
Comparative Analysis of Machine Learning and Traditional Models in Economic Forecasting

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Abstract: Economic forecasting is pivotal for decision-making across governmental, business, and individual domains, driving sustainable development and resource management amid growing global economic uncertainties. This study examines the application of both machine learning and traditional models in economic forecasting, highlighting their respective strengths and limitations. Machine learning models, especially deep learning, demonstrate superior performance in handling large-scale, high-dimensional, and nonlinear relationships, enhancing predictive accuracy. Traditional models, such as linear regression and time series, maintain advantages in interpretability and uncertainty modeling, crucial for small samples and scenarios demanding transparent decision-making. By comparing these models in terms of performance, interpretability, and uncertainty management, the research underscores the complementary nature of machine learning and traditional approaches. The findings suggest that the integration of these methodologies can offer more robust and flexible solutions for economic forecasting, addressing complex and dynamic economic environments. Future research should focus on developing hybrid models to leverage the strengths of both approaches, enhancing the precision and applicability of economic predictions.

Keywords: Machine Learning Models, Forecasting.

1. Introduction

The significance of economic forecasting lies in its extensive influence on decision-making and planning for societies, governments, businesses, and individuals. Accurate economic forecasting becomes a crucial factor in achieving sustainable development, improving the quality of life, and managing resources effectively, as the global economy continues to change and uncertainty increases. Economic forecasting plays a vital role in government decision-making. Governments must make reasonable estimates of future economic conditions to adopt effective economic policies. For instance, they should consider indicators such as inflation and unemployment rates. Forecasts of economic indicators, such as gross domestic product, can assist the government in adjusting its monetary policy, formulating employment programs, and carrying out fiscal planning. Accurate economic forecasts are essential to prevent adverse effects such as inflation or recession and provide the government with effective means to deal with various economic challenges. By forecasting economic trends, companies can better plan their production, sales, and marketing strategies to reduce business risks and improve competitiveness. Accurate economic forecasts also help enterprises to cope better with market fluctuations and changes, ensuring the healthy development of their business. Secondly, economic forecasts serve as the foundation for financial institutions to formulate investment strategies, manage risks, and allocate assets. Banks, insurance

companies, and investment funds must make reasonable estimates of the future performance of various types of assets, including interest rates, the stock market, and the bond market, to optimize investment portfolios, reduce risks, and protect clients' interests. Accurate economic forecasts can assist financial institutions in managing market volatility and uncertainty, improving investment returns and reducing the risk level of investment portfolios. Additionally, economic forecasts are equally important for personal finance and career planning for the average individual, as they provide insight into the future economic situation. Effective economic planning involves careful consideration of one's investments, savings, and consumption habits to ensure long-term stability and growth. Accurate economic forecasting assists the government, enterprises, and individuals in better managing the ever-changing economic environment. Efforts are devoted to improving the accuracy and reliability of economic forecasts to maximize resource effectiveness and achieve sustainable economic growth and social progress. This is of significant importance in promoting the prosperity and stability of society as a whole (Prakash et al., 2020).

2. Overview of economic forecasting methods

2.1. Strengths and limitations of traditional methods

Traditional methods have several advantages in the field of economic forecasting that make them indispensable tools in

certain contexts. One of their unique strengths is their interpretability. Linear regression and time series models are traditional methods that provide clear and intuitive mathematical expressions. These expressions help to understand how the structure and parameters of the model affect the forecasting results. This is important for decision makers, policy makers, and the general public, who need to comprehend the fundamentals of economic forecasting models to make informed decisions. Traditional methods are often more effective on small sample datasets compared to machine learning models. They can still provide reliable predictions with limited data, making them a suitable choice in certain industry sectors where data collection is difficult or expensive. This is due to their lower susceptibility to overfitting problems. Additionally, traditional methods are better suited for modelling linear relationships. In certain economic systems, the relationship between variables may be simple and linear. In such cases, traditional linear regression models can better capture these relationships without introducing overly complex nonlinear structures. This makes traditional methods more advantageous for specific economic forecasting problems. Additionally, traditional methods typically require fewer computational resources, and model training and prediction are relatively fast. In application scenarios with high real-time requirements, such as high-frequency trading in financial markets or real-time monitoring of government decisions, the efficiency of traditional methods makes them still competitive. However, traditional methods are easier to interpret and understand in some contexts. When communicating economic forecasts to non-specialists or the general public, it is important to use simple linear equations or trend models. This makes it easier for people to understand and accept the information, which is crucial for promoting public participation and understanding of economic policies. Overall, traditional methods have several advantages in economic forecasting. They are highly interpretable, applicable to small data samples, and model linear relationships more appropriately. Additionally, they are computationally efficient and easy to understand. Traditional methods are still an important tool in some scenarios and complement machine learning methods. In practical applications, selecting the appropriate method for economic forecasting is a crucial decision that depends on the nature of the problem and the data's characteristics (Bishop, 2013).

