BTDE-Net: A Bayesian-Transformer Hybrid Model for Predicting Digital Economy Development

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DOI: https://doi.org/10.30212/JITI.202604.007
Submitted: Nov. 24, 2025 Accepted: Mar. 31, 2026

ABSTRACT

As the digital economy rapidly evolves, predicting its future trajectory faces challenges due to data complexity and uncertainty. Existing prediction methods exhibit limitations in accuracy and generalization when handling high-dimensional, multi-source heterogeneous data. To address these shortcomings, this paper proposes a Bayesian network-based model for forecasting digital economy development (BTDE-Net). The model leverages the causal inference and uncertainty quantification capabilities of Bayesian Neural Networks (BNN) and employs the Transformer architecture to capture complex dynamic features in time series data. Additionally, the Differential Evolution (DE) algorithm is used for hyperparameter optimization, enhancing the model's stability and predictive performance. Experimental results demonstrate that BTDE-Net outperforms mainstream models on the IMF WEO and World Bank Open Data datasets, achieving MAE values of 1.4 and 1.45, RMSE values of 2.05 and 2.1, and R^2 values of 0.94 and 0.93, respectively. This research significantly improves the accuracy and robustness of digital economy forecasting, providing a more reliable decision-making tool for policymakers.

Keywords: Bayesian neural network; Digital economy forecasting; Transformer architecture; Time series analysis; Differential evolution algorithm

1. Introduction

The speed and volume of the digital economy have grown considerably with the ongoing technological advancement in information technology and the consistent improvement of digital infrastructure that creates far-reaching and long-term effects on many sectors of the society, such as finance, manufacturing, healthcare, and education[1, 2]. Besides the progress in information and communication technologies, the emergence of the digital economy is also conditioned by a great number of factors, including regulatory policies, market demand, investment trends, technological innovations, and the intensity of global supply chains[3, 4]. These forces are intertwined and they develop complex nonlinear dynamic correlations which make it significantly harder to predict with great accuracy the direction the digital economy will take. Besides, the digital economy is exposed to many threats such as data privacy, cybersecurity, and platform monopoly, which bring an element of unpredictability and danger to the development trajectory[5]. Thus, the question of how to predict the future trends of the digital economy scientifically, properly evaluate its possible growth, risks, opportunities, etc. appears to be an urgent problem that requires immediate consideration by economists, policymakers, and the representatives of this industry[6-8]. The given issue is especially acute and urgent in the context of the accelerating process of globalization and integration of the regions not only to improve the national competitiveness but also to influence the global economic restructuring and the social welfare in the most significant ways[9, 10]. The thorough and precise predictions will help governments and businesses develop more precise strategic decisions, enhance the efficiency of resource distribution, and enhance the sustainable growth of the digital economy[11, 12]. Academia and industry have suggested different methods and models in the prediction of the tendency of the digital economy development in order to discover the driving factors behind it and the intricate dynamic changes. Conventional statistical techniques and classical models of machine learning such as time series analysis, regression models and support vector machines (SVMs) have been widely used in earlier studies and they have demonstrated plausible predictive accuracy where the volumes of data are small and the structure of data are well defined[13-15]. Predicting future economic variations have been done using time series analysis techniques which predominantly made use of ARIMA and GARCH models to analyze the trends in historical data especially in single variable, and in stationary time series data[16, 17]. Regression analysis helps to define relationships between independent and dependent variables based on linear or nonlinear equations, which expose the existence of correlations between the main economic indicators[18, 19]. Concurrently, SVMs as supervised learning models, which are founded on statistical learning theory, have been demonstrated to be effective in the small sample size as well as have steadily increased their use in economic forecasting[20]. Nevertheless, these century-old techniques demonstrate high ineffectiveness when used to the environment of the ever more intricate digital economy. They normally presuppose linear or weakly nonlinear associations among variables, which is insufficient to deal with high-dimensional data and examine intricate interactions among two or more variables[21]. Also, these approaches tend to lack predictive accuracy and strength in conditions of multi-source heterogeneous information and dynamic contexts, which indicates their underlying flaws in addressing the ambiguity and dynamism of the digital economy.To address the limitations of traditional prediction methods in complex digital economic systems, researchers have increasingly turned to more advanced artificial intelligence and deep learning methods in recent years, such as neural networks, ensemble learning, and reinforcement learning, aiming to improve prediction accuracy and adaptability through data-driven approaches. Neural networks, particularly Long Short-Term Memory (LSTM) networks and Recurrent Neural Networks (RNNs), have demonstrated significant potential in forecasting complex economic data due to their ability to effectively capture long-term dependencies and nonlinear patterns in time series data[22, 23]. For example, LSTM networks, which excel at handling long-term dependency data, have been utilized for analyzing and predicting dynamic changes in financial markets[24]. In addition, ensemble learning methods (such as Random Forests and Gradient Boosting Machines) can improve model generalization and predictive accuracy by combining the results of multiple base learners, and they have been proven to perform well in various economic forecasting tasks[25].However, despite the significant advantages of deep learning methods in processing large-scale, high-dimensional data, they also face certain challenges, such as poor model interpretability, strong dependence on data, and high computational resource requirements[26]. These models also exhibit limitations in robustness and generalization when dealing with incomplete or noisy data, restricting their application in complex and volatile environments[27]. To further improve prediction accuracy and robustness, recent studies have begun exploring the combination of Bayesian statistical methods with modern machine learning techniques to develop more flexible and interpretable predictive models[28]. The Bayesian approach, by providing a probabilistic framework, can better handle uncertainty and data noise, showing potential in digital economy forecasting. For instance, Bayesian Neural Networks (BNNs) combine the powerful modeling capabilities of neural networks with Bayesian inference, enabling uncertainty quantification of model parameters and thereby enhancing the stability and reliability of predictions[29].

