

Improving econometric models using artificial intelligence and machine learning

تحسين النماذج القياسية الاقتصادية باستخدام الذكاء الاصطناعي والتعلم الآلي

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Abstract:

One of the key applications of machine learning in economics is enhancing the predictive accuracy of econometric models. Conventional econometric approaches often rely on strict statistical assumptions, which constrain their capacity to address data complexity and uncertainty. By integrating them with machine learning methods—such as artificial neural networks—these models can be extended to achieve greater flexibility and forecasting power. This paper takes the case of using univariate modelling techniques to predict construction outputs, where the regression tree was used instead of the least squares method. It also explores three other univariate modelling techniques: Box-Jenkins, neural network autoregression (NNAR), and support vector machine (SVM). Furthermore, it provides an example of a regression estimation method in Python. Finally, the core feature of artificial intelligence is data processing for decision-making.

Keywords: Artificial Intelligence, Machine Learning, Econometrics, Regression Tree, Forecasting.

Jel Classification Codes: C18; C53; C14

Abstract in Arabic:

أحد التطبيقات الرئيسية للتعلم الآلي في الاقتصاد هو تحسين دقة التنبؤ بالنماذج الاقتصادية القياسية. غالبًا ما تعتمد مناهج الاقتصاد القياسي التقليدية على افتراضات إحصائية صارمة، مما يحد من قدرتها على معالجة تعقيد البيانات وعدم اليقين. من خلال دمجها مع أساليب التعلم الآلي - مثل الشبكات العصبية الاصطناعية - يمكن توسيع نطاق هذه النماذج لتحقيق مرونة وقدرة تنبؤ أكبر.

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تتناول هذه الورقة البحثية حالة استخدام تقنيات النمذجة أحادية المتغير للتنبؤ بمخرجات البناء، حيث تم استخدام شجرة الانحدار بدلاً من طريقة المربعات الصغرى. كما تستكشف ثلاث تقنيات أخرى للنمذجة أحادية المتغير: بوكس-جينكينز، والانحدار التلقائي للشبكة العصبية (NNAR)، وآلة دعم المتجهات (SVM). علاوة على ذلك، تقدم مثالاً على طريقة تقدير الانحدار في بايثون. وأخيراً، فإن الميزة الأساسية للذكاء الاصطناعي هي معالجة البيانات لاتخاذ القرارات.

Keywords (in Arabic): شجرة الانحدار، التنبؤ، القياس الاقتصادي، التعلم الآلي، الذكاء الاصطناعي، شجرة الانحدار، التنبؤ.

Jel Classification Codes: C18; C53; C14

Introduction

It has been five decades since the first regression tree algorithm was introduced. Since then, new methods have emerged that greatly surpass the capabilities of earlier approaches. Contemporary classification trees are capable of dividing data not just through linear splits on variable subsets, but also by incorporating models like nearest neighbor, kernel density, and others within those divisions. Regression trees are now versatile enough to incorporate nearly all conventional statistical models. The widespread availability of software—often freely accessible—has further accelerated the use and popularity of these techniques across the scientific community. This paper reviews key developments in the field and offers a concise assessment of the core principles that support some of the most widely used algorithms (Loh, 2014).

With the increasing volume and complexity of economic data, and the move toward a digital economy and a data revolution, it has become imperative to keep pace with this tremendous growth by developing modern techniques for analyzing data and making the most of it. AI is defined as a set of systems capable of mimicking human intelligence in learning, analyzing, and developing systems on their own. Econometric models are important tools for understanding economic behaviour and analyzing economic changes. These models typically represent specific assumptions about the behaviour of individuals, firms, governments, and other economic agents. These models are used to analyse the impact of various economic policies, such as taxes, government spending, international trade policies, and others, on the economy as a whole. Although these models provide a framework for understanding the economy and analyzing the impact of economic policies, they are not considered absolutely accurate and may need to be modified to suit the current circumstances of each country or economic region. In

addition, they rely on specific assumptions and theories, which means that they do not necessarily represent all aspects of economic reality.