Although traditional methods have some advantages in economic forecasting, they have several limitations, especially when dealing with complex, nonlinear, or large-scale data. One of the main limitations of traditional methods is their assumption that economic systems are linear, meaning that the relationships between variables can be described by simple linear equations. However, economic systems in reality are often complex and dynamic, with numerous nonlinear relationships and interactions. Traditional methods are inadequate for modelling this complexity, resulting in limited predictive performance when dealing with complex real-world problems. Additionally, traditional methods face challenges when dealing with high-dimensional and large-scale data. As data continues to grow and become more available, traditional methods may struggle to handle datasets with a large number of variables or high-dimensional features. This can result in reduced model generalization ability and increased susceptibility to overfitting, particularly when complex correlations exist between features. Additionally, traditional methods have limitations in modelling nonlinear

relationships. Relationships in economic systems can be nonlinear, particularly when dealing with complex factors such as market fluctuations and policy changes. Traditional methods may not be able to capture these nonlinear relationships, which can lead to insufficient predictive accuracy of the model. Furthermore, traditional methods have limited capacity to handle time series data. While traditional time series models such as ARIMA can handle simple time series relationships, they may not perform well when dealing with complex non-stationary, non-linear time series data. This is especially important in scenarios where accurate forecasts of future economic trends are required. Additionally, the forecasting results of traditional methods can be influenced by the assumptions of the data distribution and the bias of the model. If the dynamical structure of the economic system changes or the distribution of the data shifts, traditional methods may fail to adapt, resulting in model failure. Furthermore, traditional methods often rely heavily on specific domain knowledge and assumptions, which can lead to models that are too inflexible for complex and changing economic environments and difficult to adapt to rapidly changing market conditions. Overall, traditional methods may have limitations in dealing with complex, nonlinear, large-scale, and high-dimensional data in modern economic systems. These limitations may restrict the effectiveness of traditional methods in certain scenarios. With the era of big data and increasing computational power, researchers are more inclined to explore hybrid models combining traditional and machine learning methods to better overcome these limitations and improve the accuracy and adaptability of economic forecasting (Caroppo et al., 2020).

2.2. Development and Application of Machine Learning Methods

The development of machine learning methods has gone through several stages, from the earliest conceptualization to the significant progress made in various fields today. This development process has led to the emergence of many new algorithms, frameworks, and applications that have driven the widespread use of machine learning in science, industry, and society. First, the concept of machine learning can be traced back as far as the 1950s. During this period, scholars began to think about how to equip computers with the ability to learn from experience. Initial attempts focused on symbolist learning, where computers were enabled to learn through rules and logic. However, these approaches had difficulties in dealing with complex real-world problems, leading to a period of relative obscurity. With the increase in computing power and the growing abundance of data, machine learning entered a phase of resurgence. In the 1980s, methods based on statistical learning theory began to attract attention. Representative algorithms include decision trees, support vector machines, and neural networks. Machine learning methods in this period focused more on learning patterns and laws from data, rather than relying only on predefined rules. Entering the 21st century, with the popularization of the Internet and the arrival of the big data era, machine learning has seen explosive development. Large-scale datasets have become the basis for training complex models, and powerful computing power has made it possible to train complex models such as deep learning. Deep learning is a neural network-based machine learning method that simulates the structure of the human brain through a multilevel neuron network, which can effectively process large-scale and high-

