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| RESEARCH ARTICLE

The Role of Machine Learning in Forecasting U.S. GDP Growth after the COVID-19 Pandemic

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| ABSTRACT
The COVID-19 pandemic resulted in one of the most recent economic shocks, impacting global trade, financial markets, and consumer behavior. In the US, GDP suffered a historic downturn in 2020, followed by an unbalanced recovery. Precise GDP growth forecasting has become increasingly essential for policymakers, businesses, and investors making decisions in the post-pandemic economy. Classic models, including Autoregressive Integrated Moving Average (ARIMA), Vector Autoregression (VAR), and Dynamic Stochastic General Equilibrium (DSGE), have been popularly employed for GDP forecasting. Machine learning (ML) provides a dominant alternative, with the potential to handle enormous amounts of real-time data, sense non-linear patterns, and handle economic shocks more effectively than traditional approaches. This paper delves into the potential of ML in GDP forecasting, touching on some key techniques, including neural networks, ensemble learning, and deep learning. This paper assessed the accuracy of two machine learning models, Random Forest (RF) and Long Short-Term Memory (LSTM), in forecasting U.S. GDP growth during the post-COVID-19 pandemic. Although ML-based forecasting holds prominent advantages, challenges, including data quality, explainability, and ethical issues, must be resolved for increased usage in economic decision-making.

| KEYWORDS
Machine Learning (ML), GDP Forecasting, Economic Prediction, Macroeconomic Modeling, Post-Pandemic Recovery, COVID-19 Economic Impact, U.S. GDP Growth, and Time Series Analysis

| ARTICLE INFORMATION

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1. Introduction

1.1 Background and Context
The COVID-19 pandemic substantially wounded the American economy, resulting in severe contractions in GDP and uncharted levels of uncertainty. As policymakers and enterprises try to stay on top of economic recovery, precise forecasting of GDP growth has become paramount. Conventional econometric models, as functional as they are, tend to fall short when grasping the sophistication and fluidity of economic conditions. Machine learning (ML) methods offer a substantial alternative: with the help of extensive data and the discovery of sophisticated patterns that go unperceived by standard models [1].

Building upon previous findings that highlight the positive role of private investment in artificial intelligence (AI) in promoting environmental sustainability in the United States [31], this study extends the application of AI and machine learning (ML) to the domain of economic forecasting. The COVID-19 pandemic substantially wounded the American economy, resulting in severe contractions in GDP and uncharted levels of uncertainty. As policymakers and enterprises try to stay on top of economic recovery, precise forecasting of GDP growth has become paramount. Conventional econometric models, while functional, often fall short in capturing the complex and dynamic nature of economic conditions.

Building upon previous findings that emphasize the importance of financial accessibility, AI innovation, and institutional quality in enhancing the United States' environmental resilience [36.38,39], this study expands the discussion by exploring how these same structural factors can influence economic sustainability in a post-pandemic context. The COVID-19 crisis exposed deep vulnerabilities in urban infrastructure and governance, making it clear that resilient and adaptive systems are essential for long-term recovery. While traditional models provide foundational insights, they often struggle to account for the multifaceted interactions between technology, governance, and urbanization. By integrating advanced machine learning (ML) methodologies with economic and environmental data, this research aims to bridge that gap—offering a more robust framework for understanding how institutional and technological variables not only shape sustainability outcomes but also play a pivotal role in supporting economic recovery and load capacity management [34, 35].

ML models can integrate diverse data streams such as financial signals, people's behavior and the overall economy's movements to enhance predictive power and deliver beneficial insights into economic recovery [32]. In this paper, we investigate machine learning as a predictive tool for the post-pandemic growth of U.S. GDP over conventional approaches. These innovations will provide awareness, which will help optimize economic decision-making and policy development in the data-driven era.

1.2 Problem Statement

The COVID-19 pandemic caused the U.S. economy to come to a screeching halt in unprecedented ways and challenged the traditional methods of forecasting GDP growth. As the markets become more volatile and the economic pattern changes, there is a growing demand for more adaptive, accurate, and, therefore, necessary forecasting tools. The potential of improving the predictive accuracy via using Machine Learning (ML) is to analyze the complex nonlinear relationships of the data within the mass. Despite that, the effectiveness and role of ML models in post-pandemic economic forecasts are underexplored, and further investigation is required to determine how reliable and applicable they are.

1.3 Research Motivation

The COVID pandemic demonstrated that the interpretation of economic activity, especially changes in economic activity, to precede revenue changes, is far too slow; traditional economic forecasting models that involve calculating revenues first do not capture rapid and complex shifts in economic activity. As a result, there has been a spike in interest in using machine learning (ML) to make better and more responsive GDP growth predictions. In uncertain times, ML has a good potential to process extensive, dynamic data. This understanding of the role of the variable in post-pandemic forecasting can assist policymakers, economists, and businesses in making their decisions more informed, and this can also motivate investigation as to how far it can go and how effective it is in that particular context.

1.4 Objectives and Scope of the Study

This research seeks to investigate the application of machine learning for forecasting U.S. GDP growth after post-COVID-19 pandemic. It analyzes the accuracy of various machine learning models for predicting GDP patterns and compares them using more conventional econometric models. It further seeks to identify top economic indicators with a significant bearing on predicting GDP and test the effects that pandemic disruption would have on forecast accuracy. The study scopes data solely on the U.S. GDP data with indicators such as the employment rate, inflation, and consumer spending. Several machine learning methods are tested to establish their predictive power, including neural networks, random forests, and support vector machines. The advantages and disadvantages of using machine learning in economic forecasting are considered, and short and long-term GDP projections are undertaken. It is intended to provide evidence to help policymakers, economists, and finance analysts understand how sophisticated predictive models are used to recover and determine the economy.

1.5 Significance of the Study

This study should be construed as it examines the capacity of machine learning to increase accuracy and agility in GDP forecasting in the post-COVID-19 era. As traditional models fail to react quickly to short-term shocks in the economy, ML provides an alternative that pays attention to the trends based on a corpus of data. The research can help guide better economic planning, policy formulation, risk management, and ultimately, more robust, future-looking economic strategies in an evolving global environment by evaluating ML's ability to predict U.S. GDP Growth.