The naive forecast has satisfactory performance but is surpassed by more sophisticated models. Moreover, neural network methodologies surpass the econometric technique for forecast accuracy, but the econometric methodology offers advantages in elucidating pricing determinants for subsequent application of the created models. (Emil and Dogan and Wolf, 2020, p1179).

Given the above, we can pose the following question:

How can econometric models be improved by integrating AI and ML methods in ways that preserve interpretability while enhancing predictive accuracy and adaptability to complex data environments?

From this problem, the following testable hypotheses can be framed:

H1: Econometric models combined with machine learning techniques (e.g., regression trees, SVM, neural networks) yield markedly superior forecasting accuracy compared to conventional econometric models (e.g., OLS, Box–Jenkins) when utilized on economic time series data.

H2: The selection of an integration method (sequential, parallel, or embedded) affects the balance between accuracy and interpretability, with sequential methods (such as a regression tree followed by Box–Jenkins on residuals) yielding a more equitable result.

H3: In practical fields like construction output forecasts, integrated models surpass solo models in addressing nonlinearities, structural breaks, and unobserved shocks, while preserving pertinent policy insights.

This study aims to explore recent trends in econometrics, particularly those related to technological developments. With artificial intelligence contributing to the acceleration and improvement of many tasks previously performed manually or using traditional statistical software, it becomes necessary to identify the most prominent assistive technologies in the field of econometrics. We will highlight the advantages gained from adopting modern approaches, in addition to providing an exploratory overview of one method used to estimate a regression model using artificial intelligence.

THE FIRST TOPIC: Artificial Intelligence and Machine Learning in Economics

Economic theorists and practitioners have sought an economic theory capable of explaining all economic activity. Inflation may be modeled, and concepts such as inflation targeting can be devised. Artificial intelligence (AI) is a scientific discipline that examines and replicates the functioning of

nature, akin to the human intellect. AI is particularly used in areas where modeling a phenomenon is difficult. Artificial intelligence methods used in economic analysis encompass neural networks. These tools are applied to address major economic challenges, including disentangling causality from correlation, modeling stock market behavior, examining inflation dynamics, and optimizing investment portfolios. Game theory is often utilized to simulate stock market behavior, while control system methods are applied in the design of inflation-targeting policies. Furthermore, an important dimension of research explores how economic interdependence relates to interstate conflict. (Tshilidzi, 2020, P02) .

The fundamental quality of robotics—artificial intelligence in general—is that it "allows output without labor" (Sachs, (J.D.), Benzell, (S.G.), and LaGarda, 2015, p. 10). Economists frequently employ phrases like "automation," "robotics," "digitization," and "computation" to denote the concept of artificial intelligence (AI). Consequently, numerous scientists have defined the domain of AI to encompass robotics, neural networks, machine learning, and symbolic systems. It is important to recognize that automation and robotics do not inherently constitute artificial intelligence; they might merely be trained to do specific jobs or a series of tasks. Automation is the technology that enables a process or operation to be executed with minimum human intervention (Taddeo, (M.) and Floridi, (L.) 2018, p. 751), and workers can supervise and monitor them. Thus, the fundamental characteristic of AI is "data processing for decision-making," which distinguishes it from mere automation.

Industrial robotics, or AI investments, have become transformative resources and technologies thanks to unprecedented developments. Thanks to deep learning, AI has rapidly found applications in economic and social sectors, enhancing its scope and impact. This widespread integration of AI has enhanced its ability to penetrate society, leverage resources, and foster growth.

Artificial intelligence is typically defined within two broad categories. The first encompasses systems intended to imitate human thought and behavior, incorporating cognitive abilities that allow them to engage in decision-making, problem-solving, and learning—activities commonly linked to intelligence. The second views intelligence through outcomes, classifying a system as intelligent if it consistently selects the most effective action given the knowledge available. These systems depend on computational models that enable perception, reasoning, and execution. (Georgiev, (D.), 2004, p. 145).

Machine learning allows systems to improve their performance automatically through experience rather than explicit programming. It begins with observations or datasets and seeks to uncover patterns that can guide better decisions and predictions when faced with new information. A multitude of problems can be addressed by supplying appropriate "training data" (the "sample") for the suitable learning algorithms. Good quality data must be used, and this requires a "data cleaning" and "data preparation" phase. Machine learning outcomes depend on the quality of the data.

