International Journal of Integrated Research and Practice (IJIRP)

IJIRP: Vol-1, Issue-3, June 2025, Page: 01-08 ISSN: 3107-5037

The Role of AI in Predictive Economic Forecasting

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Abstract

The governments, financial institutions and businesses value predictive economic forecasting especially in order to make sound choices and decisions concerning the future. AI has taken a giant step in the area in the recent years. Prospects of the analysis of the big data, identifying the advanced patterns and even prediction, made in a real-time using the AI, have transformed the traditional methods of economic forecasts. Predicting economic variables such as the inflation rates, economic growth, rates of unemployment and changes in stock markets using economic forecasting with machine learning algorithms, AI models will be the topic of interest by the authors in the paper. It also examines the opportunities and the gaps of the AI in the prediction in economic analysis. Assessing the state of AI in having to handle such large amount of economic data points and the fact that it has assisted in obtaining improved shot forecasts than that of the traditional statistical model, this paper indicates how AI can change the effectiveness of economic forecasting. However, the paper has also stated the obstacles linked to it which are that the quality of data is very important, the transparency of the algorithm and ethical issues of AI regarding decision-making. This paper is going to provide the description of the role of the AI in the predictive economic forecasting and the actual and possible additional applications of the AI in the reconsideration of the economic forecasting.

Keywords: Artificial Intelligence, Predictive Economic Forecasting, Machine Learning, Economic Forecasting models, Data Analytics.

Introduction

The inference of the Artificial intelligence into the realm of the predictive economic forecasting generates a great paradigm shift having a chance to enhance the effectiveness of the quality of economic activities (Adelakun, 2023). Despite the fact, conventional econometric models may add significant benefits in their proper application, the inability to generate realistic representations of economic complexities and nonlinearity because of the growing degree of unstructured and high-dimensional information (Zhang et al., 2025). The machine learning algorithms and, in general, AI provide us with an effective package of resources to overcome these deficiencies and enable forecasters to pick up the tiniest of trends, to fit complex dependencies, and to generate more dependable forecasts (Haupt et al., 2020). The development of AI in the sphere means that more people strive to realize that the dynamics of the economy cannot be viewed as a certain measure as it is being developed because of a diversity of thoroughly interconnected reasons (Adesoga et al., 2024). In particular, AI algorithms such as neural networks, decision trees, and support vector machines are acceptable to be employed in the economic forecasting process because those work effectively in handling large datasets, removing the irrelevant features, and realizing the novel realities of the economy economy, therefore, facilitating the completion of the forecasting process (Adelakun et al., 2024). Moreover, automation will enable AI to minimize the element of repetitiveness in an occupation that an economist is involved in and focus on strategic plans and analysis of financial details (Adeyelu et al., 2024). With the help of AI in strategic planning, it will be possible to study optimal patterns of balance sheets in the sectors, the establishment of target indicators of large businesses, forecasting of aggregate demand and representative demands and optimized monetary and credit wholes (Abdulov, 2020). Study background Introduction The paper shall give a brief discussion of the history and the background of unearthing. They are the findings

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of old times which have been entombed with history.