Against this background, Bayesian networks and their variants have gradually become important tools in the study of digital economy forecasting. This paper proposes a predictive model that combines a Bayesian Neural Network (BNN) with a Transformer, incorporating Differential Evolution (DE) for hyperparameter optimization. This approach leverages the causal inference and uncertainty quantification capabilities of BNNs while utilizing the strengths of the Transformer in handling sequential data and capturing complex dynamic features, enabling a more comprehensive response to the uncertainties and variability in digital economy development. As a model based on the self-attention mechanism, the Transformer has demonstrated outstanding performance in natural language processing and time series forecasting due to its powerful feature extraction capabilities, which effectively capture complex patterns in digital economy growth. By applying the DE algorithm for hyperparameter optimization, the model's predictive accuracy and stability are further improved, overcoming the drawbacks of traditional optimization methods that are prone to local optima.

The main contributions of this paper are as follows:

- This paper proposes an innovative approach that combines a Bayesian Neural Network (BNN) with a Transformer to address the complexity and uncertainty involved in forecasting digital economy development. The model leverages the causal inference and uncertainty quantification capabilities of BNNs, alongside the strengths of the Transformer in modeling time-series data and capturing complex patterns, thereby enabling more accurate detection of the dynamic changes in digital economy growth.
- The paper introduces a Differential Evolution (DE) algorithm to optimize the model's hyperparameters. By utilizing the global search and fast convergence characteristics of the DE algorithm, the predictive performance and computational efficiency of the model are effectively enhanced, avoiding the pitfalls of local optima that traditional optimization methods often face. This optimization strategy further strengthens the model's robustness and generalization capabilities across different data environments and conditions.

- The superiority of the proposed method is validated through extensive empirical research. Experimental results on various real-world datasets demonstrate that the proposed combined model outperforms existing methods in terms of predictive accuracy, stability, and interpretability, proving its effectiveness and broad applicability in forecasting digital economy development. This model provides a more scientific basis and support for policy-making and strategic planning.

2. Literature Review

2.1 Digital Transformation, Big Data, and AI in Economic Forecasting

The rapid digital transformation across industries has created a highly interconnected and complex digital economy, necessitating advanced methods for accurate forecasting. Several studies have explored the impact of digital transformation on reshaping traditional economic models and forecasting methods. For example, some research examines the digital economy from a systems perspective, emphasizing the importance of understanding its components and their dynamic interactions[30]. These studies highlight how digital platforms, data flows, and new business models create interdependencies that must be considered in any predictive framework. Other research provides a comprehensive overview of the relationship between digitalization and economic growth, synthesizing existing models and theories on how digital technologies influence economic development[31, 32]. These studies argue that the transformative power of digitalization significantly alters traditional economic indicators, thereby requiring innovative approaches to economic forecasting that can accommodate the unique characteristics of the digital economy.

