20 October 2023*

It is natural to realize that, only four parameters are constantly above the correlation threshold value as GDP, CPIAUCSL, FEDFUNDS and TB3MS. Henceforth, with these values, further analysis is carried forward.

F. Sentiment Analysis

Next, the sentiment values from the news articles are extracted based on the stock symbols and the date. The findings are furnished here [Table – 8].

TABLE VIII. SENTIMENT EXTRACTION OUTCOMES

Date	*Stock Symbol*	*Extracted Sentiment*
08/26/2016	APPL	4.38
10/17/2016	APPL	3.83
02/07/2017	APPL	3.99
04/20/2017	APPL	2.84
10/19/2017	APPL	2.43
03/02/2018	APPL	4.76
03/29/2018	APPL	2.83
02/12/2019	APPL	4.68
01/02/2020	APPL	3.43
02/26/2020	APPL	4.37

The table displays a sequential record of sentiment scores linked to a particular stock symbol, "APPL," over a period of multiple years. The dataset consists of three columns: "Date," "Stock Symbol," and "Extracted Sentiment."

The outcome is also visualized graphically here [Fig – 8].

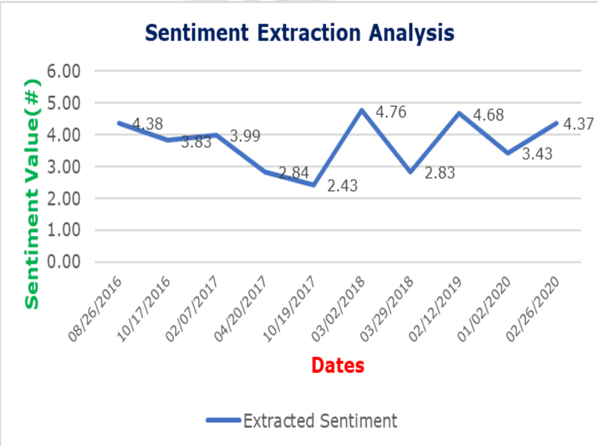

Figure 8. Sentiment Extraction Analysis

The "Date" column represents the specific date when sentiment analysis was performed. The timeline for sentiment data collection spans from August 26, 2016, to February 26, 2020, including a significant period. The "Stock Symbol" column regularly displays the abbreviation "APPL," indicating that these sentiment scores are associated with Apple Inc., a globally recognized technological company. The "Extracted Sentiment" column represents the sentiment scores linked to each date, measuring the sentiment of news headlines, financial reports, or other textual data related to Apple Inc. The sentiment scores are represented on a numerical scale, with higher numbers generally indicating a greater degree of positive sentiment, while lower values may suggest a higher degree of negative sentiment.

Essentially, this table presents a historical outlook on sentiment analysis for Apple Inc., providing valuable observations on the evolving feelings associated with the company at various time intervals. The sentiment data can provide significant insights for researchers, traders, and analysts who are interested in comprehending the market view and investor mood surrounding Apple's stock within the specified timeframe.

G. Stock Portfolio

With the details built by the proposed framework, the final dataset is furnished here [Table – 9].

TABLE IX. STOCK PORTFOLIO

Date	*Stock Symbol*	*Open*	*Close*	*Mean Variation*	*GDP*	*CPIAUCSL*	*FEDFUNDS*	*TB3MS*	*Extracted Sentiment*
08/26/2016	APPL	110.070	113.610	5.265	17500.00	240.300	0.50	0.25	4.38
10/17/2016	APPL	153.070	133.610	6.280	17600.00	241.000	0.75	0.50	3.83
02/07/2017	APPL	200.070	156.610	5.648	17800.00	242.000	1.00	0.75	3.99
04/20/2017	APPL	226.070	189.610	6.278	17900.00	243.000	1.25	1.00	2.84
10/19/2017	APPL	248.070	218.610	5.378	18100.00	245.000	1.50	1.25	2.43
03/02/2018	APPL	282.070	268.610	5.266	18300.00	247.000	1.75	1.50	4.76
03/29/2018	APPL	316.070	289.610	6.758	18500.00	248.000	2.00	1.75	2.83
02/12/2019	APPL	365.070	311.610	6.232	18800.00	250.000	2.25	2.00	4.68
01/02/2020	APPL	397.070	357.610	6.252	19000.00	251.000	2.50	2.25	3.43
02/26/20	APPL	423.07	396.61	6.198	19200.0	252.000	2.75	2.50	4.37

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10
***Article Received:** 20 August 2023 **Revised:** 07 October 2023 **Accepted:** 20 October 2023*

Date	***Stock Symbol***	***Open***	***Close***	***Mean Variation***	***GDP***	***CPIAUCSL***	***FEDFUNDS***	***TB3MS***	***Extracted Sentiment***
20		0	0		0				