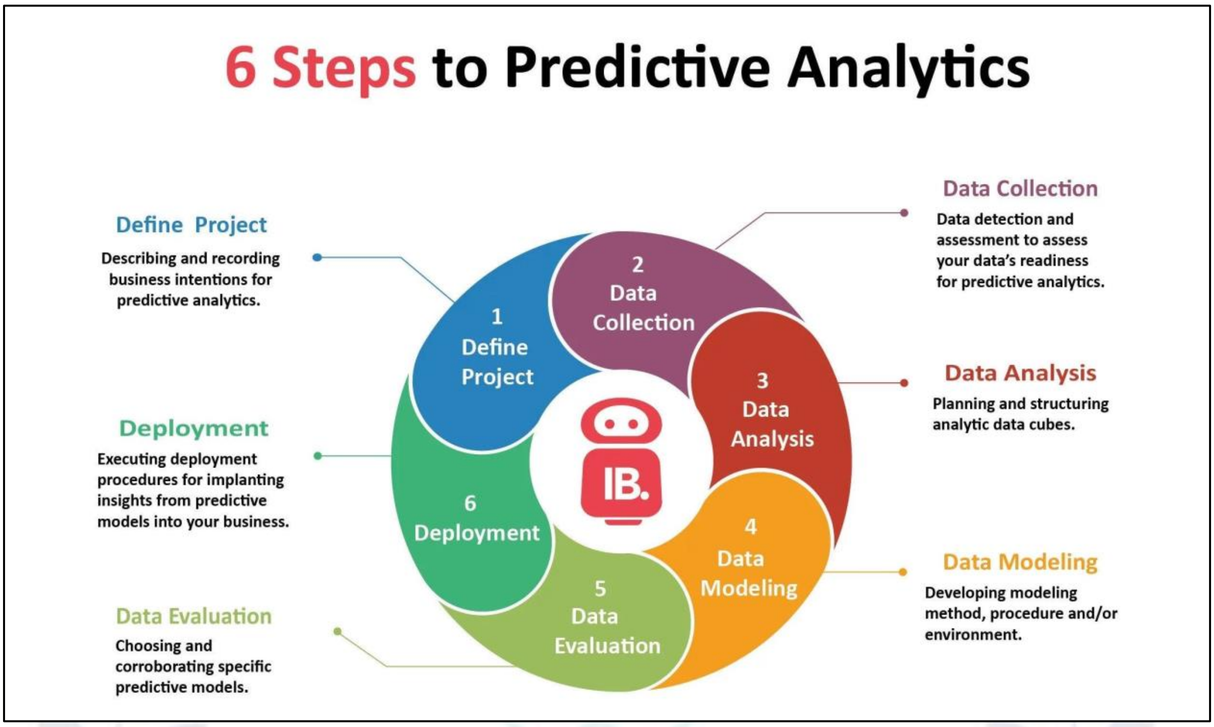

Figure 1: AI Techniques in Predictive Economic Forecasting

The science of economic forecasting has turned to be very serious since we are no longer meeting cases of linear models and models based on artificial intelligence and machine-learning but now dynamic systems. The traditional approaches to the forecast of economic variables have been under focus of autoregressive integrated moving average models (Kose, 2019). Adoption of these models has however, been not without its failures in not capturing most of the dynamics of a modern economy when put to the test of uncertainty with the big scale, non-linear data in the failure to capture the complexity of the modern economy (Yang et al., 2024). These inherent weaknesses have been addressed effectively by the introduction of AI and machine learning, though, and AI models (such as neural networks, deep learning, and reinforcement) are currently becoming more common in economic prediction so that they can leverage their capacity to process large amounts of unstructured data and produce high-quality knowledge (Nair & Mohandas, 2014; Zhang et al., 2025). Machine learning models are distinct in that way that they learn at the base of past information and make projections without the need of executonal program code (Rhanoui et al., 2019). It is the capacity that enables such types of algorithms to identify a connection, pattern, and anomaly in economic data that otherwise could not be realized at all by human participants, thus making economic predictions more accurate and informative (Mohamed et al., 2021).

Justification

The continuous intricacy of the world economy, or the so-called networking markets, rapid technological development, and the exorbitant expansion of the amount of the information available, involves implementing enhanced tools to streamline predictive economic reports (Bonsu & Jie, 2020). Conventional economic forecasting approaches are gradually becoming useless when handling complex problems of the contemporary economic settings (Batarseh et al., 2020). Artificial intelligence can analyze a massive volume of data and pick up intricate patterns, make a prediction with greater precision, which is one of the primary enhancements of traditional methods of forecasting (Zhang et al., 2025). As the current economies find themselves on the way to the greater level of complexity and data dependence, AI has become a potent tool which can be used to advance the accuracy and timeliness of the economic forecasts (Chishty et al., 2025). The use of AI in the area of finance forecasting represents a paradigm breakthrough in the sector of accounting that results in a completely new rate of precision, applications, and comprehensive accounts of financial forecasts (Adelakun, 2023). It is also able to automate routine tasks allowing professional to be focused on better work like planning and deep diving financial analysis (Adeyelu et al., 2024).