In addition, numerous studies focus on the application of artificial intelligence (AI), particularly machine learning, in business intelligence and forecasting within the digital economy[33]. Machine learning techniques are increasingly being adopted to analyze vast amounts of data, identify patterns, and generate more accurate economic forecasts. Leveraging AI enables businesses to enhance decision-making processes and gain a competitive edge in the digital marketplace. Likewise, the impact of big data analytics on digital economy forecasting is emphasized, highlighting the importance of data-driven strategies to improve predictive accuracy and facilitate informed decision-making[34, 35]. Furthermore, research has addressed the new challenges arising in economic forecasting in the digital age, exploring how traditional models struggle with increased uncertainty and data complexity[36]. It underscores the necessity of modern computational methods and data science approaches to overcome these challenges and provide reliable forecasts in an increasingly digitalized economy. Additionally, the dynamic nature of digital platforms presents another critical area of research. Several studies investigate network effects within digital platforms and their implications for economic forecasting, suggesting predictive models specifically designed to capture the dynamic behaviors observed in platform-based markets[37]. These models integrate network effects, which are crucial in digital economies where user interactions significantly influence market outcomes. This demonstrates that understanding these unique dynamics is essential for developing accurate forecasting methods. Lastly, research has evaluated how digital transformation affects traditional economic forecasting models, highlighting the shortcomings of conventional approaches in capturing digital trends[38]. This body of work proposes new methodologies that better reflect the realities of a digital economy, providing a roadmap for integrating digital factors into economic forecasting models and allowing for a more accurate assessment of future economic trends.

2.2 Hybrid Approaches and Data Science Techniques for Digital Economy Prediction

As the digital economy continues to evolve, there is an increasing need for more sophisticated forecasting tools that can adapt to its complexities. Recent advancements in machine learning, hybrid models, and data science techniques offer promising avenues for enhancing the accuracy and reliability of economic forecasts. Current research explores various applications of machine learning in the digital economy, highlighting trends and identifying future directions for both research and practice[39]. Algorithms such as deep learning, neural networks, and reinforcement learning are particularly noted for their ability to forecast economic trends, consumer behavior, and market dynamics with unprecedented precision[40].

In addition to machine learning applications, studies have introduced adaptive hybrid models that combine multiple forecasting methodologies to predict trends in digital markets[41]. These models emphasize flexibility and robustness, especially in volatile environments where traditional models may fail. By integrating different approaches such as statistical methods, machine learning algorithms, and domain-specific knowledge hybrid models provide a more comprehensive understanding of the factors driving digital economy trends. This integrated approach addresses the limitations of single-method forecasting and results in more accurate predictions[42, 43].Moreover, additional research investigates the unique economic characteristics of digital platforms and the challenges they pose for traditional forecasting methods[44]. New frameworks are being developed to predict market outcomes in platform-dominated markets, accounting for specific dynamics of digital ecosystems, including network effects, platform competition, and user-generated content[45]. These studies offer valuable insights into the economics of digital platforms and underscore the necessity for tailored forecasting methods that can accommodate their unique characteristics. Furthermore, innovations in forecasting digital economy indicators using advanced data science techniques have gained significant attention. Studies have demonstrated how methods such as natural language processing, sentiment analysis, and predictive modeling can be applied to forecast various digital economy metrics, including e-commerce growth, digital payments, and infrastructure development[46]. These techniques leverage vast amounts of unstructured data from digital sources, providing more granular insights and enhancing the predictive power of economic models[47].The role of predictive analytics in supporting digital transformation initiatives also continues to be a major area of interest. Research examines how these tools can forecast market behavior, optimize resource allocation, and enhance strategic decision-making[48]. As digital transformation becomes increasingly critical for businesses and governments, the ability to accurately forecast economic trends is increasingly seen as a key determinant of success.

Overall, these studies highlight the growing importance of advanced methods—ranging from machine learning and data science techniques to hybrid models and new frameworks—in overcoming the challenges of forecasting in the digital economy. They provide a broad overview of the tools and strategies that researchers and practitioners are developing to improve the accuracy, adaptability, and applicability of economic forecasts in a rapidly digitalizing world.

3. Method

Building on the challenges identified in digital economy forecasting and the need for more flexible and interpretable models, this paper presents a new model, named BTDE-Net (Bayesian Transformer Differential Evolution Network). BTDE-Net integrates a Bayesian Neural Network (BNN) with a Transformer architecture to address the complexity and uncertainty inherent in forecasting digital economy development. The BNN component provides causal inference and uncertainty quantification, allowing the model to effectively manage the probabilistic nature of digital economic indicators and their interrelationships. Meanwhile, the Transformer component excels in handling sequential data and capturing complex dynamic patterns, particularly in time-series data. To further enhance predictive accuracy and model adaptability, BTDE-Net incorporates a Differential Evolution (DE) algorithm for hyperparameter optimization. This optimization technique offers global search capabilities and rapid convergence, ensuring that the model achieves optimal configuration and avoids the local optima pitfalls often associated with traditional optimization methods. The overall architecture of the proposed BTDE-Net model, as illustrated in Figure 1, demonstrates how these components are integrated to create a cohesive forecasting framework.