THE SECOND TOPIC: The Effects of Artificial Intelligence and Machine Learning on the Economy

Artificial intelligence technology has influenced productivity and the economy, although the current industrial revolution seems markedly distinct as it may alter the roles of humans and machines in production and societal interactions. Artificial intelligence technology may endow machines with "intelligence," enabling them to supplant human labor in various domains (Brynjolfsson, E. and McAfee, A., 2014, p. 52). Within the framework of the "Solow Paradox," the recent slowdown in productivity growth is explained by the delayed diffusion of advanced AI technologies. Historical precedents—such as energy, information, and mobile communication technologies—demonstrate similar patterns, where roughly 25 years of modest growth typically precede a decade of accelerated productivity gains. Analysts suggest that AI will likely follow this trajectory. Accordingly, the present "Solow Paradox" can be understood as a temporary lag in technology adoption and transfer, a recurring phenomenon observed throughout economic history. (Agrawal, (A.) and Gans, (J.) and Goldfarb, (A.), 2018, p. 121). Productivity improvements are largely concentrated in sectors that produce information technology rather than those that merely use it. In IT-using industries, the reported gains in labor productivity are not the result of higher output stemming from technological efficiency. Instead, they primarily reflect reduced output and accelerated declines in labor, rather than genuine advances in technology. (Agrawal, (A.) and Gans, (J.) and Goldfarb, (A.), 2018, p. 390).

Artificial intelligence makes efficient markets possible. These markets account for all available information, display the intrinsic value of assets, and allocate capital accordingly. With AI, there is finally a (remote) chance that a scripted version of financial markets will become a reality. This will require a proactive and internationally regulatory approach (Schmidhuber,

2015, p. 39). Artificial intelligence has become emblematic of both the present and future of the financial industry, influencing every aspect of its operations. Modern finance is now inseparable from digital technologies and algorithms that deliver the speed and precision required to process and analyze the massive volumes of data produced by institutions and markets on a daily basis. Consequently, the financial sector—together with high-tech, telecommunications, automotive, and manufacturing industries—has been among the earliest adopters of AI. (Njegovanović, 2018, p. 68). The financial sector, along with high-tech, telecommunications, automotive and assembly sectors, are among the early adopters of AI (Bughin, (J.) and Hazan, (E.) and Ramaswamy, 2017, PP. 2-4.)

THE THERD TOPIC: Integrating econometric models with artificial intelligence and machine learning algorithms

Machines are progressively adept at doing "intelligent" tasks. Facebook identifies faces in photographs, Siri comprehends vocal commands, and Google interprets web pages. Artificial intelligence became feasible when researchers shifted from a procedural approach to an experimental methodology for addressing intelligence tasks. For instance, face recognition algorithms do not rely on predetermined rules for identifying specific pixel combinations, grounded in human comprehension of facial features. This resemblance to econometrics prompts inquiries: Do these algorithms merely employ conventional methods on novel and extensive datasets?

We propose a conceptual framework for machine learning that assigns it a distinct role inside the econometric toolkit. The essence of our comprehension is that machine learning not only offers novel capabilities but also addresses a distinct issue. Its appeal lies in the ability to uncover patterns that generalize beyond the training data, making the models effective for new and unseen cases. The efficacy of machine learning in artificial intelligence activities is mostly attributable to its capacity to uncover intricate, previously unarticulated systems. It harmonizes intricate and adaptable functional data forms without merely overfitting; it identifies functions that perform effectively on out-of-sample data (Sendhil and Jann, 2017, p. 87-88). The combination of AI and econometric models can be leveraged to improve economic models and predict future scenarios. This advanced combination can significantly transform the way economic data is analyzed and the economic future is forecasted. This data can be combined to benefit from forecasting processes to improve industry and economic

decision-making. Using machine learning techniques, econometric models can be trained to analyze data better. These techniques can significantly improve economic performance, as the extracted results can be used to improve industrial economic activity and identify areas in need of improvement.