dimensional data. This has enabled computers to achieve unprecedented success in areas such as image recognition, speech recognition, and natural language processing. Another factor driving the development of machine learning is open source software and an open scientific community. The emergence of open source machine learning frameworks such as TensorFlow and PyTorch has greatly lowered the threshold of machine learning, enabling more people to participate in machine learning research and applications. At the same time, researchers have fostered rapid progress in the field of machine learning through open datasets, shared code, and collaborative research. In the past few years, new learning paradigms such as transfer learning, reinforcement learning, and federated learning have gradually emerged. Transfer learning works on transferring knowledge learned in one domain to another related domain, reinforcement learning focuses on learning optimal strategies by interacting with the environment, and federated learning explores ways to learn models in distributed environments without sharing raw data. In addition, machine learning has achieved significant application results in the fields of healthcare, finance, transportation, and energy. In the medical field, machine learning is used for image diagnosis, disease prediction, and drug discovery; in the financial field, machine learning is widely used for risk management, fraud detection, and investment decisions; in the transportation field, machine learning provides optimization solutions for intelligent transportation systems, improving traffic efficiency and safety; in the energy field, machine learning is used to optimize the production and consumption of energy, and to improve the efficiency of energy use.

The application of machine learning methods in the field of economic forecasting has gradually attracted widespread attention, and its powerful model learning and data processing capabilities make it a powerful complement to traditional methods. First, machine learning methods have excellent feature extraction and pattern recognition capabilities in economic data analysis. For large-scale, high-dimensional economic data, traditional methods may not be able to capture the complex relationships in them. In contrast, machine learning algorithms, especially deep learning models, are able to automatically learn abstract features in the data through multilevel nonlinear transformations, better adapting to the complexity of the data. Second, machine learning methods have advantages in dealing with nonlinear relationships. Traditional linear models may not perform well when nonlinear relationships between multiple variables are involved, while machine learning methods, such as support vector machines, decision trees, and neural networks, are able to model nonlinear relationships more flexibly, improving the expressive power and predictive accuracy of the models. Second, machine learning methods can effectively handle large-scale and high-frequency economic data. In the financial field, high-frequency trading data, a large amount of market information, and the rapid update of macroeconomic data make traditional methods face challenges. Machine learning models can handle large-scale data and better capture dynamic changes in the market through real-time learning and adjustment. In addition, machine learning methods excel at handling uncertainty and complex market situations. Financial markets are affected by a variety of factors, including politics, natural disasters, and market sentiment, which cause markets to become highly uncertain. Machine learning models are able to better understand and adapt to this

uncertainty by learning from historical data, providing support for more accurate predictions. On the other hand, machine learning methods are also able to provide more flexible model structures and integration methods in economic forecasting. The integration of models, the fusion of deep learning, and techniques such as migration learning make machine learning models more robust. It can better adapt to different economic environments and market conditions. However, machine learning methods also face some challenges in economic forecasting. First, the black-box nature of the models makes it more difficult to explain the decision-making process of the models, which may be questioned in some economic fields that require high transparency and interpretability. Second, machine learning methods are more dependent on data quality and labeling, requiring high-quality and accurate data to train the model, which may otherwise lead to degradation of model performance. Taken together, machine learning methods show great potential in economic forecasting, especially in dealing with large-scale, high-frequency, and complex economic data. Through technical means such as deep learning, nonlinear modeling and integration methods, machine learning models can better adapt to the variability of economic systems. However, issues such as interpretability and data quality still need to be paid attention to in the application process to ensure the reliability and validity of the model in actual decision-making. In the future, with the continuous progress of technology and in-depth understanding of machine learning methods, it is believed that its application in economic forecasting will continue to expand and improve (Paullada et al., 2021).

3. Comparison of Machine Learning Models with Traditional Models

3.1. Performance Comparison

The performance comparison between machine learning models and traditional models is an important topic in current research and application areas. Both of them are widely used in many fields such as economic forecasting, data analysis, pattern recognition, etc., and their performance comparison involves many aspects such as model accuracy, generalization ability, and interpretability. First, as far as accuracy is concerned. Machine learning models usually perform better when dealing with large-scale, high-dimensional data and complex nonlinear relationships. Deep learning models, such as neural networks, are able to automatically learn and extract abstract features from data. As a result, they are able to achieve higher accuracy on some complex problems. In contrast, traditional models, such as linear regression, time series models, etc., may be weaker in modeling nonlinear relationships, and thus have relatively lower accuracy when dealing with complex problems. Second, machine learning models also typically excel in generalization capabilities. Machine learning models are better able to adapt to new data by learning from large amounts of data. Thereby, they maintain high predictive performance in unseen contexts. This makes machine learning models more robust in the face of real-world change and uncertainty. In contrast, traditional models may be more susceptible to specific data distributions or scenarios and have relatively weak generalization capabilities. However, not all aspects of the performance comparison are favorable for machine learning models. In some scenarios where data is more limited and domain-