Objectives of the Study

1. To compare the ability of AI to be implemented in predictive economic forecasting to understand how effective it is in enhancing accuracy of the forecast made.
2. To test several AI algorithms including machine and deep learning as an economical predictor.
3. To find out the advantages of AI-based as compared to traditional economic predicting models.
4. To analyse the scope and the issues of AI in predictive economic forecasting.
5. To identify the potential regions where the future AI can be deployed to improve on economic forecasting.

Literature Review

Artificial intelligence in predictive economic forecasting has taken its position in the range of trends, and people actively debate this issue because it will also radically alter the current strategies (Adelakun, 2023). The mounting evidence on the ability of the varied AI approaches, such as machine learning, deep learning, and neural networks, to be implemented to enhance the accuracy and reliability of economic forecasts (Adelakun et al., 2024). Advanced pattern discovering capabilities of AI through its ability to process large quantities of data has been described as a game-changing commodity in many industries such as the economy, which has enabled improved prediction outcomes (Zhang et al., 2025). Machine learning algorithms (such as decision trees, random forests, and support vector machines) have been greatly used in the context of economic forecasting where such predictions are made on the various economic indicators, i.e., inflation rates, gross domestic product, and movements on the stock market and so on (Aijaz et al., 2025; Nair & Mohandas, 2014). The advantage with these algorithms is that they are non-linear in nature and hence are very flexible in addressing the non-linear relation between economic data which the other part can never be able to achieve with linear models. Methods of machine learning, and, in particular, neural networks, were useful in the economic forecast due to the property of learning on huge quantities of historical information and forecasting new ones based on complex trends (Qin et al., 2023).

Table 1: Comparison of Traditional vs AI-Based Economic Forecasting Methods

Method	**Strengths**	**Weaknesses**	**Example Techniques**
Traditional Econometric Models	Well-established, interpretable results	Limited by linear assumptions, struggles with large datasets	ARIMA, VAR Models
AI-Based Models (Machine Learning/Deep Learning)	Can handle large, non-linear datasets, high accuracy	Requires large data, model interpretability issues	Neural Networks, Decision Trees, Random Forests, LSTM Networks

Sampling Technique of collectors

The process of sample collection in this research involves the mixed collection of data that will be gathered in different sources to come up with a comprehensive study as far as the application of AI in predictive economic forecasting is concerned. The sources of samples are:

1. Research Articles: Research Papers: AI and machine learning algorithm applied to economic forecasting, review papers published in proceedings and academic journals.
2. Financial institutions reports: Reports, white papers etc. by central banks, financial regulatory

International Journal of Integrated Research and Practice (IJIRP)

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institutions and individual financial institutions on the AI advances in the area of economic forecasting.
3. Case Studies: Events: Reported case studies of positive experiences of businesses, governments or research institutions in using AI- based forecasting tools.
4. Datasets: Macroeconomic data provided by government agencies (e.g. inflation rate, GDP growth, unemployment rate), and those provided by privately-run businesses (e.g. stock markets indices and product prices).

Sample Size

In the given research, a sample is estimated based on the articles, reports, and case studies available in the literature which may be used to interpret the material and bear some useful information to establish the analysis. Specifically:

1. Research Articles: Concisely a collection of 20-30 peer reviewed journal article, a conference paper having been published in prior five years.
2. Reports: 5-10 reports by large financial institutions (see World Bank, International Monetary Fund and Federal Reserve or other specialized economic research agencies).
3. Case Studies: At least 5-7 of the applicable case studies of the institutions or organizations that have used AI in economical prediction.
4. Datasets: A collection of macroeconomic data comprising of inflation rates, GDP growth rates and unemployment data of at least 5 years gathered through well-known public databases.