An integrated model can be created that can analyze economic data and predict the future. Machine learning, for example, can be used to analyze large and complex economic data and obtain valuable information about trends and patterns in the economy. Furthermore, artificial neural networks can be used to improve standard economic models, and deep learning can also be used to analyze economic data related to currencies, stocks, and other economic indicators.

These techniques can also be used to predict stock market changes and forecast future trends in financial markets. They can also be used to analyze GDP data and compare it with previous years. At the same time, these algorithms can analyze interest and return data on deposits and investments and forecast them very accurately. Their ability to analyze data and predict price changes in the real estate market is also not excluded. They can also be used to interpret international trade data and identify trends and patterns of international trade (Tshilidzi Marwala, 2020).

Econometric models have historically served as a fundamental element in economic forecasting and policy evaluation. Their dependence on statistical assumptions (linearity, stationarity, homoscedasticity) facilitates interpretability and theoretical foundation but frequently constrains prediction capability in intricate, high-dimensional contexts. Conversely, artificial intelligence (AI) and machine learning (ML) methodologies are proficient at identifying nonlinearities, interactions, and patterns within extensive datasets, however this proficiency compromises interpretability. This comparative analysis elucidates the distinctions between traditional econometrics and hybrid econometric-machine learning methodologies regarding their techniques, applicability, predictive precision, and interpretability.

Here’s the comparison formatted into a clean table:

Approach	Core Tools	Strengths	Limitations
Traditional Econometrics	OLS, Vector Autoregression (VAR), Box–Jenkins ARIMA models	High interpretability; clear diagnostic tools (ACF, PACF, residual checks); strong theoretical foundation	Difficulty handling nonlinearities, structural breaks, and large/complex datasets
Econometrics with AI/ML	Regression Trees, Support Vector Machines (SVM), Neural Network Autoregression (NNAR), Bayesian ML with Kalman Filters	High predictive accuracy; flexible with nonlinear relationships; handles unstructured or high-dimensional data	Lower interpretability; requires large datasets; risk of overfitting without careful design

- A critical comparative framework of the existing literature is lacking**
- Box and Jenkins (2015) laid the foundation for ARIMA modeling, demonstrating its value for time-series forecasting. With **limitations of:** These models struggle with nonlinearities, structural breaks, and large, high-dimensional datasets
 - Schmidhuber (2015) reviewed deep learning’s success in uncovering hidden patterns in unstructured data.
 - Ka Chi Lam & Oshodi (2016) showed that SVM and NNAR models outperform ARIMA in construction output forecasting.
 - **Limitations:** While ML achieves higher accuracy, it faces the **“black box” problem**, where predictions are difficult to interpret in economic policy contexts

THE FIRST REQUIREMENT: Enhancing Econometric Forecasting Accuracy with Artificial Intelligence

A major application of machine learning in economics lies in enhancing the predictive accuracy of econometric models. Traditional econometric models often rely on the a priori statistical assumptions adopted by econometric

models, which limits their ability to handle complexity and data uncertainty. Therefore, the importance and utility of machine learning algorithms emerges. These algorithms enable economic models to learn recurring patterns from large data sets, which contributes to improving the accuracy of economic forecasts.

Machine learning techniques have been combined with techniques such as the Kalman Filter, borrowed from the field of wave and signal processing in electronics engineering, to estimate Vector Autoregression (VAR) models. These models help estimate unobserved patterns in economic data, such as aggregate shocks from both the supply and demand sides, allowing for the estimation of nonlinear models. These models can estimate the time-varying magnitude of economic shocks, such as shocks to aggregate supply and demand, and shocks to monetary policy and financial markets. These models abandon some assumptions in traditional econometrics, such as the assumption of constant variance, as economic shocks, from a standard perspective, are unobserved components that can significantly impact the economy. Machine learning techniques, combined with Bayesian statistics, identify and measure the time-varying nature of these shocks by analyzing patterns and anomalies in data that cannot be measured using traditional econometric methods. This is where Bayesian econometrics comes in. This field combines machine learning techniques with Bayesian statistics, making it suitable for handling more complex nonlinear models, big data, and data containing significant uncertainty.