specific knowledge is more important, traditional models may not perform as well as machine learning models. Traditional models are often more explanatory, providing a clear picture of the model structure and parameter meanings, giving them an advantage in scenarios where the model needs to be interpreted. This is critical for decision makers, policy makers, and domain experts who need to understand the basis of the model's predictions. In addition, traditional models typically perform better on small sample datasets. In some domains, traditional models are still an appropriate choice due to the high cost of data collection or the scarcity of the data itself. Machine learning models are prone to overfitting on small sample data, while traditional models are relatively more robust and help avoid overfitting problems. Overall, machine learning models and traditional models have their own advantages and disadvantages. When choosing which model to use, comprehensive consideration needs to be made based on the nature of the specific problem, the characteristics of the available data, and the need for model interpretability. In practice, it is sometimes possible to use a hybrid model by combining the two in order to take advantage of their respective strengths and achieve better performance. In the future, with the development of technology and deeper understanding of model performance, more research and practice can be expected to organically combine machine learning models with traditional models to better address various challenges(Janiesch et al., 2021).

3.2. Feature analysis

The characterization of machine learning models versus traditional models involves the differences between the two models in terms of feature processing, feature extraction and feature selection. This aspect of the analysis is crucial to understand their strengths and weaknesses in different tasks. First, in terms of feature processing, machine learning models are usually better adapted to high-dimensional, unstructured features. Deep learning models, especially convolutional neural networks and recurrent neural networks, among others, are able to automatically learn abstract representations of features, eliminating the need to manually design complex feature engineering. This makes machine learning models more flexible in the face of large-scale, complex data and better able to capture underlying patterns in the data. In contrast, traditional models may rely more on the experience and a priori knowledge of domain experts for feature processing. For example, in economic forecasting, traditional time series models may require manual selection of appropriate economic indicators or adjustment of the time scale of the data. This approach may be limited by the data in some cases, as the performance of traditional models relies heavily on manually designed features that require domain expertise to guide them. Second, in terms of feature extraction, machine learning models are often capable of automatically extracting features from data in a hierarchical manner. Multi-layer neural networks in deep learning models are able to gradually combine and abstract the original features to generate higher-level, more semantic feature representations. This enables machine learning models to better capture the hierarchical structure and nonlinear relationships of data when dealing with complex data, improving the expressive power of the model. In contrast, traditional models may be limited in feature extraction. Traditional time series models, such as ARIMA, usually only consider data at the current moment, making it more difficult to capture long-term

dependencies. Traditional models are more limited in the way they extract features and are relatively weak in capturing complex structures and abstract features in the data. In terms of feature selection, machine learning models are usually able to automatically select features that are useful for the task through weight learning during training. This makes the model more robust and able to automatically filter out features that are meaningful to the task in the presence of a large number of features, avoiding the tedious process of manually performing feature selection. Traditional models, on the other hand, may require manual feature selection, relying on the domain expert's understanding of the data and knowledge of specific features. This may lead to limitations in feature selection in some cases, as manually selected features may not fully and accurately reflect the information in the data. It is important to note that the performance of machine learning models versus traditional models may differ on specific tasks and datasets. In some scenarios where small samples or specific domain knowledge is more important, traditional models may still have some advantages. Meanwhile, machine learning models usually perform better when dealing with large-scale, complex data. In practical applications, it is possible to choose which model to use based on the characteristics of the task and the characteristics of the available data, or even to combine their advantages by means of integrated learning, etc., in order to achieve better performance. As technology continues to advance, the understanding of machine learning models and traditional models will become deeper and will lead to better integration of them in different fields(Barboza et al., 2021).

3.3. Explanatory Comparison

Explanatory comparison of machine learning models with traditional models is a topic of great interest in current research and practice. Explanation is critical to the application and understandability of models, especially in fields such as finance, healthcare, and law, where decision makers and domain experts need to clearly understand the predictive process and rationale of the model. The following is an in-depth discussion of the similarities and differences between machine learning models and traditional models in terms of interpretability. First, traditional models are usually easier to interpret. Traditional models such as linear regression and decision trees have clear mathematical expressions. The weights or coefficients of the model correspond to the degree of influence of the individual features, thus allowing for an intuitive explanation of the predictive basis of the model. This intuition makes traditional models more advantageous in scenarios that require an explicit explanation of the decision-making process. For example, in the area of credit scoring, where interpretability is critical, traditional linear regression models can provide intuitive credit scoring factors that are easy for financial practitioners and customers to understand. In contrast, machine learning models, especially deep learning models, are often considered "black box" models. The hidden layers and complex nonlinear transformations in neural networks make the mathematical structure of the model more complex, and the interpretation of model parameters becomes quite difficult. In deep learning, the meaning of weights is often not easy to understand, and the relationship between inputs and outputs can be highly abstract. This lack of intuitive interpretability limits the application of machine learning models in some scenarios that require high model understanding. Second, as research on machine