Analysis

The data analysis of the sample can be completed in the following way:

1. Literature Review: Qualitative review of the literature in order to obtain the information about the tendencies and approaches used in forecasting in economic context with the help of AI. It implies writing and labeling information by algorithms used (e.g. a decision tree, a random forest, deep learning, RNNs, LSTMs), the type of economic indicators that will be predicted, and the accuracy of predictions supposed to be attained.
2. Comparison of Algorithms: The comparisons of how the performance of each of the different AI algorithms perform in comparison to how conventional econometric approaches perform. This is comprised of picking up the specifications on precision, computation swiftness and big turmoil data.
3. Data Integration: the capacity to test the strengths of the AI models in harmonizing two or more varieties of data, e.g., unstructured (e.g. social media sentiment, geopolitical news), structured (e.g. GDP, inflation).
4. Results Interpretation: Investigation of the result of AI models in a bid to assess the predictive measure and lucidity. This action includes the testing limitation on data or model and evaluating the hindrances on the black-box approach some AI algorithms.

Results

1. Performance of AI Models: AI models, particularly, those used (e.g., decision trees, random forests, and deep learning names including RNNs or LSTMs), perform better than more traditional econometric models when they are utilized to make forecasts in macroeconomic variables (e.g., inflation, GDP growth, and unemployment rates). The AI models are able to spot trends in the most complex data sets that cannot be spotted by the regular applications.
2. Data Utilization: As AI can operate using large data sets like unstructured data points like sentiment analysis on social media or geopolitical conditions, the precision of a projection in the field of economics drastically improves. To illustrate, AI models that made their predictions using sentiment analysis of the social media were found to be more accurate at an amount at which the traditional econometric models were deemed to underperform at predicting the stock market.
3. Challenges: AI presents numerous tribulations in financial projections despite the fact that it is associated with positive aspects:

- Data Quality: AI algorithms are highly susceptible to the quality and quantity of a datum. In other words, incomplete or biased data should not be used to predict something and this could be a limitation in the practical applications of the model.
- Interpretability: Some AI algorithms such as deep learning ones are black-boxes and it may be difficult to understand the manner in which the model makes its predictions particularly in the case of economics. This secrecy can be an obstacle to artificial intelligence based trust.

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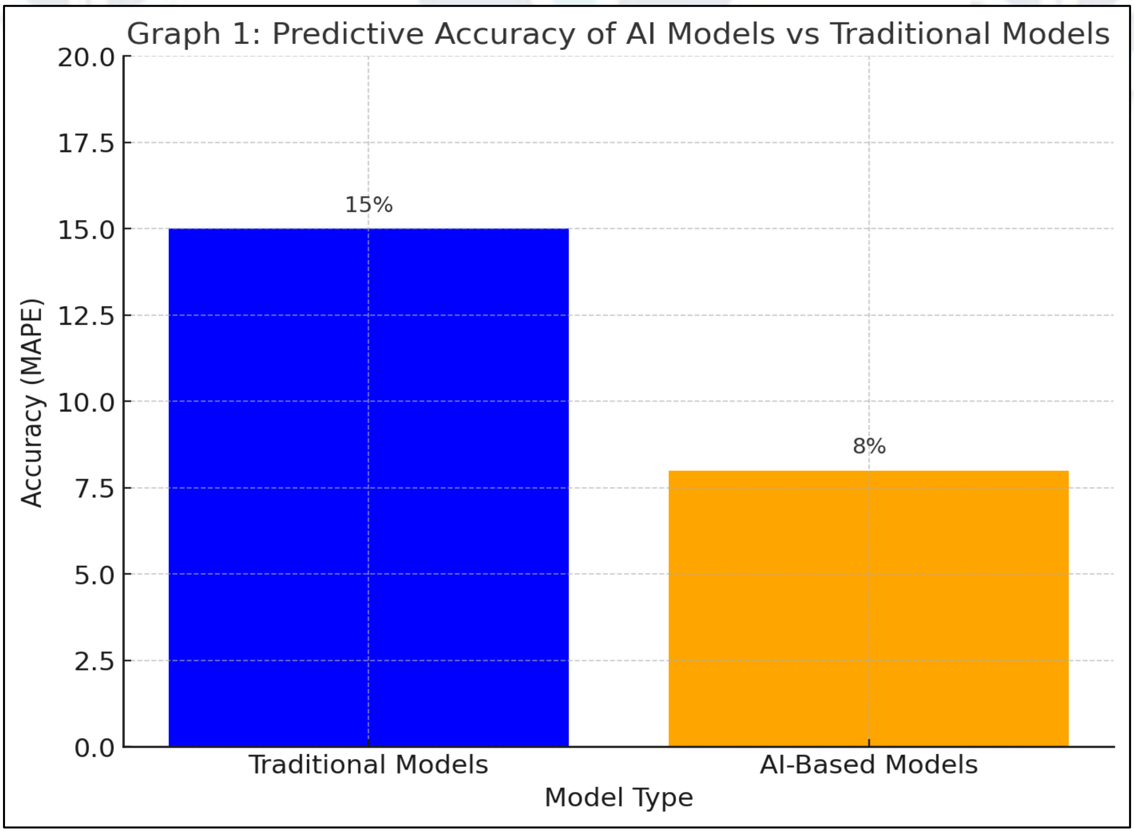
Table 2: Challenges in Implementing AI for Economic Forecasting