Performance is weakened when the mathematical model is incomplete, when nonlinear relationships are present, or when errors follow non-Gaussian distributions that the model cannot adequately capture (Sukkeun Kim; Ivan Petrunin; Hyo-Sang Shin, 2022). In the majority of comparisons between ML and traditional econometric models. However, in certain cases the best results emerge from combining the two, as integrated approaches can leverage the strengths of each. Neither machine learning nor econometric models consistently outperform the other across all contexts; instead, their complementarity often produces the most reliable outcomes. This perspective is particularly relevant when considering studies from 2016, by which time machine learning had already become a well-established field. (Maria and Javier and Sigeru, 2022, p. 87).

THE SECOND REQUIREMENT: Standard Modeling from Linear Least Squares to Regression Trees with AI

Regression trees represent a common class of machine learning functions. In traditional regression, one must manually decide which interaction terms to include, a process that quickly becomes impractical in complex settings. A clear example can be seen in face recognition, where predicting features such as a “nose” depends on intricate, nonlinear interactions among many pixels. Machine learning techniques, however, are able to automatically identify and model these interactions without the need for manual specification.

The sample is composed of housing data with categorical (Type) and continuous (Baths, Rooms, UNITSF) features. The regression tree splits the dataset into smaller groups to predict an economic outcome (likely log house price or rental value).

1. Variables in the Sample

The dataset used to build this regression tree includes housing characteristics:

- **Type:** A categorical variable (here values 2, 3, 7). Likely refers to housing type (e.g., apartment, condo, single-family).
- **Baths:** Number of bathrooms in the unit.
- **Rooms:** Number of total rooms.
- **UNITSF:** Unit square footage (size of the house in square feet).
- **Target Variable:** The numbers in the leaf nodes (e.g., 9.2, 9.8, 12.8). These represent **predicted values** — often interpreted as house price (in log form), rental index, or property value, depending on the dataset.

2. Structure of the Tree

- **Root Split (Top Node):**
The first condition is on **Type**. If the property’s type equals 2, 3, or 7 → follow the **Yes** branch; otherwise → follow the **No** branch.
- **Second-Level Splits:**
 - On the **Yes** side: split on number of bathrooms ($\text{Baths} < 1.5$).
 - On the **No** side: also split on bathrooms.
- **Third-Level Splits:**

- If **Baths** < 1.5 (Yes branch): split on **Rooms** < 4.5 or **UNITSF** < 1122.5.
- If **Baths** ≥ 1.5 (No branch): split on **Rooms** < 6.5 or **Baths** < 2.5.

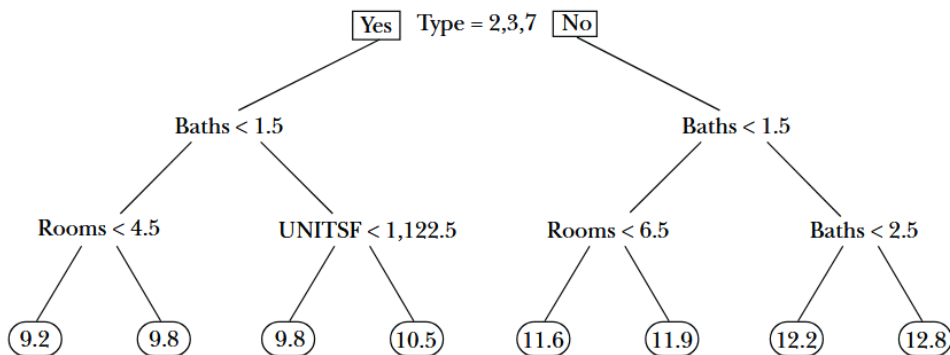
3. Interpretation of Leaves (Predicted Values)

The numbers at the end of each branch (9.2, 9.8, 10.5, etc.) are **predicted outcomes** for observations that fall into that category:

- A unit of **Type** = 2, 3, or 7, with **Baths** < 1.5 and **Rooms** < 4.5 → prediction = **9.2**.
- A unit of other Types, with **Baths** ≥ 1.5 and **Baths** ≥ 2.5 → prediction = **12.8**.

This shows how **different combinations of categorical and continuous housing features** lead to different predicted property values.