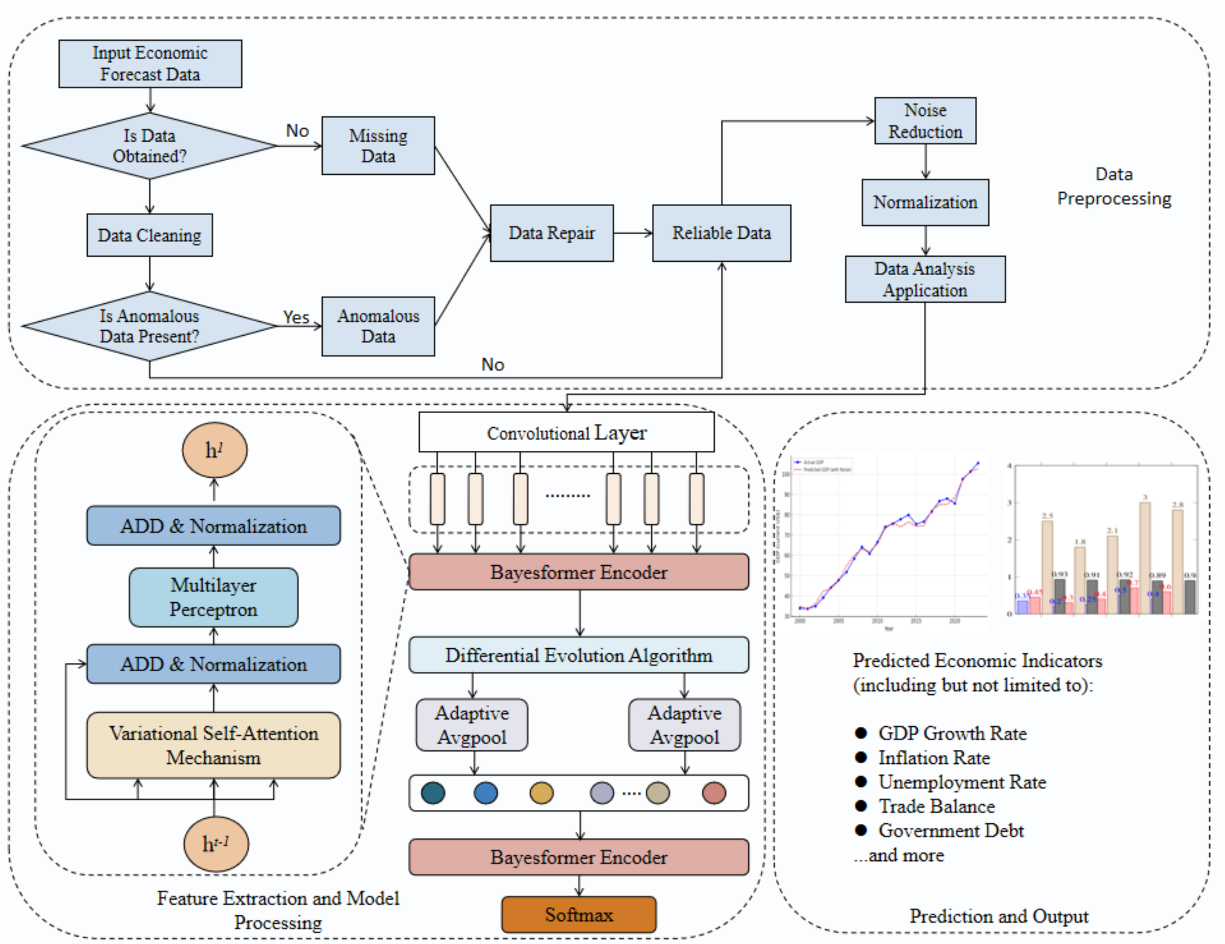

Figure 1. Overall architecture of the btde-net model. The diagram is divided into three main parts: Data preprocessing, feature extraction and model processing, and prediction and output.