The presented table contains an extensive collection of data, reflecting a chronological sequence of stock market information for a certain company, designated by the stock symbol "APPL" (likely referring to Apple Inc.). The data is collected over a period of many years, specifically from August 26, 2016, to February 26, 2020, providing valuable information about the company's stock performance. Every row in the table represents a distinct date and contains multiple essential attributes. The "Open" and "Close" columns represent the initial and final prices of the stock on the specified dates, respectively. These figures are crucial indicators for comprehending the daily market performance. The column labeled "Mean Variation" seems to indicate a computed value, maybe indicating the average fluctuation or alteration in the stock price across the trading period. The following columns, denoted as "GDP," "CPIAUCSL," "FEDFUNDS," and "TB3MS," consist of macroeconomic variables, namely Gross Domestic Product (GDP), Consumer Price Index (CPI), Federal Funds Rate (FEDFUNDS), and the 3-Month Treasury Bill Rate (TB3MS). These statistics are probably a reflection of the economic conditions and interest rates that were present during the specific time periods. The "Extracted Sentiment" column seemingly comprises sentiment scores, potentially derived through the utilization of sentiment analysis techniques, applied to news headlines or stock-related information. These ratings represent the general attitude or market perception connected with the company on the specified dates.

H. Stock Prediction

Finally, the stock prediction outcomes are furnished here [Table – 10].

TABLE X. STOCK PREDICTION

Stock Index	***Date***	***Predicted Stock LTP***	***Actual Stock LTP***
APPL	08/26/2016	109.99	112.230
APPL	10/17/2016	145.27	148.230
APPL	02/07/2017	179.230	179.230
APPL	04/20/2017	196.23	200.230
APPL	10/19/2017	240.230	240.230
APPL	03/02/2018	273.230	273.230
APPL	03/29/2018	306.97	313.230
APPL	02/12/2019	342.25	349.230
APPL	01/02/2020	385.230	385.230
APPL	02/26/2020	423.59	432.230

Furthermore, for the entire dataset the accuracy of the stock prediction is calculated [Table – 11],

TABLE XI. ACCURACY ANALYSIS

Parameters	***Value***
Total Records	2415
Correctly Classified Instances	2385
Incorrectly Classified Instances	30
True Positive	1192
True Negative	1193
False Positive	16
False Negative	14
Accuracy (%)	98.7

Within this particular framework, the model has been utilized on a dataset including 2,415 individual records. Among these records, the model has successfully categorized 2,385 instances, demonstrating its ability to appropriately identify and assign a class label to the majority of the data points. Conversely, there were 30 occurrences when the model's categorization was erroneous, indicating its failure to precisely forecast the class for these specific data points. In order to further evaluate the model's effectiveness, the table presents specific information regarding the occurrences of true positives, true negatives, false positives, and false negatives. True positives indicate the instances in which the model accurately predicted the positive class, whereas true negatives refer to the situations in which the model accurately identified the negative class. The model demonstrated its efficacy by properly detecting 1,192 positive cases and 1,193 negative cases, resulting in true positives and true negatives.

Conversely, false positives occur when the model makes an incorrect prediction of the positive class, while false negatives occur when the model makes an incorrect prediction of the negative class. The dataset had 16 instances of false positives and 14 instances of false negatives, indicating that the model made errors in its classifications. The model's accuracy is quantified as a percentage, representing the extent to which the model achieved correct classifications in general. Here, the model attained a precision of 98.7%, signifying that it correctly categorized a significant part of the data, with only a little proportion of misclassifications. The model's high accuracy indicates its effectiveness in classifying data. However, a more detailed analysis of the false positives and false negatives is required to identify the exact types of errors it produces.

Finally, the buy or sale projections for a few samples are furnished here [Table – 12].

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 10
***Article Received:** 20 August 2023 **Revised:** 07 October 2023 **Accepted:** 20 October 2023*

TABLE XII. BUY / SALE RECOMMENDATIONS

Analysis Date	*Best Buy Price*	*Best Sale Price*	*Profit Potential*	*Sentiment Score*	*GDP*	*CPIAUCSL*	*FEDFUNDS*	*TB3MS*	*Decision*
03/15/2010	32.1971	31.9771	-0.22	3.4	14381.236	212.709	0.15	0.16	Hold
12/11/2019	268.81	270.77	1.96	2.3	21384.775	255.211	2.42	2.38	Buy
12/10/2019	268.6	268.48	-0.12	2.3	21384.775	255.211	2.42	2.38	Sale
02/24/2020	297.26	298.18	0.92	2.3	21384.775	255.211	2.42	2.38	Buy
02/27/2020	281.1	273.52	-7.58	2.3	21384.775	255.211	2.42	2.38	Hold