Shallow Regression Tree for Predicting Home Values



Source: Maria E. Perez-Pons, Javier Parra-Dominguez, Sigeru Omatu, Enrique Herrera-Viedma⁴, Juan Manuel Corchado, MACHINE LEARNING AND TRADITIONAL ECONOMETRIC MODELS: A SYSTEMATIC MAPPING STUDY, JAISCR, 2022, Vol. 12, No. 2, pp87.

A clear example is provided by regression trees, a common class of ML functions. Similar to a linear model, a regression tree links each set of input features—such as housing characteristics—to a predicted outcome. The prediction process follows a tree structure in which each node splits the data

into two branches based on the value of a single variable. For instance, the number of bathrooms may determine whether the observation proceeds to the left branch (fewer than two bathrooms) or the right branch (two or more bathrooms). Once a terminal node, or leaf, is reached, the model produces a prediction. As illustrated in Figure 1, the regression tree can also be expressed in linear form, where each leaf corresponds to a combination of dummy variables representing the conditions along its path.

Box-Jenkins, neural network autoregression (NNAR), and support vector machine (SVM)

In a study by (Ka Chi Lam and Olalekan Shamsideen Oshodi 2016, p. 643), Accurately forecasting construction work volume is essential for enabling stakeholders—such as contractors, consultants, and government agencies—to design effective long-term strategies for the sector. Yet, progress in construction economics has often been hindered by the scarcity of reliable quantitative data. To bridge this gap, the current study employs univariate modeling techniques to estimate construction output. Three models are examined: the Box–Jenkins approach, neural network autoregression (NNAR), and support vector machines (SVM). Of these, the Box–Jenkins method is traditionally considered the standard reference model, valued for its simplicity, strong theoretical foundation, and consistent predictive performance. Model performance was assessed using out-of-sample forecasts, and the results showed that SVM offered the most consistent and accurate predictions for housing, maintenance, and overall construction outputs over the medium term. Importantly, these univariate methods can also be adapted to historical construction data from other countries, making them particularly useful when multivariate datasets are unavailable. In practice, the SVM model developed in this study provides a valuable tool for anticipating future trends in construction output. (Ka Chi Lam, Olalekan Shamsideen, 2016, p. 643 Oshodi,). Identifying user-friendly methodologies that circumvent the risks of misspecification while also producing interpretable and appealing quantities of interest akin to the coefficients has proven challenging (Hainmueller & Hazlett, 2014).

THIRD REQUIREMENT: Regression Model Machine Learning

Consider the following example of linear regression. We have a residential dataset and want to predict house prices. The Python code for this is below.

Big data has required the development of estimation techniques that can overcome the limitations of parametric models, which are overly restrictive, and traditional non-parametric models, which can be difficult to estimate with a large number of variables. Statistical learning, or machine learning, provides new non-parametric estimation methods that perform well in a general context and with a large number of variables. However, this increased flexibility sometimes comes at the cost of significant interpretability (Arthur, Emmanuel, and Antoine, 2018, p. 158).

```
import matplotlib
matplotlib.use('TkAgg') # General backend for plots

import matplotlib.pyplot as plt
import numpy as np
from sklearn import datasets, linear_model
import pandas as pd

# Load dataset
df = pd.read_csv("Housing.csv")

# Extract features and target variable
Y = df['price']
X = df['lotsize']

# Reshape for compatibility with scikit-learn
X = X.to_numpy().reshape(len(X), 1)
Y = Y.to_numpy().reshape(len(Y), 1)

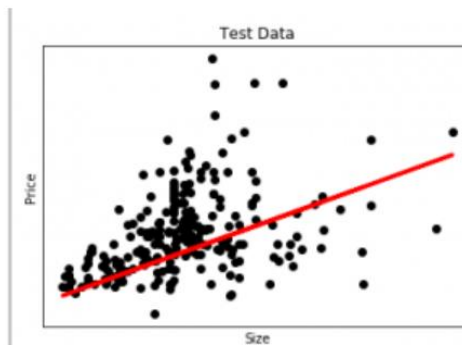
# Split data into training and testing sets
X_train = X[:-250]
X_test = X[-250:]
Y_train = Y[:-250]
Y_test = Y[-250:]
```

```
# Plot the test data
plt.scatter(X_test, Y_test, color='black')
plt.title('Test Data')
plt.xlabel('Size')
plt.ylabel('Price')
plt.xticks(())
plt.yticks(())

# Train linear regression model
regr = linear_model.LinearRegression()
regr.fit(X_train, Y_train)

# Plot predictions
plt.plot(X_test, regr.predict(X_test), color='red', linewidth=3)
plt.show()
```

Output:



In this chart, we plot the test data. The red line indicates the best-fit line for price prediction.