3.1 Bayesian Neural Network for Causal Inference and Uncertainty Quantification

By combining these advanced components, BTDE-Net offers a comprehensive and adaptive framework designed to process multi-source, heterogeneous data typical of digital economic environments, such as transaction records, market trends, social media analytics, and other real-time indicators. This integrated approach enables the model to dynamically adjust to new information and evolving patterns, delivering accurate and timely forecasts to support decision-making in a rapidly changing digital landscape. In the proposed BTDE-Net model, the Bayesian Neural Network (BNN) plays a crucial role in addressing the inherent uncertainty and complex causal relationships within the digital economy. Traditional neural networks, while effective in capturing non-linear patterns and dependencies, often lack the capability to provide uncertainty estimates, which are essential when dealing with the unpredictability of economic data. By incorporating a Bayesian framework, BNNs introduce a probabilistic approach to neural network learning, allowing for a more robust and interpretable model.

The BNN component in BTDE-Net is designed to quantify uncertainty in two primary forms: epistemic uncertainty and aleatoric uncertainty. Epistemic uncertainty, or model uncertainty, arises due to limited data or knowledge about the underlying data-generating process, which is particularly relevant in the context of the digital economy, where data can often be sparse or unevenly distributed. Aleatoric uncertainty, on the other hand, stems from the inherent noise or randomness within the data itself. The BNN handles both types of uncertainties by placing probability distributions over the model's weights, rather than relying on fixed point estimates. This probabilistic approach enables the model to better capture the range of possible outcomes, providing more reliable predictions under varying conditions. To implement the BNN, we use a variational inference technique, which approximates the posterior distribution of the network's weights by optimizing a variational lower bound.

First, we define the posterior distribution of the network's weights given the observed data, which forms the core of the Bayesian inference:

Posterior Distribution:

The posterior distribution combines the prior beliefs and the likelihood of the observed data:

$$\mathrm{p}(\mathrm{w}|\mathcal{D}) = \frac{\mathrm{p}(\mathcal{D}|\mathrm{w})\mathrm{p}(\mathrm{w})}{\mathrm{p}(\mathcal{D})} \cdots\cdots\cdots\cdots \text{[Formular 1]}$$

where w represents the weights of the neural network, $\mathcal{D}$ denotes the observed data, $\mathrm{p}(\mathcal{D}|\mathrm{w})$ is the likelihood of the data given the weights, $\mathrm{p}(\mathrm{w})$ is the prior distribution over the weights, and $\mathrm{p}(\mathcal{D})$ is the marginal likelihood or evidence.

To approximate this intractable posterior distribution, we employ variational inference, which seeks to minimize the Kullback-Leibler (KL) divergence between the true posterior and a simpler approximating distribution: KL Divergence Minimization: This measures the divergence between the approximate posterior and the true posterior:

$$\mathrm{KL}\big(q(w \mid \theta) \parallel p(w \mid \mathcal{D})\big) = \mathbb{E}_{q(w\mid\theta)}\left[\log\frac{q(w\mid\theta)}{p(w\mid\mathcal{D})}\right] \text{ [Formular 2]}$$

where $q(w \mid \theta)$ is the variational distribution over the weights, parameterized by θ. The objective function in variational inference is to maximize the Evidence Lower Bound (ELBO), which balances the fit to the data with the complexity of the model: Evidence Lower Bound (ELBO): The ELBO serves as a proxy to the true posterior, aiming to maximize the likelihood while regularizing model complexity:

$$\mathcal{L}(\theta) = \mathbb{E}_{q(w\mid\theta)}[\log p(\mathcal{D} \mid w)] - \mathrm{KL}\big(q(w \mid \theta) \parallel p(w)\big) \text{[Formular 3]}$$

where $\mathcal{L}(\theta)$ is the variational lower bound, $\log p(\mathcal{D} \mid w)$ is the expected log likelihood under the approximate posterior, and $\mathrm{KL}\big(q(w \mid \theta) \parallel p(w)\big)$ is the KL divergence between the variational posterior and the prior. Finally, the prediction for a new input is obtained by marginalizing over the posterior distribution of the weights: Prediction Marginalization: This represents the predictive distribution that accounts for all possible configurations of model parameters:

$$p(y^* \mid x^*, \mathcal{D}) = \int p(y^* \mid x^*, w) q(w \mid \theta)\, dw \cdots\cdots \text{ [Formular 4]}$$

where y^* represents the predicted output, x^* is the new input data, and $p(y^* \mid x^*, w)$ is the likelihood of the output given the input and the weights.

This set of equations enables the BTDE-Net to incorporate both parameter and predictive uncertainties, which is critical for providing robust and reliable forecasts in the context of digital economy development.