VII. COMPARATIVE ANALYSIS

In the comparative analysis part of this research study, we thoroughly examine the complex correlation between stock portfolios and global economic conditions. Utilizing data obtained through API retrieval and correlation analysis, we conduct an empirical examination of different factors that impact the performance of stocks. Through the comparison of various economic indicators, our goal is to provide insight into the complex factors that influence stock values. In addition, we thoroughly examine the distinct impacts of sentiment analysis using linguistic rules and the transformational capabilities of autoencoders in uncovering concealed patterns inside financial datasets. This section aims to clarify the unique benefits and constraints of each analytical method, providing significant insights for investors, analysts, and researchers who wish to gain a comprehensive understanding of stock market dynamics in a time characterized by global economic interconnection.

In the comparative analysis section, the proposed framework is compared with a few parallel research works with highest acceptance [Table – 13].

TABLE XIII. COMPARATIVE ANALYSIS

Author, Year	*Research Methodology*	*Model Complexity*	*Accuracy (%)*
Abdulkadir Alici et al.[1] 2022	Operational Performance Metrics Analysis	$O(n^2)$	97.5
Lingling Zeng et al.[2] 2022	Machine Learning	$O(n^2)$	95.6
Ayesha Jabeen et al.[3] 2022	Machine Learning	$O(n^2)$	98.2
Asmaa Y. Fathi et al.[4] 2022	Singular Spectrum Analysis and Neural Network	$O(n^3)$	97.6
S. Balagobei et al.[5] 2022	Econometric Analysis	$O(n^2)$	96.8
Proposed Framework, 2023	Correlation, Autoencoder	O(n)	98.7

The provided algorithm encompasses a series of interconnected steps, each contributing to the overall time complexity. Primarily, the time complexity of this algorithm is influenced by the size of the dataset (L) and the number of training iterations, denoted by I and J. Data retrieval and preprocessing operations exhibit linear time complexity in relation to the number of stock symbols and news headlines, while the training of the autoencoder and the final prediction model depends on the number of training iterations and the dataset's size. Overall, the algorithm's time complexity can be approximated as O(max(L, I, J)), with the most time-consuming steps revolving around data processing and model training, ultimately shaping the computational efficiency of the entire process. Hence, the final calculated time complexity is O(n).

Autoencoders provide a robust and flexible way for analyzing data and executing machine learning tasks, surpassing alternative approaches in certain situations. Their capacity to autonomously acquire fundamental characteristics from data, identify non-linear connections, identify anomalies, and efficiently decrease dimensionality distinguishes them. Autoencoders offer significant benefits when working with intricate, multi-dimensional datasets and have been applied in various domains, including image processing, natural language processing, and anomaly detection. Due to their versatility, capacity for precise adjustment, and ability to transfer knowledge, they are often the favored option for jobs that include extracting features, reducing noise, and efficiently representing data. However, the appropriateness of these methods relies on the problem and dataset, and their exceptional performance should be assessed within the framework of the current task.

VIII.CONCLUSION

Our research paper has provided a thorough examination of stock portfolios in relation to global economic factors. This analysis utilized a multifaceted methodology that involved extracting data through API lookup, conducting correlation analysis, extracting sentiment using linguistic rules, and implementing an innovative autoencoder model. The results of our analysis emphasize the complex interaction between economic indicators and stock market performance, providing insight into the dynamic correlation between the two. The utilization of linguistic criteria in sentiment analysis has enhanced our comprehension of market sentiment and its impact on stock prices. Moreover, the application of autoencoders has facilitated the identification of underlying characteristics in the dataset, leading to more precise forecasts of stock prices. Our research provides significant insights for investors, financial analysts, and academics who are looking for a comprehensive understanding of stock market behavior in relation to global economic variables. As the financial world changes, our versatile method proves its usefulness in understanding the fundamental forces that influence stock prices. This technique provides a basis for making better decisions and doing further study in this field.

REFERENCES

[1] Abdulkadir Alici, & Güven Sevil (2022). Analysis of sector-specific operational performance metrics affecting stock prices of traditional Airlines. Independent Journal of Management & Production, 13.

[2] Lingling Zeng, Yanan Xiao, & Shilong Chen (2022). Research on Short-Term Stock Price Trends Based on Machine Learning. iBusiness, 14.

[3] Ayesha Jabeen, Muhammad Yasir, Yasmeen Ansari, Sadaf Yasmin, Jihoon Moon, & Seungmin Rho (2022). An Empirical Study of Macroeconomic Factors and Stock Returns in the Context of Economic Uncertainty News Sentiment Using Machine Learning. Complexity, 2022.