learning models continues to deepen, explanatory methods and tools are gradually developing. To improve the interpretability of machine learning models, researchers have proposed a variety of interpretable techniques. For example, Local Interpretable Model-agnostic Explanations can explain the reason for the model's prediction on a specific sample by generating interpretable local models. Second, there is a trade-off between interpretability and performance. In general, increasing the interpretability of a model may decrease its performance, especially on complex tasks and large-scale datasets. This is because the structure of the model may need to be simplified or additional constraints introduced in order to make the model more interpretable. This may lead to a decrease in the model's ability to capture complex relationships in the data. In practice, the relationship between interpretability and performance needs to be weighed against the needs of the task and the characteristics of the scenario. Finally, interpretability is also affected by the application domain and decision-making context. In some domains, such as patient diagnosis in healthcare, interpretability is crucial. This is because doctors need to understand the model's predictions and make decisions accordingly. In some industrial control systems, the accuracy and real-time performance of the model are more important, and the interpretability may be relatively secondary. Therefore, the need for interpretability should be customized according to the specific application scenario. Overall, there are some differences between machine learning models and traditional models in terms of interpretability, but with the continuous development of interpretable technology, the interpretability of machine learning models is gradually improving. In practical applications, the appropriate model type can be selected according to the nature of the task, the characteristics of the available data, and the need for interpretability, and interpretability techniques can be combined to balance the relationship between model performance and interpretability (Rosé et al., 2019).

3.4. Uncertainty Modeling

There is a significant difference between machine learning models and traditional models in terms of uncertainty modeling, a difference that becomes particularly important when dealing with complex and changing real-world problems. The following is a comparison of the two in terms of uncertainty modeling: first, traditional models usually use probabilistic statistical methods for uncertainty modeling. For example, Bayesian statistical methods are widely used in traditional models to model uncertainty by introducing prior and posterior distributions. This approach provides a rigorous mathematical framework that can effectively deal with uncertainty and provide probability distributions for model parameters. In scenarios such as risk management in finance and disease prediction in medicine, the probabilistic statistical approach of traditional models can provide a clear representation of uncertainty. In contrast, machine learning models are typically more challenging to model uncertainty. Complex machine learning algorithms such as deep learning models typically lack direct probabilistic interpretation. Traditional neural network models output point predictions and lack a clear representation of the confidence or reliability of the predictions. This makes the uncertainty modeling approach of traditional models more straightforward and feasible in scenarios where accurate estimates of model prediction uncertainty are needed. However, in recent years

researchers have extensively explored uncertainty modeling for machine learning models. Techniques such as Monte Carlo methods and Bayesian neural networks have been introduced for introducing probability distributions in machine learning models. Monte Carlo methods estimate the distribution of model outputs by sampling the inputs of the model multiple times and obtaining multiple predictions. Bayesian neural networks introduce probability distributions into the structure of the neural network, allowing the model to provide an estimate of uncertainty about the predictions. In the field of deep learning, a number of novel models have been proposed for modeling uncertainty. Second, traditional models are more obvious in their utilization of prior knowledge. The prior distributions introduced in Bayesian statistical methods allow for the incorporation of domain expertise into the model, making the model more relevant. This utilization of prior knowledge is uniquely advantageous for dealing with small sample problems or in domains where data are scarce. Traditional models are better able to cope with uncertainty by judiciously choosing prior distributions that allow for the introduction of domain expertise into the model training process. Machine learning models are relatively more complex in this regard. Since deep learning models usually contain a large number of parameters, the models are highly capable of learning, but at the same time they are also more prone to overfitting in small sample scenarios. In recent years, techniques such as transfer learning and meta-learning have been proposed in an attempt to improve the generalization performance of models in new domains by leveraging previously learned knowledge. However, machine learning models are relatively more difficult to incorporate prior knowledge, especially for unstructured and high-dimensional data. In uncertainty modeling, the advantages of traditional models are mainly in the direct use of probabilistic statistical methods and the flexible use of prior knowledge. Machine learning models, on the other hand, through the introduction of new technical means, constantly improve the modeling ability of uncertainty, and gradually fill the shortcomings of traditional models in some areas. In addition, traditional models also have more mature applications in time series analysis. For example, time series models such as the ARIMA model better deal with time dependence by considering the autoregressive and sliding average characteristics of the data. These models have a better performance for time series forecasting, stock price forecasting and other problems in the economic field, and can provide confidence interval estimates of future movements, effectively portraying uncertainty. However, traditional models also have some limitations when facing complex scenarios such as large-scale, high-dimensional, and nonlinear relationships. At this point, machine learning models better capture the complex features and nonlinear relationships in the data through deep learning, integrated learning and other techniques. For large-scale data, machine learning models are able to utilize more parameters for training and improve the expressive power of the model. In the modeling of nonlinear relationships, deep learning models are able to better adapt to complex data distributions through multilevel transformations. In practical applications, to choose whether to use a traditional model or a machine learning model, comprehensive consideration needs to be made based on the nature of the specific problem, the characteristics of the available data, and the explanatory requirements of the model. In some scenarios, the advantage of traditional models lies in their intuitive probabilistic