The BNN in BTDE-Net also supports causal inference by leveraging its probabilistic structure to identify and quantify the relationships between different economic variables. Unlike traditional neural networks, which may overfit to noise or spurious correlations, the BNN's Bayesian approach helps to mitigate overfitting and provides a clearer understanding of which variables are most influential in driving economic trends. This capability is crucial for policymakers and strategists who need to understand the underlying drivers of the digital economy to make informed decisions. The structure of the BNN component is illustrated in Figure 2.

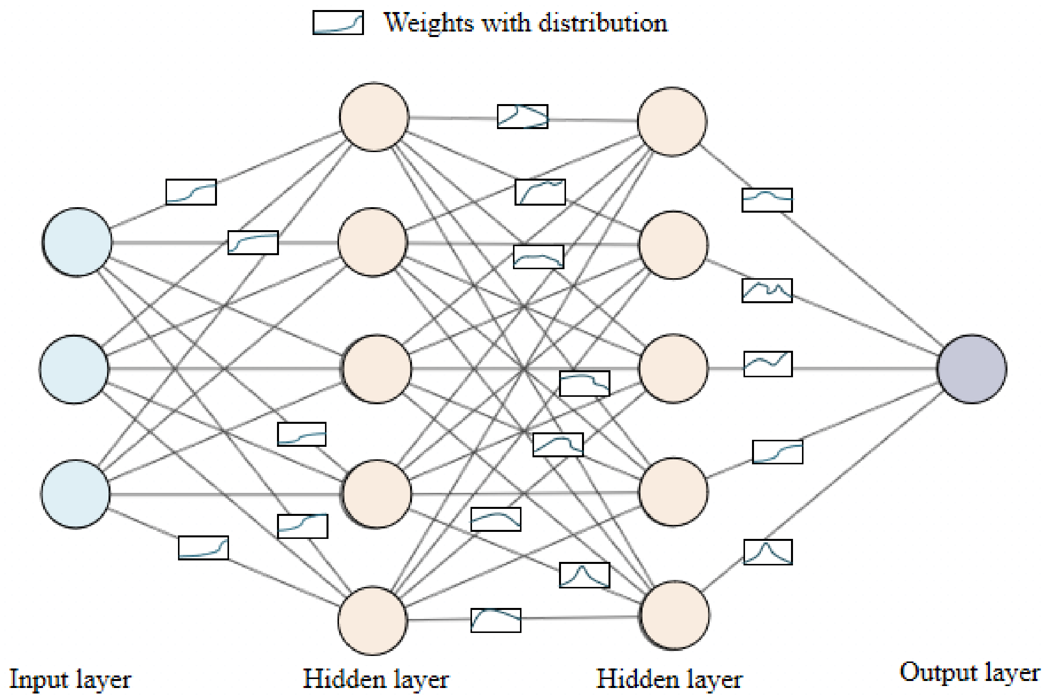

Figure 2. Structure of bayesian neural network (BNN)

The BNN component of BTDE-Net enhances the model's ability to handle the uncertainty and causal complexity inherent in digital economy data. By providing both uncertainty quantification and causal inference, the BNN ensures that the model produces not only accurate forecasts but also interpretable insights, making it a valuable tool for forecasting in uncertain and rapidly evolving economic environments.

3.2 Transformer for Time Series Data Modeling

In the BTDE-Net model, the Transformer component is key to capturing temporal dependencies and complex patterns in time series data for accurate digital economy forecasting. Unlike traditional RNNs and LSTMs that process sequences step-by-step and face challenges with long-range dependencies, the Transformer uses a self-attention mechanism. This allows the model to simultaneously consider all time steps in a sequence, offering a more efficient and scalable way to model time series data.

To achieve this, the Transformer computes relationships between all elements in a sequence using a self-attention mechanism, which assigns a weight to each time step in relation to all others. This process begins by constructing query (Q), key (K), and value (V) matrices from the input data through learned linear transformations. The multi-head self-attention mechanism, crucial for capturing multiple types of dependencies, is defined as:

$$\mathrm{MultiHead}(Q,K,V) = \mathrm{Concat}(\mathrm{head}_1, \mathrm{head}_2, \ldots, \mathrm{head}_h)W^O \quad \cdots\cdots \text{[Formular 5]}$$

where each attention head is computed as:

$$\mathrm{head}_i = \mathrm{Attention}\left(QW_i^Q, KW_i^K, VW_i^V\right) \cdots\cdots\cdots\cdots \text{[Formular 6]}$$