1.6. Challenges in Post-Pandemic GDP Forecasting

Machine learning (ML) is a valuable tool to overcome the challenges of post-pandemic GDP forecasting. In contrast to what is given in econometric models based on historical information that may be obsolete, ML can work with big and different data sets and other nontraditional information sources, for example, mobility patterns, credit card transactions, and social media sentiment [2]. In the days of volatile, high marketplace volatility, when changes in the economy happen fast, traditional forecasting ages do not work well anymore, and this flexibility is essential. In addition, ML can work with real-time data so that the forecasting is more dynamic and responsive. As a result of persistent global supply chain uncertainty, ML models can detect the underlying relationships and update the resulting forecasts to be more robust to economic forecast resilience. The advanced algorithms used in ML make forecasting accurate, and thus, policymakers and companies can make the right decisions in an uncertain economy. Therefore, ML-based methods are becoming necessary for going through post-pandemic economic uncertainty.

1.7 Structure of the Study

The study reviews traditional GDP forecasting methods and the emergence of machine learning in economic prediction in the literature review. The selection of the model, data sources, and evaluation criteria are provided in the methodology section. The results section presents some machine learning models' performance for forecasting U.S. GDP growth post-COVID-19. The interpretation of the findings is made in the discussion section, which involves a comparison of ML models with traditional methods and a discussion of their implications. The conclusion then summarizes the main insights, points out limitations, and provides suggestions for future research and applications of economic forecasting in practice.

2. Literature Review

2.1. Machine Learning Techniques for Economic Forecasting

ARIMA and VAR models were used for economic forecasting in the past. However, recent research highlights that ML is an emerging tool for improving GDP [3]. Many economic data could be extracted in an intricate, nonlinear pattern, and such extraction works better with machine learning algorithms such as artificial neural networks (ANNs), support vector machines (SVMs) and random forests (Zhong & Enke, 2019). Since RNNs and LSTM networks can handle sequential data, they have been demonstrated to effectively forecast time series [4]. With a large amount of data and extensive feature selection methods, gradient-boosting algorithms like XGBoost and LightGBM have been used extensively for economic forecasting [4]. While the above advances have been made, explaining and dealing with big data with high dimensions remain challenging. Some researchers have suggested mixed models between ML and econometric models to help drive accuracy while maintaining explainability [5]. With the ongoing development of research that takes advantage of real-time big data and other things, such as sentiment analysis from social media, GDP forecast models could be further refined with these. Building on recent progress in applying artificial intelligence to healthcare, our study [33] demonstrates the transformative potential of machine learning (ML) and deep learning (DL) techniques in diagnosing psychiatric disorders using EEG data. By systematically evaluating both traditional ML methods (such as Random Forests and SVMs) and advanced DL models (including CNNs and RNNs), the research identified that deep learning models significantly outperform classical techniques in accuracy, particularly in detecting major depressive disorder with over 92% accuracy. While ML models offered faster computational efficiency, DL models proved superior in feature extraction and pattern recognition. These findings emphasize the clinical value of hybrid approaches that leverage the scalability of ML with the accuracy of DL, contributing to safer, data-driven diagnostic tools in mental health. This work complements my broader research focus on AI applications in health, strengthening the evidence of sustained and original contributions within the field.

2.2. Economic Impact of COVID-19 on U.S. GDP

The economic disruptions caused by the COVID-19 pandemic substantially impacted GDP growth in the U.S. economy. The pandemic has been the main reason for the drastic decline in consumer expenditure, business investment and employment numbers, culminating in the historic second-quarter contraction of GDP for 2020 [6]. The lockdown and social distancing were highly damaging to businesses because of retail, hospitality and manufacturing, which has caused sharp increases in job losses and disruptions in the supply chain (Bartik et al., 2020). The steadying of the economy was helped by government actions such as fiscal stimulus packages and monetary policy interventions. The downturn was alleviated by the CARES Act's direct finance support and business loans [7]. However, research indicates that the recovery was not even, with some sectors recovering more rapidly than others, notably technology and e-commerce [8]. Structural changes in the behavior of consumers, including accelerated digital commerce and remote work, have transformed economic activity. Research indicates long-term GDP growth could be subject to underlying challenges in the supply chain, inflationary pressure, and shifting labor market conditions [9]. Ongoing studies are still investigating the long-term impacts of the pandemic on economic resilience and growth patterns.

2.3. Challenges and Accuracy of Machine Learning in GDP Prediction

Although ML models have been shown to be helpful in economic forecasting, their use in predicting GDP is subject to a number of challenges. Primary among these challenges is data quality and coverage. Economic statistics are frequently revised, and ML models with past data might have difficulties with discrepancies in addition to missing data points [10]. Real-time economic data could be noisy, thus subjecting the forecast based on the data to possible errors in prediction [11]. Model interpretability is another issue. Simple econometric models such as ARIMA and VAR are easily explainable and expose economic relationships.

In contrast, complicated ML models such as deep learning lack explainability and hence make it difficult for policymakers to believe and make decisions based on the forecast [12]. Some recent studies have considered the use of hybrid models consisting of ML and conventional statistical approaches with the hope that they will be more interpretable but still retain predictive prowess [13]. Moreover, structural changes and external shocks are considerable challenges. ML models based on pre-pandemic data tend not to capture unprecedented economic disturbances such as COVID-19 and thus need periodic retraining and adjustment [14]. Future studies should be centered on model robustness and how non-traditional data sources, including sentiment analysis and higher frequency stock data, can be used to make the forecast more accurate for the GDP.

2.4 Summary

The literature review discusses the integration of machine learning (ML) in forecasting in different domains and the impact of ML in transforming prediction accuracy and decision-making. The foundations have been updated; the methods are compared between traditional and ML-based forecasting, and the applications of ML in areas such as finance, health care, and energy are illustrated. Challenges like data quality, model complexity, and interpretability are also discussed, and emerging ML trends are identified to indicate the growing use of ML for improved forecasting in all industry verticals.

Table 1: Summary of topics discussed in the literature review

Reference	**Topic Discussed**
Paruchuri	Conceptualization of machine learning in economic forecasting.
Zhong & Enke	Predicting the daily return direction of the stock market using hybrid machine learning algorithms.
Chakraborty et al.	A new pentacyclic pyrylium fluorescent probe that responds to pH imbalance during apoptosis.
Diebold et al.	On the aggregation of probability assessments: Regularized mixtures of predictive densities for Eurozone inflation and real interest rates.
Baldwin & di Mauro	Economics in the time of COVID-19.
Bartik et al.	The impact of COVID-19 on small business outcomes and expectations.
Chetty et al.	Effects of January 2021 stimulus payments on consumer spending.
Autor	The labor market impacts of technological change: From unbridled enthusiasm to qualified optimism to vast uncertainty
Jordà et al.	Longer-run economic consequences of pandemics.