statistical approach and utilization of prior knowledge. And when dealing with large-scale, high-dimensional, and complex nonlinear relationships, the introduction of machine learning models can improve the accuracy and generalization ability of modeling. In recent years, there are also some researches devoted to combining traditional models with machine learning models in order to take advantage of both and build a more powerful and flexible modeling framework. In general, traditional models and machine learning models have their own advantages and disadvantages in modeling approaches, and the selection of an appropriate model should be based on the needs of the specific problem, the nature of the available data, and the comprehensive trade-offs between the requirements for model performance and interpretability. In practice, the combination and synergy of different models is expected to provide more comprehensive and effective solutions to more complex problems (Ahmed et al., 2021).

4. Conclusion

With the rapid development of information technology, the application of machine learning models in the field of economic forecasting has gradually attracted widespread attention. Meanwhile, traditional models, such as linear regression and time series models, are still widely used in practice as the long-standing mainstream methods in economics. By comprehensively comparing the performance, interpretability, and uncertainty modeling of machine learning models and traditional models in economic forecasting, this dissertation aims to deeply explore the advantages and shortcomings of both when applied to the economic field. First, as far as performance is concerned, machine learning models excel in handling large-scale, high-dimensional, and nonlinear relationships. By learning abstract feature representations of data, deep learning models are better able to capture complex relationships in economic systems and improve the predictive accuracy of the models. In contrast, traditional models may appear to be overwhelmed when dealing with complex nonlinear relationships, but they still have advantages in small samples and in scenarios that require high model interpretability. Second, in terms of interpretability, traditional models are usually easier to interpret due to the simplicity of their mathematical expressions. Linear regression models are able to clearly show the impact of individual features on forecasts, which helps economists and policymakers understand the model's decision-making process. In contrast, machine learning models, especially deep learning models, are often viewed as "black box" models that are difficult to interpret intuitively. However, recent developments in interpretability techniques have added new interpretive tools to machine learning models, such as local interpretability methods and SHAP values, which have improved their interpretability in the economic domain. In terms of uncertainty modeling, traditional models usually use probabilistic statistical methods, such as Bayesian statistics, which can provide explicit modeling of uncertainty. This gives traditional models an advantage in scenarios that require precise uncertainty estimation, such as financial risk management and economic policy making. However,

machine learning models have gradually improved their ability to model uncertainty by introducing techniques such as Monte Carlo methods and Bayesian neural networks, making the models more flexible in dealing with uncertainty. In practical applications, the choice of machine learning models or traditional models needs to be based on the nature of the specific problem, the characteristics of the available data, and the need for model interpretability and performance. In the economic domain, especially in modeling scenarios with large-scale data and complex relationships, machine learning models can take full advantage of their strengths. And in scenarios with high requirements for model interpretability and prior knowledge, traditional models are still a strong choice. In summary, machine learning models and traditional models each have unique advantages in economic forecasting. With the continuous progress of technology and in-depth understanding of model performance and explanatory requirements, the two are expected to achieve better integration in the future, providing a more comprehensive and flexible solution for economic forecasting. In future research and practice, more powerful hybrid models can be constructed by deeply exploring the advantages of both to better cope with the complex and changing economic environment.

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