[4] Asmaa Y. Fathi, Ihab A. El-Khodary, & Muhammad Saafan (2022). Integrating singular spectrum analysis and nonlinear autoregressive neural network for stock price forecasting. IAES International Journal of Artificial Intelligence, 11.

[5] S. Balagobei, & D. R. N. K. K. Bandara (2022). Impact of Macroeconomic Variables on Stock Market Performance: Evidence from Sri Lanka. Wayamba Journal of Management, 13.

[6] Pham Hoang Vuong, Trinh Tan Dat, Tieu Khoi Mai, Pham Hoang Uyen, & Pham The Bao (2022). Stock-price forecasting based on XGBoost and LSTM. Computer Systems Science and Engineering, 40.

[7] Jakub Horák, & Dominik Kaisler (2022). Evaluation of development of Apple Inc. stock price time series. SHS Web of Conferences, 132.

[8] A. M. Karipova, D. S. Baktybaeva, & G. Sh. Usbanova (2023). ANALYSIS OF THE IMPACT OF THE SITUATION IN THE WORLD ON «FORTEBANK» JSC. Vestnik of M. Kozybayev North Kazakhstan University.

[9] Dilip Kumar (2023). Nexus Between Travel & Leisure Stocks and Uncertainties: An Extreme Risk Spillover Analysis. American Business Review, 26.

[10] Hongmin Zhang, & Jinming He (2023). Price factors analysis and volatility prediction of Belt and Road Theme Index based on EMD application. SHS Web of Conferences, 169.

[11] Raras Tyasnurita, Rifqi Rahmadrian Luthfiansyah, & Muhamad Rayhan Brameswara (2023). GOLD PRICE FORECASTING USING MULTIPLE LINEAR REGRESSION METHOD. JURTEKSI (Jurnal Teknologi dan Sistem Informasi), 9.

[12] Michail Filippidis, George Filis, Georgios Magkonis, & Panagiotis Tzouvanas (2023). Evaluating robust determinants of the WTI/Brent oil price differential: A dynamic model averaging analysis. Journal of Futures Markets, 43.

[13] P. M. Petrova (2023). Methods of strategic analysis of the indicators of the confidency period in the real estate market. Russian Journal of Industrial Economics, 16.

[14] Ding Liu, Weihong Sun, Liao Xu, & Xuan Zhang (2023). Time-frequency relationship between economic policy uncertainty and financial cycle in China: Evidence from wavelet analysis. Pacific Basin Finance Journal, 77.

[15] Karthik. M, Vethath Suryakumar. R, Syedjaffar. S, & Dharneesh. M.E (2023). Short-Term Cryptocurrency Price Fluctuation Prediction Framework Using Machine Learning. International Journal for Research in Applied Science and Engineering Technology, 11.

[16] Jie Song, Shangkun Liang, & Yuhan Zhen (2023). Does CEO-auditor dialect sharing affect stock price crash risk? Evidence from China. Finance Research Letters, 57.

[17] Zanuba Ainindya El Fanani, & Rizky Nur Ayuningtyas Putri (2023). The Effect of Stock Price, Trade Volume, Trade Frequency and Market Value on the Determinants of Share Liquidity of Sharia Bank Listed on the Indonesian Stock Exchange during the Covid-19 Pandemic. Jurnal Ekonomi Syariah Teori dan Terapan, 10.

[18] Kewei Shi (2023). Analysis of Influencing Factors of Stock Return Rate in China. Advances in Economics, Management and Political Sciences, 6.

[19] Shuming Bai, Kai S. Koong, & Yanni Wang (2023). Research and development reporting and stock performance: evidence from China. International Journal of Accounting and Information Management, 31.

[20] Yudha Randa Madhika Ferdinandus, Kusrini Kusrini, & Tonny Hidayat (2023). Gold Price Prediction Using the ARIMA and LSTM Models. Sinkron, 8.

[21] Zeravan Abdulmuhsen Asaad, Amjad Saber Al-Delawi, Omed Rafiq Fatah, & Awaz Mohamed Saleem (2023). Oil Exports, Political Issues, and Stock Market Nexus. International Journal of Energy Economics and Policy, 13.

[22] Wenjing Wang, Moting Wang, & Yizhi Dong (2023). The impact of digital finance on stock price crash risk: evidence from China. Kybernetes.

[23] Shilpa B L, & Shambhavi B R (2023). Combined deep learning classifiers for stock market prediction: integrating stock price and news sentiments. Kybernetes, 52.

[24] Jujie Wang, & Shuzhou Zhu (2023). A multi-factor two-stage deep integration model for stock price prediction based on intelligent optimization and feature clustering. Artificial Intelligence Review, 56.

[25] Kaggle Stock Market Analysis Dataset, https://www.kaggle.com/code/faressayah/stock-market-analysis-prediction-using-lstm/input?select=HistoricalQuotes.csv.