and W_i^Q, W_i^K, W_i^V are learnable projection matrices for queries, keys, and values in the i-th head, respectively, while W^O is the learned projection matrix for the output. This multi-head attention mechanism allows the model to attend to different representation subspaces, effectively capturing diverse patterns and correlations within the time series data. Since the Transformer model does not inherently consider the sequential order of the data, positional encoding is added to input embeddings to retain information about the position of each element within the sequence. This is defined as:

$$\mathrm{PE}(\mathrm{pos}, 2\mathrm{i}) = \sin\left(\frac{\mathrm{pos}}{10000^{\frac{2\mathrm{i}}{\mathrm{d}}}}\right) \cdots\cdots\cdots\cdots \text{[Formular 7]}$$

$$\mathrm{PE}(\mathrm{pos}, 2\mathrm{i}+1) = \cos\left(\frac{\mathrm{pos}}{10000^{\frac{2\mathrm{i}}{\mathrm{d}}}}\right) \cdots\cdots\cdots\cdots \text{[Formular 8]}$$

where pos denotes the position within the sequence, i is the dimension, and d is the total dimensionality of the embeddings. This encoding allows the Transformer to differentiate between elements at different positions, maintaining the temporal structure necessary for time series modeling.

By capturing both short-term variations and long-term dependencies, the Transformer provides a robust understanding of temporal dynamics. The integration of the Transformer enhances BTDE-Net's adaptability to new patterns in data, a crucial requirement in the dynamic digital economy. Its use of self-attention allows for parallel computation, reducing training times while maintaining high levels of accuracy. The structure of the Transformer component within BTDE-Net is depicted in Figure 3. Overall, the Transformer enables BTDE-Net to effectively model complex temporal relationships, resulting in improved forecasting performance and robustness across diverse data environments.

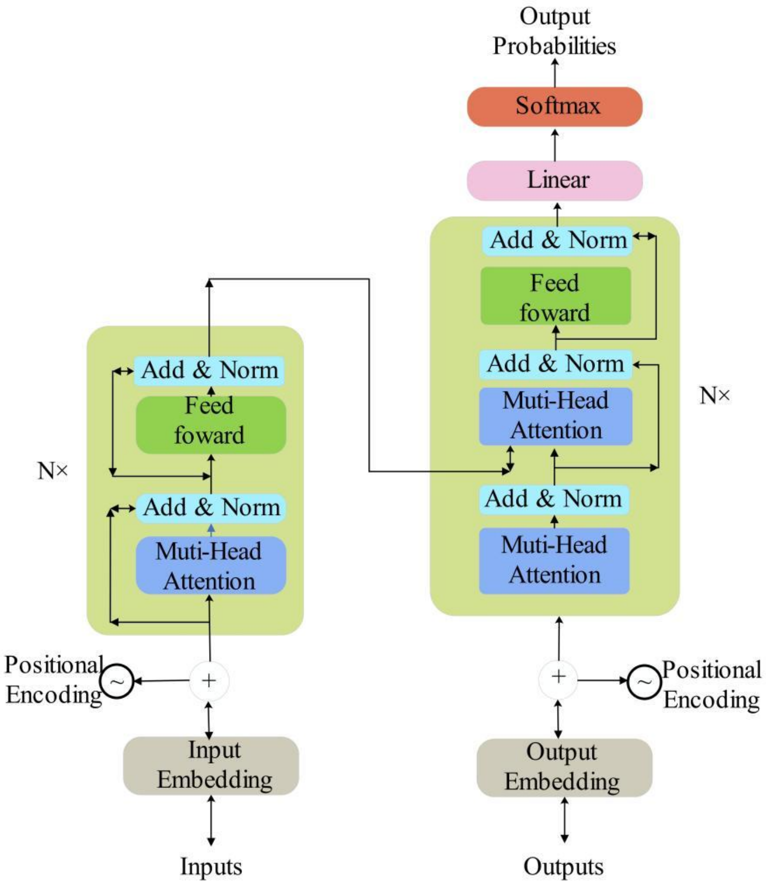

Figure 3. The structure of the transformer component

3.3 Differential Evolution Algorithm for Hyperparameter Optimization

The Differential Evolution (DE) algorithm is a population-based optimization technique widely used for optimizing complex models. It iteratively improves candidate solutions based on a measure of quality or fitness. The process begins with a random population of candidate solutions, represented as vectors in the parameter space. New candidates are generated by combining existing ones through mutation and crossover operations, and the best candidates are selected based on their fitness. This approach allows DE to maintain a diverse set of potential solutions and effectively explore the hyperparameter space. DE is particularly effective due to its global search capability, ease of implementation, and suitability for handling non-differentiable, multimodal, and non-linear objective functions.