To make a single prediction using a linear regression model:

```
print("Predicted price for a lot size of 5000: " +  
      str(round(regr.predict([[5000]])[0][0])))
```

Conclusion

This paper's investigation has shown that artificial intelligence (AI) and machine learning (ML) are potent instruments for improving the predictive performance and flexibility of econometric models. Conventional

econometric methods like OLS, VAR, and Box–Jenkins ARIMA are vital because of their interpretability, theoretical foundation, and capacity to guide policy formulation. Nonetheless, their efficacy is frequently restricted by inflexible statistical assumptions, inadequate ability to model nonlinear dynamics, and challenges in managing extensive or unstructured datasets. Conversely, AI and ML techniques—spanning regression trees, support vector machines (SVM), neural networks, and deep learning—provide substantial flexibility, reveal latent structures within data, and markedly enhance forecasting efficacy in intricate economic scenarios.

This paper critically demonstrates that econometrics and machine learning should be seen as complimentary rather than substitutive paradigms. Empirical evidence from various fields, including construction output forecasting (Ka Chi Lam & Oshodi, 2016), electricity reserve price modeling (Emil, Dogan & Wolf, 2020), and housing price estimation (Perez-Pons et al., 2022), demonstrates that machine learning models consistently surpass traditional econometric methods in predictive accuracy. However, this advantage frequently compromises interpretability, a critical aspect when models are designed to inform economic policy or investment choices. Econometrics specializes in elucidating causal relationships and offering insights into fundamental economic principles, while machine learning largely thrives in producing reliable predictions among complexity and noise.

The results underscore the promise of hybrid frameworks as a compromise. The integration of econometric models with machine learning techniques, such as residual modeling, Kalman filter augmentation, or ensemble methods, yields improved forecasting capabilities while preserving a degree of interpretability. This is especially pertinent for contemporary economies marked by volatility, structural disruptions, and nonlinear interdependencies among variables. Hybrid models synchronize predictive efficacy with policy significance, thus equipping decision-makers with more dependable and pragmatic instruments.

Nonetheless, the use of AI and ML into econometrics presents obstacles. Data quality issues are paramount; as the phrase "garbage in, garbage out" indicates, the efficacy of machine learning methods is significantly reliant on the presence of clean, representative, and comprehensive datasets. Secondly, there are apprehensions about interpretability and transparency; intricate machine learning algorithms, such as deep neural networks, function as "black boxes," so eroding trust in their outputs for policy formulation. Third, the implementation challenges—spanning computational expenses and the necessity for specialized technical

proficiency—may hinder acceptance, especially in developing countries or resource-limited organizations. Ultimately, the issues of privacy and security in the management of sensitive economic and financial data must not be disregarded, especially as dependence on digital infrastructures increases.

The use of AI and ML into econometric modeling signifies a fundamental transformation in economic analysis and forecasting methodologies. Although classical econometrics is essential for causal inference and theoretical understanding, AI and ML broaden the scope of possibilities in prediction and pattern identification. By adopting hybrid models that integrate the advantages of both techniques, economists may formulate procedures that are both precise and comprehensible, guaranteeing that economic decision-making is anchored in thorough analysis while adapting to the opportunities presented by the digital era.