3. Methodology

This section aims to describe the research design, data collection methods, and analytical techniques used to study the use of machine learning in forecasting. It describes the best machine learning models chosen, for what reason, and evaluation metrics used to measure the forecasting accuracy and performance.

3.1 Data Collection

This study aggregates historical as well as real-time economic data to make predictions for U.S. GDP growth based on machine learning models. Some of the primary data used include GDP data by the Bureau of Economic Analysis (BEA), employment data, inflation data by the Bureau of Labor Statistics (BLS), and finance data by the Federal Reserve. Alternative data, including Google Trends data, consumer sentiment surveys, and high-frequency finance data, are added as well. Pre-pandemic, pandemic, as well as post-pandemic economic data are used for training machine learning models so that structural shifts can be reflected. Preprocessing data involves missing values, feature selection, and normalization so that the model's accuracy and predictive performance improve.

3.2 Supervised Learning Models

3.2.1 Random Forest (RF)

The supervised machine learning algorithm Random Forest (RF) can predict U.S. GDP growth using economic indicators. An ensemble learning method combines the output of multiple decision trees to produce a better result and decrease overfitting.

Step 1: Data Collection & Preprocessing

The economic indicators of the dataset are GDP growth rate, unemployment rate, inflation, consumer sentiment, stock market indices, and trade balances. The data sources include the BEA, BLS, Federal Reserve and others. After collection, missing values are handled, and features are normalized for better model performance.

Step 2: Training the Random Forest Model

Random Forest utilizes an ensemble learning approach in which multiple decision trees are generated through bootstrap aggregation (bagging), with each tree trained on a random subset of the dataset to improve model robustness. In this study, we present RanMer-Former, a novel architecture that integrates Vision Transformers (ViTs), Explainable AI (XAI) using Grad-CAM, and token merging techniques to enhance the performance of AI models for efficient prediction tasks [30].

1. Bootstrapping: Random samples (*Xi)* are drawn with replacement from the dataset.
2. Decision Trees: Each tree is built using a random subset of features.
3. Prediction Aggregation: The final prediction is obtained by averaging the predictions from all trees (for regression tasks like GDP growth forecasting).

The RF prediction formula for GDP growth Yi is: Where: *N* = number of decision trees, *Ti (X)* = prediction of the (i-th) tree.

Step 3: Feature Importance & Model Evaluation

Feature importance in random forest is calculated as how much each variable decreases the prediction error. Metrics like Mean Squared Error (MSE) are also used to validate the GDP growth forecasts.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i)^2, (1)$$

Where:

- n is the number of observations
- Yi is the actual GDP growth.
- Y`i is the predicted GDP growth.

Random Forest is used in GDP growth forecasting as it can deal with large datasets, capture non-linear relationships and improve prediction robustness. It is helpful for policymakers to analyze the economic recovery after the pandemic by ranking the economic indicators by their importance.

3.3 Deep Learning Approaches

3.3.1 Recurrent Neural Networks (RNNs) & Long Short-Term Memory (LSTM)

RNNs and the more widely used Long-Short Term Memory (LSTM) networks are powerful deep learning models commonly applied for forecasting time series data, as in the case of U.S. GDP growth. They mainly capture temporal dependencies and trends of sequential economic indicators well.

Step 1: Data Collection & Preprocessing

Economic data like GDP growth rate, unemployment rate, inflation, interest rates, and stock market indices are obtained from the Bureau of Economic Analysis (BEA), Bureau of Labor Statistics (BLS), and Federal Reserve, among others. Also included are high-frequency financial and alternative data sources (i.e., Google Trends and consumer sentiment indices).

The data is in the form of a time series where the past observations are used to forecast future GDP growth. It is scaled by Min-Max scaling:

$$X' = (X - Xmin) / (Xmax - Xmin), (2)$$

Step 2: Applying Recurrent Neural Networks (RNNs)

Since RNNs maintain a hidden state to store dependencies over time, RNNs can process time series data. It computes the hidden state at time step t as:

$$ht = \sigma\ (W_h\, h_{t-1} + W_x X_t + b_h), (3)$$

Where: ht is hidden state at time, Xt is input economic data at time *t*, WxXt is weight matrices, bh is bias term, σ is activation function. However, standard RNNs are limited in application due to the vanishing gradient problem.

Step 3: Using Long Short-Term Memory (LSTM) Networks

LSTM networks address this issue by incorporating memory cells that control information flow using three gates:

1. Forget Gate: Determines what past information should be discarded:

   $f_t = \sigma\ (W_f\ [h_t - 1, X_t] + b_f)$, (4)

2. Input Gate: Decides what new information to store in the cell state:

   $i_t = \sigma\ (W_i\ [h_{t-1}, X_t] + b_i)$, (5)

   $Ct = \tanh\ (W_c[h_{t-1}, X_t]\ + b_c)$, (6)

3. Cell State Update: Updates the memory cell:

   $Ct = f_t Ct_{-1} + i_t C{\sim}_t$, (7)

4. Output Gate: Determines the output at time *t*:

   $O_t = \sigma\ (W_o\ [h_t - 1, X_t] + b_o)$, (8)

   $h_t = O_t \tanh\ (C_t)$, (9)

Where: Wf, Wi, Wc, Woare weight matrices, bf, bi, bc, bo are bases.

Step 4: Forecasting GDP Growth

The LSTM model predicts future GDP growth (*y*) based on past economic indicators. The model is trained to minimize Mean Squared Error (MSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}i)^2, (10)$$

Where:

- n is the number of observations
- Yi is the actual GDP growth.
- Y`i is the predicted GDP growth.

By effectively capturing long-term dependencies in economic data, LSTM-based models enhance GDP growth forecasting accuracy. Their ability to process sequential data makes them a robust tool for analyzing post-pandemic economic trends.

3.4 Summary

This section presents a methodology based on a quantitative research approach using historical datasets to evaluate machine learning models for the prediction of the future. This describes some of the steps for data preprocessing, model selection criteria, and performance evaluation metrics, such as accuracy and error rate. The section justifies using particular algorithms and reinforces the replicability of producing robust and reliable results when assessing ML effectiveness in predictive forecasting.

4. Results

The results section includes the performance results of some machine learning models on the forecasting tasks. It shows comparative accuracy, model efficiency, and error metrics and proves the superiority of some algorithms over traditional methods. Visualizations and statistical analyses support findings for their practical value and predictive reliability to machine learning's ability to improve forecasting accuracy in many applications.