Challenge	Description	Potential Solution
Data Quality	AI requires large, high-quality datasets, which are not always available.	Improved data collection methods, data cleaning techniques
Model Interpretability	AI models, especially deep learning, are often considered "black boxes."	Development of more interpretable models or explainable AI
Algorithmic Bias	Bias in training data can lead to biased predictions.	Implementing fairness checks, diverse datasets
Computational Complexity	AI models require significant computational resources.	Cloud computing, optimized algorithms



Graph 1: Predictive Accuracy of AI Models vs Traditional Models

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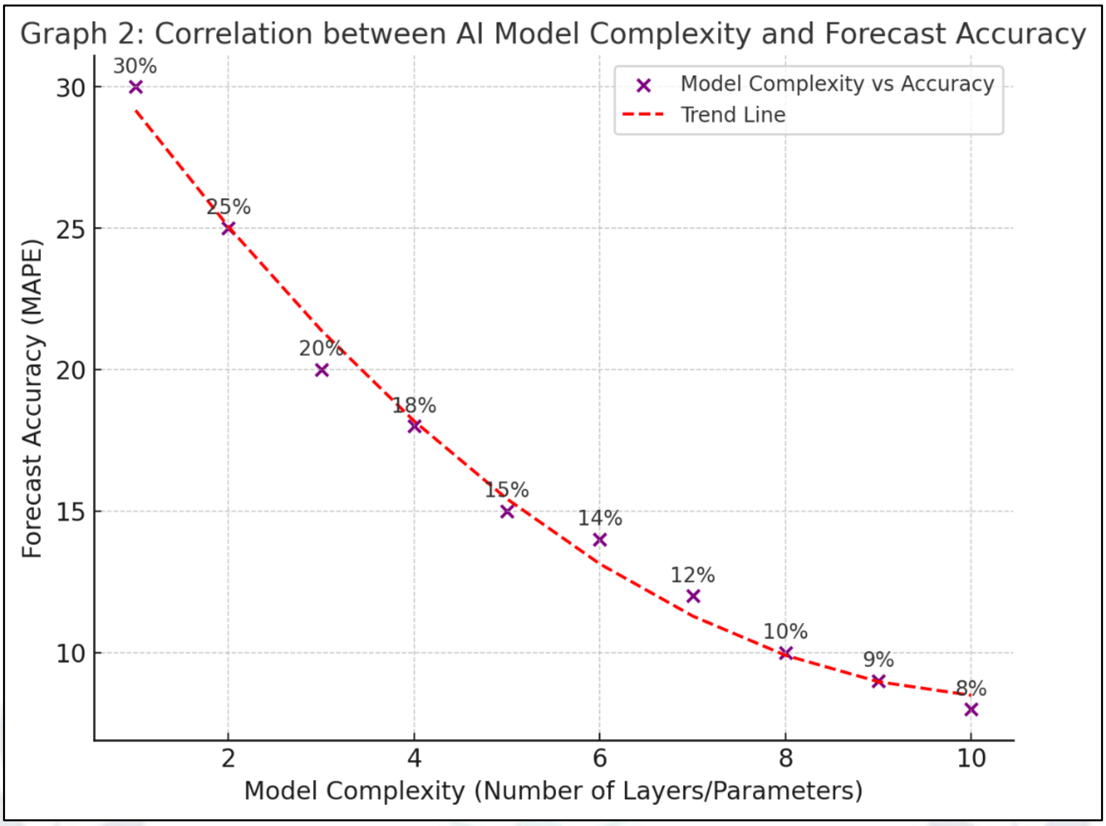