Despite the tremendous benefits of using AI in econometrics, there are challenges facing the use of these techniques in economic models. These include:

- **Data quality:** The performance of econometric models and AI algorithms may depend on the quality of the data used to train and analyze them. Therefore, the data quality must be high, reliable, and appropriate for the intended purpose.
- **Interpretability:** Understanding how econometric models and AI algorithms work is important in economic decision-making. However, some AI algorithms can be difficult to interpret, making it difficult to understand the reasons behind the results obtained. □
- **Predicting the Future:** Technologies used in economics can face challenges in predicting the future, as rapid changes in markets and social and political developments can lead to the inability to accurately forecast economic outcomes.
- **Security and Privacy Issues:** Measures must be taken to protect sensitive data and ensure it is not misused. Data used in analysis must also be ensured to comply with local and international laws and regulations.
- **Implementation Capability:** Technologies used in economics can face challenges in their ability to be effectively implemented. For example, some artificial intelligence algorithms may require massive computing resources or the development of new skills among users.

References

1. Agrawal, (A.) and Gans, (J.) and Goldfarb, (A.), (2018) Prediction machines: the simple economics of artificial intelligence, Harvard Business Press, USA.
2. Arthur Charpentier, Emmanuel Flachaire and Antoine Ly, (2018), Econometrics and Machine Learning, *ECONOMIE ET STATISTIQUE / ECONOMICS AND STATISTICS* N° 505-506.
3. Brynjolfsson, (E.) and McAfee, (A.), (2014) The second machine age: Work, progress, and prosperity in a time of brilliant technologies, W.W Norton & Company, New York.
4. Bughin, (J.) and Hazan, (E.) and Ramaswamy, (S.) and Others,(2017), Artificial intelligence: The next digital frontier, journal Of McKinsey Global Institute.
5. Emil Kraft, Dogan Keles, Wolf Fichtner, (2020) Modeling of frequency containment reserve prices with econometrics and artificial intelligence, journal of forecasting, Volume39, Issue8.
6. E.S.Emmanuel , el.at , (2021) Handbook research on Machine learning Applications in Economics , 1st Edition , IGI Global , U.S.A .
7. Georgiev, (D.), (2004), Consciousness operates beyond the timescale for discerning time intervals: implications for Q-mind theories and analysis of quantum decoherence in brain, journal Of NeuroQuantology, Vol. 2, No, 2, NeuroQuantology.
8. Hainmueller, J., & Hazlett, C. (2014). Kernel Regularized Least Squares: Reducing Misspecification. *Political Analysis*, 22, 143–168. doi: doi:10.1093/pan/mpt019
9. Ka Chi Lam, Olalekan Shamsideen Oshodi, (2016), Using Univariate Models for Construction Output Forecasting: Comparing Artificial Intelligence and Econometric Techniques, *Journal of Management in Engineering*, Vol. 32, No. 6.
10. Loh, W.-Y. (2014). Fifty Years of Classification andRegression Trees. *International Statistical Review*, 82(3), 329–348. doi: doi:10.1111/insr.12016
11. Maria E. Perez-Pons, Javier Parra-Dominguez, Sigeru Omatu, Enrique Herrera-Viedma4 , Juan Manuel Corchado, (2022), MACHINE LEARNING AND TRADITIONAL ECONOMETRIC MODELS: A SYSTEMATIC MAPPING STUDY, *JAISCR*, Vol. 12, No. 2.
12. Njegovanović, (A.), (2018), Artificial intelligence: Financial trading and neurology of decision, Sumy State University, Vol. 2, No. 2.

13. Sachs, (J.D.), Benzell, (S.G.) and LaGarda, (G. (2015) *Curse or Blessing? A Basic Framework*, National Bureau of Economic Research, 2015.
14. Schmidhuber, (J.), (2015), *Deep learning in neural networks: An overview*, Neural networks, Elsevier, Vol. 61.
15. Taddeo, (M.) and Floridi, (L.), (2018), *How AI can be a force for good*, journal of Science, Vol. 361, No. 6404, American Association for the Advancement of Science, 2018.
16. Tshilidzi Marwala , (2020), *Artificial Intelligence and Economic Theory* , 1st Edition , Springer , U.S.A.
17. Sukkeun Kim; Ivan Petrunin; Hyo-Sang Shin, (2022), *A Review of Kalman Filter with Artificial Intelligence Techniques*, Integrated Communication, Navigation and Surveillance Conference (ICNS).
18. Sendhil Mullainathan and Jann Spiess, (2017), *Machine Learning: An Applied Econometric Approach*, Journal of Economic Perspectives—Volume 31, Number 2.