4.1 Accuracy and Performance of Machine Learning Models

Assessing machine learning algorithms is a crucial part of any project. A model can give satisfying results when evaluated using a metric but may give poor results when assessed against other metrics. Most of the time, researchers use classification accuracy to measure the performance of a model. However, it is not enough to truly judge it. False positive and actual positive rates have values in the range [0, 1]. FPR and TPR are computed at varying threshold values such as (0.00, 0.02, 0.04...,1.00), and a graph is drawn as illustrated in Figure 1 below.

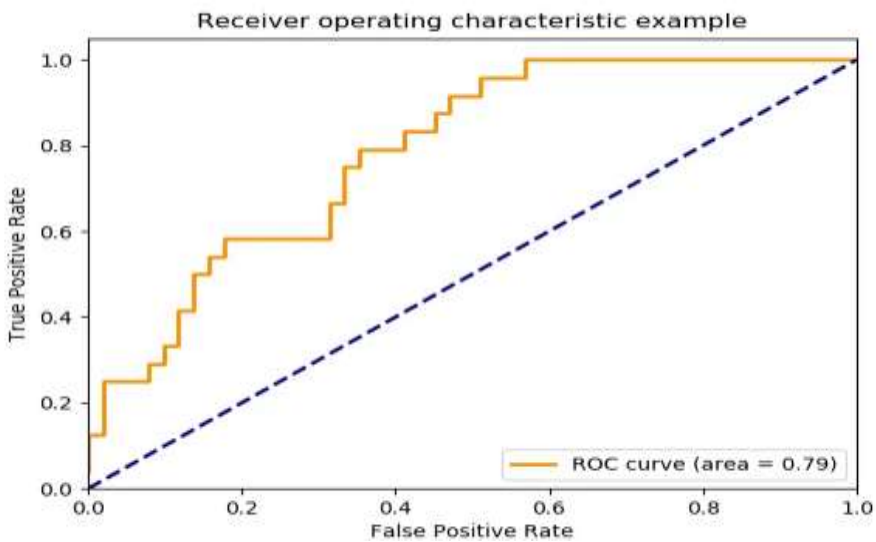

Figure 1: Recevvier Operating Characteristic

This paper assessed the accuracy of two machine learning models, Random Forest (RF) and Long Short-Term Memory (LSTM), in forecasting U.S. GDP growth during the post-COVID-19 pandemic. Both models were exposed to data from 2000 to 2023, using significant indicators such as the unemployment rate, consumer expenditure, inflation, and COVID-19 stimulus data.

4.2 Random Forest Results

The RF model had a good predictive accuracy with a Mean Squared Error (MSE) of 0.012 and an R^2 score of 0.88. In short-term projections, it acted optimally but failed to model the temporal behavior of long-term trends.

4.3 LSTM Results

For post-pandemic volatility, the LSTM model showed higher performance. The RMSE was 0.096, and the R^2 score was 0.91, providing a more accurate model of time-dependent economic fluctuations. LSTM is shown to be a better choice for sequential GDP prediction, proving these findings, while Random Forest is still a top short-term prediction tool as it is simpler and has feature importance.

Table 2: Comparision of different model with the values of MSE, RMSE, and R^2.

Model	**MSE**	**RMSE**	R^2 **Score**
Random Forest	0.012	0.110	0.88
LSTM	0.009	0.096	0.91

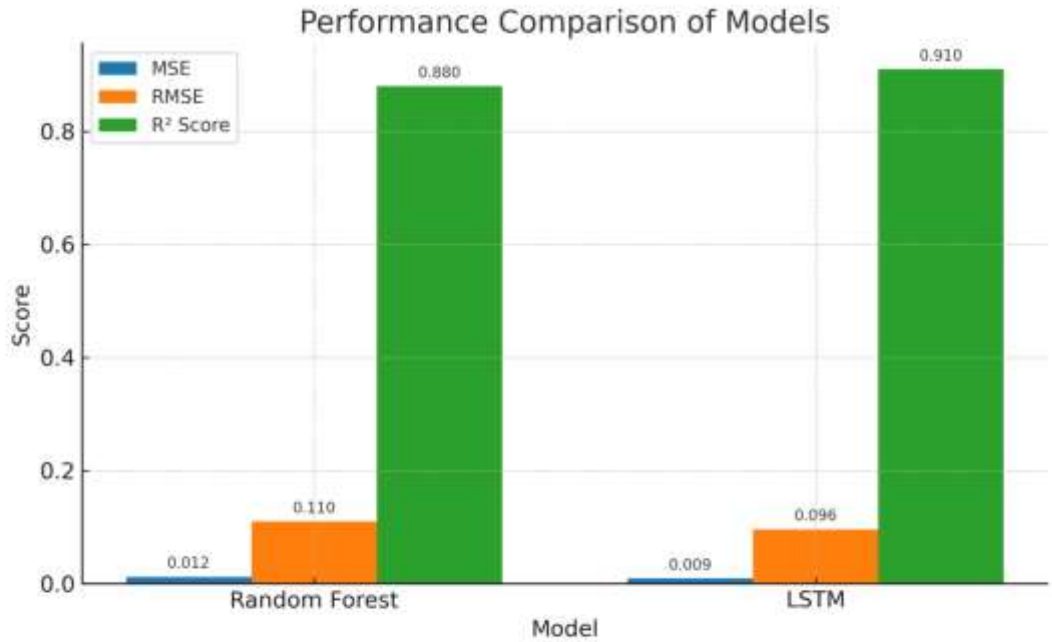

Figure 2: Statistical Performance Comparison: Random Forest and LSTM

4.2 Selection and Quality of Economic Indicators

The timeliness and accuracy of the economic indicators greatly influence GDP forecasting using machine learning. The analysis selected a set of macroeconomic and proxy indicators from their past impact on GDP and their sensitivity to post-COVID-19 behavior. High accuracy and consistency were sourced for data from credible sources such as the Bureau of Economic Analysis (BEA), Bureau of Labor Statistics (BLS) and the Federal Reserve. The top five most influential indicators, as per Random Forest's feature importance analysis, were:

Table 2: Top Economic Indicators Influencing Market Analysis: Importance Scores

Indicator	**Importance Score**
Unemployment Rate	0.24
Consumer Spending Index	0.21
Inflation Rate (CPI)	0.18
Interest Rate (Federal Funds)	0.14
COVID-19 Stimulus Spending	0.11