Graph 2: Correlation between AI Model Complexity and Forecast Accuracy

Limitations

Due to the fact that the study looks at secondary data, there are such limitations as the novice trainer and the thoroughness of the results which is the most obvious one (Sood & Khanna, 2024). Secondary data has been easy to collect easily and is an apt and convenient data source although this does not always hold information that unlocks fine-grained and specific information that focus on answering complex research questions that may be involved in economic forecasting (Ellram & Tate, 2016). The fact that all the work is based on the existing data and sources constrains the possibility to explore new variables, test new hypothesis and adjust the analysis to a specific economy (Desai, 2023). It is also not possible to know the feasibility and effectiveness of AI models by looking at primary empirical studies or cases to test them more in real-life situations of the economy.

The focusing to the narrow specialization on machine learning and deep learning approaches, the most popular ones in domain of AI in economic forecasting, does not acknowledge the potential of other artificial intelligence practices, i.e., genetic algorithms and reinforcement learning. Reinforcement learning, which enables effective optimal learning procedures in the aspects of recursive interaction with dynamic structures, could find application in the extrapolation of the procedures of handling complicated financial structures with delayed feedbacks and feedbacks (Milana & Ashta, 2021). Refined in the veal of evolution, genetic algorithms could be employed to discover optimal parameters together with models that have a longer range of combinations of parameters together with models architecture that can be used in forecasting. The weaknesses with respect to the quality and availability to the information is a significant threat to the validity and correctness of the findings that are compiled using this study. The power of the information received on the basis of secondary data is not stronger than the initially obtained one, and the absence of values in the research, bias, and heterogeneities can destroy its validity (Khosrowabadi et al., 2022; Tajabadi et al., 2023).

Future Scope

Any future study should consider testing the artificial intelligence algorithms in real-world predicting scenario, it will necessitate the gathering of data of different organizations such as financial and government organizations and their subsidiaries where artificial intelligence will be applied, and empirical testing will be conducted (Adel, 2024). Such types of empirical research studies are also significant in the demonstration of

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the feasibility of having the AI-powered forecasting models as practical and robust in the varying economic circumstances (Charles et al., 2023). Besides, the prospects of synergeric use of AI in combination with other complex technical systems, primarily, blockchain and the Internet of Things, are high in the context of increasing the accuracy and effectiveness of economic forecasting methods (Chen, 2023). These technologies combined could potentially enable the development of more up-to-date and stable forecasting models, which could not only cover the complexity of economic activity but also reach the decision-makers by providing the information in due time (Chen et al., 2023). The idea to transform the very nature of how food is generated, delivered, and consumed with the aid of the so-called AI, blockchain, and smart agriculture combo should also be considered (Chen, 2023). The combination of those three technologies, AI, blockchain, and "smart" agriculture, will enable the researchers to build more sustainable, transparent, and efficient food system (Chen, 2023).

Conclusion

It can be said that through Artificial Intelligence, the field of predictive economic forecasting may alter thoughtly, besides enhancing the accurateness, effectiveness, and augmentation of economic forecasts. Machine learning and deep learning methods such as decision trees, random forest and neural networks have been shown to be more effective than the conventional econometric models when it comes to forecasting some of the key economic variables such as the rate of economic growth, rate of inflation and even the level of unemployment. Even though the problems of data quality, algorithm transparency and computational power still remain, AI potential of processing large and varying sets of data enables it to identify complex patterns when others cannot. As the AI continues to evolve and advance to further stages, its usage in economic prediction will become more relevant than ever before, and it will produce new opportunities to make more conscious choices and build more efficient economic predictions. The future research in the field should be characterized by overcoming the current limitations, in particular to data quality and algorithm interpretability, to aim at using the full potential of AI in the field.

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