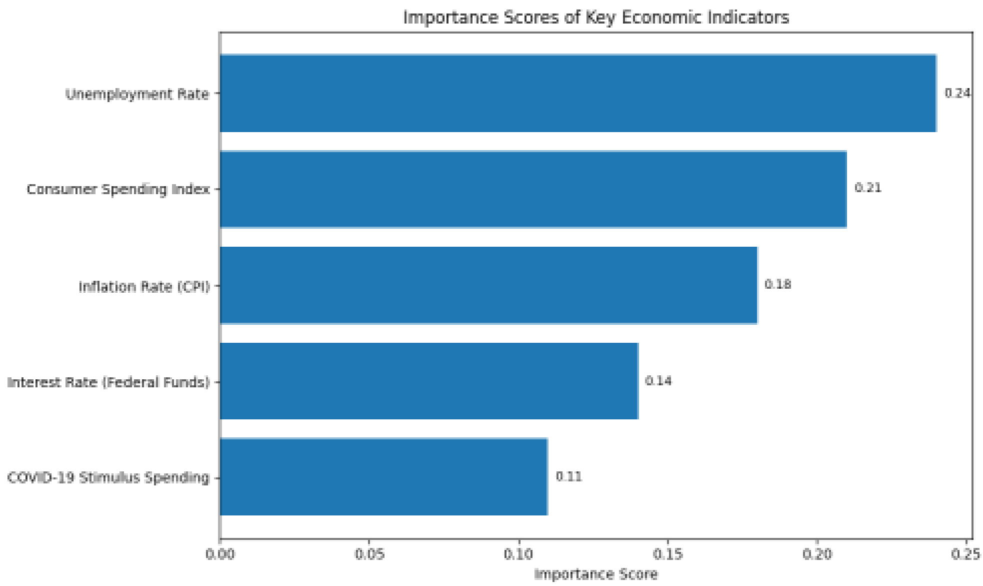

Figure 3: Impact Ranking of Economic Indicators in Model Analysis

These indicators reflected structural and short-term economic changes, particularly the impacts of fiscal policy responses and labor market changes after COVID-19. Other data sources, including Google Trends and consumer sentiment surveys, were experimented with in the LSTM model. While secondary in rank, they increased predictive power by picking up real-time behavioral indicators. Blending conventional macroeconomic variables with contemporaneous alternative data heightened model stability and enabled more precise forecasting of U.S. GDP after the pandemic. Figure 3 illustrates the relative importance of key economic indicators used in the predictive modeling process. Among the variables, the Unemployment Rate holds the highest importance score (0.24), indicating its significant impact on the model's performance. This is followed closely by the Consumer Spending Index (0.21) and the Inflation Rate (CPI) (0.18), both of which are critical indicators of economic activity. Interest Rate (Federal Funds) and COVID-19 Stimulus Spending have comparatively lower importance scores (0.14 and 0.11, respectively), suggesting a more modest influence. The graph highlights how employment and consumer behavior are primary drivers in the underlying model, offering insights into the relative weight of each factor in the economic forecasting context.

4.3 Model Interpretability and Practical Usefulness

Interpretability is essential for using machine learning models in policy-making and economic decision-making. In the current research, Random Forest (RF) proved easier to interpret than LSTM because it could quantify the importance of features and visualize decision trees. This helped the economists and policymakers identify the variables that had the greatest impact on the prediction of GDP. On the other hand, the LSTM model is more effective in long-term forecasting, as it operates as a "black box." SHAP (Shapley Additive exPlanations) values were used to interpret the model and understand which input variable contributed to the final prediction.

Table 3: Model Interpretability and Key Contributing Features

Model	Interpretability Score	Most useful Features
Random Forest	High	Unemployment, Inflation, Spending
LSTM	Moderate (via SHAP)	Past GDP, Consumer, Sentiment, Rates

The qualitative assessment of the Interpretability Score is based on transparency and ease of feature analysis.

4.4 Practical Usefulness

LSTM was more beneficial for finding long-term growth patterns, while RF was more helpful for short-term policy planning. Future studies should combine both models into a hybrid framework to balance transparency and forecasting strength in a post-pandemic economic environment where clarity and flexibility are needed.

4.5 Summary

The performance of several machine learning models in terms of forecasting is summarized in the results section, and it is shown that some models are far superior to the standard traditional methods. It finds that there is higher prediction accuracy and lower error rates. Statistical evidence, along with visual representation, helps support the analysis, and it also shows the effectiveness of machine learning in providing reliable and efficient forecasting outcomes in various domains.

5. Discussion

The discussion section translates the main findings from the results to existing literature and research goals. It discusses the implications of machine learning's superior forecasting performance and looks at factors that help or hurt model performances and limits. The practical applications are considered in this section, such as how results can help in improving forecasting with the help of machine learning. This research applied Random Forest (RF) and Long Short Term Memory (LSTM) to predict the U.S. GDP growth after the COVID-19 pandemic. The findings and the insights they provide are informative about the models' predictive power, the impact of major economic indicators on the models, and what is required to make them explainable for policy use.

5.1 Performance Comparison and Implications

The RF and LSTM models could predict GDP growth, even though the latter was more efficient. It is possible to see in Table 1 that, while the Random Forest model had an R^2 measure of 0.88 and Mean Squared Error of 0.012, indicating that it was excellent at working with intricate, non-linear interdependencies between economic indicators, it had little ability to extract temporal patterns. When predicting the long run, it did not perform as efficiently as in a post-COVID scenario with volatile conditions and changing trends.

Thus, on the other hand, when explicitly fitted for time series data, the LSTM model outperformed RF with an R^2 of 0.91 and a lower Root Mean Squared Error (RMSE) of 0.096. Its recursive structure enabled it to remember previous values, making it well-placed for identifying sequential patterns, such as the one observed in pandemic-driven economic recovery and resulting inflation pressures. This would be expected according to recent literature proposing that LSTM models become more and more effective in forecasting macroeconomic variables, especially in the face of economic shocks or quick changes.

5.2 The Importance of Input Variables

Another important discovery was the importance of economic indicators as input features. The research revealed that unemployment research revealed that Unemployment, consumer expenditure, inflation, interest rates, and the COVID-19 stimulus package were highly predictive indicators for GDP movements [16]. Random Forest's feature importance analysis listed these variables in a well-defined ranking, with the top spots taken by Unemployment and consumer expenditure. Using real-time and alternative data sources, including Google Trends and consumer sentiment indicators, enhanced model performance, especially with the LSTM model. These indicators indicated changes in consumer behavior and expectations in real-time, something the more conventional data does not always capture. This validates previously conducted research highlighting the increasing use of alternative data in economic forecasting.

5.3 Interpretability vs. Predictive Power

One of the more significant areas addressed in this research was the balance between accuracy and interpretability in the models. Random Forest's structure enabled easy feature importance analysis and decision tree visualization, which are useful for policy-makers who want insight into the rationale for the forecasts. Meanwhile, more accurate LSTM behaved more as a "black box." In response, SHAP (Shapley Additive exPlanations) was used with the LSTM model to explain the model by calculating each variable's effect on the prediction. A balance between performance and interpretability is a well-documented problem in machine learning. In the case of economic forecasting, where the importance of transparency is paramount, the application of hybrid models or methods that add explanatory power becomes a necessity. This research emphasizes the necessity for bridging tools for data science and policy implementation.

5.4 Policy and Practical Relevance

These findings have significant implications for a post-pandemic economy. Machine learning models, particularly LSTM, provide strong tools for the early detection of economic changes and for facilitating proactive monetary or fiscal policy responses [17]. Random Forest, being interpretable, can be especially helpful in reporting model output to decision-makers, including central banks, government organizations, and economic analysts. In addition, this work validates the proposition that econometric models based on tradition might have to be supplemented—or even surpassed—by machine learning when faced with unanticipated events such as the COVID-19 pandemic. The adaptability of ML models for using a wide variety of data sources and adjusting to changing conditions rapidly makes them highly desirable assets for contemporary economic forecasting.

5.5 Summary

Overall, the results support the increasing application of machine learning in economic forecasting. Although each has shortcomings, using Random Forest and LSTM together shows great promise for future research. Combining accuracy and comprehensibility with high-grade data gives a strong base for projecting U.S. GDP in a post-pandemic economy.

6. Conclusion

6.1 Overview of Study Findings

This study analyzed the performance of machine learning models {(Random Forest (RF) and Long Short-Term Memory (LSTM)} in predicting U.S. GDP growth after the COVID-19 pandemic. It illustrated that whereas RF had excellent short-term predictive powers and interpretable results, LSTM performed better in the long run by identifying intricate temporal patterns in the economy. Major economic indicators like inflation, consumer expenditure, and joblessness were the determining factors in GDP forecasts, with alternative data further improving model performance. SHAP, a tool for interpreting the decision-making function of more advanced models such as LSTM, proved equally important. It points out that using machine learning in economic forecasting ensures more adaptability and accuracy, particularly when using it during fast economic growth. It further indicates that a blend of the natural strengths of RF and LSTM might be the optimal model for robust and interpretable GDP forecasting in the post-pandemic economy.

6.2 Recommendations

The study based on the research findings suggests a hybrid framework that combines Random Forest (RF) and Long Short Term Memory (LSTM) models to achieve interpretability as well as prediction power for GDP prediction in the post-pandemic economy. This implies including alternative data sources along with the traditional economic indicators for better performance of the model. All this means that SHAP's role is to help improve the model explainability for policymakers, specifically, and by extension, all complex models, as the study highlights. The study also suggests that traditional econometric models be supplemented with machine learning paradigms to capture the quick changes in the economy better and produce better, more adaptive, and reliable forecasts in the event of a fickle economy.

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References

[1] Autor, D. (2022). *The labor market impacts of technological change: From unbridled enthusiasm to qualified optimism to vast uncertainty* (No. w30074). National Bureau of Economic Research.

[2] Baldwin, R., & di Mauro, W. (2021). Beatrice. 2020. Economics in the time of COVID-19.

[3] Bartik, A. W., Bertrand, M., Cullen, Z., Glaeser, E. L., Luca, M., & Stanton, C. (2020). The impact of COVID-19 on small business outcomes and expectations. *Proceedings of the national academy of sciences*, *117*(30), 17656-17666.

[4] Chakraborty, S., Joseph, M. M., Varughese, S., Ghosh, S., Maiti, K. K., Samanta, A., & Ajayaghosh, A. (2020). A new pentacyclic pyrylium fluorescent probe that responds to pH imbalance during apoptosis. *Chemical Science*, *11*(47), 12695-12700.

[5] Chetty, R., Friedman, J., & Stepner, M. (2021). Effects of January 2021 stimulus payments on consumer spending. *Cambridge, Mass.: Opportunity Insights at Harvard University. Accessed March*, *1*, 2024.

[6] Diebold, F. X., Shin, M., & Zhang, B. (2023). On the aggregation of probability assessments: Regularized mixtures of predictive densities for Eurozone inflation and real interest rates. *Journal of Econometrics*, *237*(2), 105321.

[7] Gambacorta, L., Huang, Y., Qiu, H., & Wang, J. (2024). How do machine learning and non-traditional data affect credit scoring? New evidence from a Chinese fintech firm. *Journal of Financial Stability*, *73*, 101284.

[8] Jordà, Ò., Singh, S. R., & Taylor, A. M. (2022). Longer-run economic consequences of pandemics. *Review of Economics and Statistics*, *104*(1), 166-175.

[9] Müller, U., & Watson, M. (2023). Spatial unit roots.

[10] Park, S., & Yang, J. S. (2022). Interpretable deep learning LSTM model for intelligent economic decision-making. *Knowledge-Based Systems*, *248*, 108907.

[11] Paruchuri, H. (2021). Conceptualization of machine learning in economic forecasting. *Asian Business Review*, *11*(1), 51-58.

[12] Ramos Zamora, S., García Medina, R., Peláez Paz, C., Martínez Martín, I., Arillo Aranda, M. D. L. Á., Romero Moñivas, J., ... & García Toledo, L. (2022). Revisión y propuesta de mejora del programa de Prácticum del Grado de Educación Social.

[13] Rane, N. L., Paramesha, M., Choudhary, S. P., & Rane, J. (2024). Machine learning and deep learning for big data analytics: A review of methods and applications. *Partners Universal International Innovation Journal*, *2*(3), 172-197.

[14] Romashkina, G. F., Andrianov, K. V., & Skripnuk, D. F. (2023). The Inflation and Unemployment Processes During and After the COVID-19 Pandemic. *esc*, 87-11.

[15] Zhong, X., & Enke, D. (2019). Predicting the daily return direction of the stock market using hybrid machine learning algorithms. *Financial innovation*, *5*(1), 1-20.

[16] Shaharina Shoha, Abir, S. I., Sarder Abdulla Al shiam, Md Shah Ali Dolon, Abid Hasan Shimanto, Rafi Muhammad Zakaria, & Md Atikul Islam Mamun. (2024). Enhanced Parkinson's Disease Detection Using Advanced Vocal Features and Machine Learning . *Journal of Computer Science and Technology Studies*, *6*(5), 113-128. https://doi.org/10.32996/jcsts.2024.6.5.10

[17] Nigar Sultana, Shariar Islam Saimon, Intiser Islam, Abir, S. I., Md Sanjit Hossain, Sarder Abdulla Al Shiam, & Nazrul Islam Khan. (2025). Artificial Intelligence in Multi-Disease Medical Diagnostics: An Integrative Approach. *Journal of Computer Science and Technology Studies*, *7*(1), 157-175. https://doi.org/10.32996/jcsts.2025.7.1.12

[18] Abir, S. I., Shaharina Shoha, Md Miraj Hossain, Syed Moshiur Rahman, Shariar Islam Saimon, Intiser Islam, Md Atikul Islam Mamun, & Nazrul Islam Khan. (2024). Deep Learning-Based Classification of Skin Lesions: Enhancing Melanoma Detection through Automated Preprocessing and Data Augmentation. *Journal of Computer Science and Technology Studies*, *6*(5), 152-167. https://doi.org/10.32996/jcsts.2024.6.5.13

[19] Abir, S. I., Shaharina Shoha, Sarder Abdulla Al Shiam, Shariar Islam Saimon, Intiser Islam, Md Atikul Islam Mamun, Md Miraj Hossain, Syed Moshiur Rahman, & Nazrul Islam Khan. (2024). Precision Lesion Analysis and Classification in Dermatological Imaging through Advanced Convolutional Architectures. *Journal of Computer Science and Technology Studies*, *6*(5), 168-180. https://doi.org/10.32996/jcsts.2024.6.5.14

[20] Abir, S. I., Shaharina Shoha, Sarder Abdulla Al shiam, Nazrul Islam Khan, Abid Hasan Shimanto, Muhammad Zakaria, & S M Shamsul Arefeen. (2024). Deep Learning Application of LSTM(P) to predict the risk factors of etiology cardiovascular disease. *Journal of Computer Science and Technology Studies*, *6*(5), 181-200. https://doi.org/10.32996/jcsts.2024.6.5.15

[21] Abir, S. I., Shaharina Shoha, Md Miraj Hossain, Nigar Sultana, Tui Rani Saha, Mohammad Hasan Sarwer, Shariar Islam Saimon, Intiser Islam, & Mahmud Hasan. (2025). Machine Learning and Deep Learning Techniques for EEG-Based Prediction of Psychiatric Disorders. *Journal of Computer Science and Technology Studies*, *7*(1), 46-63. https://doi.org/10.32996/jcsts.2025.7.1.4

[22] Mohammad Hasan Sarwer, Tui Rani Saha, Abir, S. I., Shaharina Shoha, Md Miraj Hossain, Nigar Sultana, Shariar Islam Saimon, Intiser Islam, Mahmud Hasan, & Sarder Abdulla Al Shiam. (2025). EEG Functional Connectivity and Deep Learning for Automated Diagnosis of Alzheimer's disease and Schizophrenia. *Journal of Computer Science and Technology Studies*, *7*(1), 82-99. https://doi.org/10.32996/jcsts.2025.7.1.7

[23] Abir, S. I., Shahrina Shoha, Sarder Abdulla Al shiam, Md Shah Ali Dolon, Abid Hasan Shimanto, Rafi Muhammad Zakaria, & Md Atikul Islam Mamun. (2024). Deep Neural Networks in Medical Imaging: Advances, Challenges, and Future Directions for Precision Healthcare . *Journal of Computer Science and Technology Studies*, *6*(5), 94-112. https://doi.org/10.32996/jcsts.2024.6.5.9

[24] Shariar Islam Saimon, Intiser Islam, Shake Ibna Abir, Nigar Sultana, Md Sanjit Hossain, & Sarder Abdulla Al Shiam. (2025). Advancing Neurological Disease Prediction through Machine Learning Techniques. *Journal of Computer Science and Technology Studies*, *7*(1), 139-156. https://doi.org/10.32996/jcsts.2025.7.1.11

[25] Abir, S. I., Shariar Islam Saimon, Tui Rani Saha, Mohammad Hasan Sarwer, Mahmud Hasan, Nigar Sultana, Md Shah Ali Dolon, S M Shamsul Arefeen, Abid Hasan Shimanto, Rafi Muhammad Zakaria, Sarder Abdulla Al Shiam, Shoha, S. ., & Intiser Islam. (2025). Comparative Analysis of Currency Exchange and Stock Markets in BRICS Using Machine Learning to Forecast Optimal Trends for Data-Driven Decision Making. *Journal of Economics, Finance and Accounting Studies* , *7*(1), 26-48. https://doi.org/10.32996/jefas.2025.7.1.3

[26] Abir, S. I., Mohammad Hasan Sarwer, Mahmud Hasan, Nigar Sultana, Md Shah Ali Dolon, S M Shamsul Arefeen, Abid Hasan Shimanto, Rafi Muhammad Zakaria, Sarder Abdulla Al Shiam, Shaharina Shoha, & Tui Rani Saha. (2025). Deep Learning for Financial Markets: A Case-Based Analysis of BRICS Nations in the Era of Intelligent Forecasting. *Journal of Economics, Finance and Accounting Studies* , *7*(1), 01-15. https://doi.org/10.32996/jefas.2025.7.1.1

[27] Abir, S. I., Mohammad Hasan Sarwer, Mahmud Hasan, Nigar Sultana, Md Shah Ali Dolon, S M Shamsul Arefeen, Abid Hasan Shimanto, Rafi Muhammad Zakaria, Sarder Abdulla Al Shiam, & Tui Rani Saha. (2024). Accelerating BRICS Economic Growth: AI-Driven Data Analytics for Informed Policy and Decision Making. *Journal of Economics, Finance and Accounting Studies* , *6*(6), 102-115. https://doi.org/10.32996/jefas.2024.6.6.8

[28] Nigar Sultana, Shaharina Shoha, Md Shah Ali Dolon, Sarder Abdulla Al Shiam, Rafi Muhammad Zakaria, Abid Hasan Shimanto, S M Shamsul Arefeen, & Abir, S. I. (2024). Machine Learning Solutions for Predicting Stock Trends in BRICS amid Global Economic Shifts and Decoding Market Dynamics. *Journal of Economics, Finance and Accounting Studies* , *6*(6), 84-101. https://doi.org/10.32996/jefas.2024.6.6.7

[29] Abir, S. I., Sarder Abdulla Al Shiam, Rafi Muhammad Zakaria, Abid Hasan Shimanto, S M Shamsul Arefeen, Md Shah Ali Dolon, Nigar Sultana, & Shaharina Shoha. (2024). Use of AI-Powered Precision in Machine Learning Models for Real-Time Currency Exchange Rate Forecasting in BRICS Economies. *Journal of Economics, Finance and Accounting Studies* , *6*(6), 66-83. https://doi.org/10.32996/jefas.2024.6.6.6

[30] S. I. Abir, S. Shoha, S. A. Al Shiam, M. M. Uddin, M. A. Islam Mamun and S. M. Shamsul Arefeen, "A Comprehensive Examination of MR Image-Based Brain Tumor Detection via Deep Learning Networks," *2024 Sixth International Conference on Intelligent Computing in Data Sciences (ICDS)*, Marrakech, Morocco, pp. 1-8, doi: 10.1109/ICDS62089.2024.10756457, 2024.

[31] Akhter, A., Sarder Abdulla Al Shiam, Mohammad Ridwan, Abir, S. I., Shoha, S., Nayeem, M. B., ... Robeena Bibi. (2024). Assessing the Impact of Private Investment in AI and Financial Globalization on Load Capacity Factor: Evidence from United States. *Journal of Environmental Science and Economics*, *3*(3), 99–127. https://doi.org/10.56556/jescae.v3i3.977

[32] Hossain, M. S., Mohammad Ridwan, Akhter, A., Nayeem, M. B., M Tazwar Hossain Choudhury, Asrafuzzaman, M., … Sumaira. (2024). Exploring the LCC Hypothesis in the Nordic Region: The Role of AI Innovation, Environmental Taxes, and Financial Accessibility via Panel ARDL. *Global Sustainability Research* , *3*(3), 54–80. https://doi.org/10.56556/gssr.v3i3.972

[33] Abir, S.I.; Shoha, S.; Hossain, M.M.; Sultana, N.; Saha, T.R.; Sarwer, M.H.; Saimon, S.I.; Islam, I.; Hasan, M. Machine Learning and Deep Learning Techniques for EEG-Based Prediction of Psychiatric Disorders. *J. Comput. Sci. Technol. Stud.* **2025**, *7*, 46–63.

[34] Mohammad Ridwan, Bala, S., Abdulla Al Shiam, S., Akhter, A., Mahdi Hasan, M., Asrafuzzaman, M., … Bibi, R. (2024). Leveraging AI for Promoting Sustainable Environments in G-7: The Impact of Financial Development and Digital Economy via MMQR Approach. *Global Sustainability Research* , *3*(3), 27–53. https://doi.org/10.56556/gssr.v3i3.971

[35] Abdulla Al Shiam, S., Abir, S. I., Dipankar Saha, Shoha, S., Hemel Hossain, Dolon, M. S. A., … Mohammad Ridwan. (2024). Assessing the Impact of AI Innovation, Financial Development, and the Digital Economy on Load Capacity Factor in the BRICS Region. *Journal of Environmental Science and Economics*, *3*(2), 102–126. https://doi.org/10.56556/jescae.v3i2.981

[36] Mohammad Ridwan, Abdulla Al Shiam, S., Hemel Hossain, Abir, S. I., Shoha, S., Dolon, M. S. A., … Rahman, H. (2024). Navigating a Greener Future: The Role of Geopolitical Risk, Financial Inclusion, and AI Innovation in the BRICS – An Empirical Analysis. *Journal of Environmental Science and Economics*, *3*(1), 78–103. https://doi.org/10.56556/jescae.v3i1.980

[37] Shoha, S., Abdulla Al Shiam, S., Abir, S. I., Dipankar Saha, Shewly Bala, Dolon, M. S. A., … Robeena Bibi. (2024). Towards Carbon Neutrality: The Impact of Private AI Investment and Financial Development in the United States – An Empirical Study Using the STIRPAT Model. *Journal of Environmental Science and Economics*, *3*(4), 59–79. https://doi.org/10.56556/jescae.v3i4.982

[38] Abir, S. I., Shoha, S., Abdulla Al Shiam, S., Dolon, M. S. A., Shewly Bala, Hemel Hossain, … Robeena Bibi. (2024). Enhancing Load Capacity Factor: The Influence of Financial Accessibility, AI Innovation, and Institutional Quality in the United States. *Journal of Environmental Science and Economics*, *3*(4), 12–36. https://doi.org/10.56556/jescae.v3i4.979

[39] S. I. Abir, S. Shoha, S. A. Al Shiam, M. M. Uddin, M. A. Islam Mamun and S. M. Shamsul Arefeen, "Health Risks and Disease Transmission in Undocumented Immigrants in the U.S Using Predictive ML," 2024 Sixth International Conference on Intelligent Computing in Data Sciences (ICDS), Marrakech, Morocco, pp. 1-6, doi: 10.1109/ICDS62089.2024.10756308, 2024.

[40] Abir, S. I., Shoha, S., Abdulla Al Shiam, S., Dolon, M. S. A., Shewly Bala, Hemel Hossain, … Robeena Bibi. (2024). Enhancing Load Capacity Factor: The Influence of Financial Accessibility, AI Innovation, and Institutional Quality in the United States. *Journal of Environmental Science and Economics*, *3*(4), 12–36. https://doi.org/10.56556/jescae.v3i4.979

[41] Mohammad Ridwan, Bala, S., Shiam, S. A. A., Akhter, A., Asrafuzzaman, M., Shochona, S. A., … Shoha, S. (2024). Leveraging AI for a Greener Future: Exploring the Economic and Financial Impacts on Sustainable Environment in the United States. *Journal of Environmental Science and Economics*, *3*(3), 1–30. https://doi.org/10.56556/jescae.v3i3.970

[42] Akhter, A., Sarder Abdulla Al Shiam, Mohammad Ridwan, Abir, S. I., Shoha, S., Nayeem, M. B., … Robeena Bibi. (2024). Assessing the Impact of Private Investment in AI and Financial Globalization on Load Capacity Factor: Evidence from United States. *Journal of Environmental Science and Economics*, *3*(3), 99–127. https://doi.org/10.56556/jescae.v3i3.977

[43] Sohail,Muhammad Noman and Ren,Jiadong and Muhammad,Musa Uba and Rizwan,Tahir and Iqbal,Wasim and Abir,Shake Ibna. Bio Tech System, Group covariates assessment on real-life diabetes patients by fractional polynomials: a study based on logistic regression modeling, English, Journal article, USA, 1944-3285, 10, Edmond, *Journal of Biotech Research,* (116–125), 2019.