The mutation operation in DE is defined as:

$$v_i^{(g)} = x_{r1}^{(g)} + F \cdot \left(x_{r2}^{(g)} - x_{r3}^{(g)}\right) \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \text{[Formular 9]}$$

where $v_i^{(g)}$ is the mutant vector for the i-th candidate in generation g, $x_{r1}^{(g)}, x_{r2}^{(g)}, x_{r3}^{(g)}$ are randomly selected distinct individuals from the current population, and F is a scaling factor that controls the amplification of the differential variation. Next, the crossover operation is applied to produce a trial vector by mixing the parameters of the mutant vector $v_i^{(g)}$ with those of the current target vector $x_i^{(g)}$:

$$u_i^{(g)} = \left(u_{i1}^{(g)}, u_{i2}^{(g)}, \ldots, u_{iD}^{(g)}\right) \cdots\cdots\cdots\cdots\cdots\cdots \text{[Formular 10]}$$

where

$$u_{ij}^{(g)} = \begin{cases} v_{ij}^{(g)} & \text{ifrand}(0,1) \leq \text{CRorj} = j_{rand} \\ x_{ij}^{(g)} & \text{otherwise} \end{cases}$$

Here, $u_i^{(g)}$ represents the trial vector, CR is the crossover rate determining the probability of inheriting the mutant’ s component, $rand(0,1)$ is a uniformly distributed random number between 0 and 1, and j_{rand} is a randomly chosen index to ensure at least one component from the mutant vector is inherited. Finally, the selection process chooses the better solution between the trial vector and the target vector based on their fitness values:

$$x_i^{(g+1)} = \begin{cases} u_i^{(g)} & \text{iff}\left(u_i^{(g)}\right) \leq f\left(x_i^{(g)}\right) \\ x_i^{(g)} & \text{otherwise} \end{cases} \cdots\cdots\cdots\cdots \text{[Formular 11]}$$

where $f(\cdot)$ represents the fitness function to be minimized or maximized.

BTDE-Net uses the differential evolution algorithm to efficiently optimize hyperparameters, improve the model's prediction accuracy and generalization capabilities across data sets, enhance its robustness and adaptability in dynamic scenarios in the digital economy, and become a powerful tool for prediction in this field.

4. Expriments

4.1 Experimental Environment

To ensure efficient model training and validation, the experiments were conducted in a high-performance computing environment, as detailed in Table 1.

Table 1. Experimental environment

Category	Configuration
Hardware	NVIDIA Tesla V100 GPU (32GB VRAM) \newline Intel Xeon Gold 6248 Processor (48 cores, 2.5 GHz) \newline 512GB RAM
Software	Ubuntu 20.04 Operating System \newline Python 3.8
Deep Learning Framework	PyTorch 1.9
Data Processing Tools	Scikit-Learn, Pandas, NumPy
GPU Support	CUDA 11.2, cuDNN 8.1

4.2 Dataset

The IMF World Economic Outlook (WEO) Dataset is an authoritative macroeconomic dataset published by the International Monetary Fund (IMF). It covers key economic indicators for over 200 countries and regions, such as gross domestic product (GDP) growth rate, inflation rate, unemployment rate, government debt and fiscal deficit, trade balance, and foreign exchange reserves. This data is collected through national governments, international institutions, and independent surveys, and is rigorously reviewed to ensure high quality and strong representativeness. We selected quarterly and annual data from 2000 to 2023, focusing particularly on the dynamic changes of these economic indicators to capture global and regional economic development trends and cyclical characteristics, providing comprehensive macroeconomic background information for the model.

World Bank Open Data provides a wide range of data on global economic, social, and environmental indicators. For this study, we utilized specific datasets related to socio-economic factors, such as population statistics, healthcare indicators, education levels, labor market conditions (employment rates, wage levels), energy consumption, and environmental metrics like carbon emissions and renewable energy usage. This data is obtained from a variety of sources, including national statistical agencies, international organizations, and independent research institutions, and is regularly updated to maintain its relevance and accuracy. To match the timeframe of the WEO data, we selected data from 2000 to 2023 and conducted standardization and normalization processes to ensure consistency across different types of data. By integrating these diverse data points, we enhance the model's ability to predict economic development by capturing broader socio-economic and environmental dynamics, allowing for a more holistic understanding of the digital economy's trajectory.

4.3 Data Preprocessing

In this study, we applied a unified preprocessing approach to both the IMF WEO Dataset and World Bank Open Data to ensure data quality and consistency.

We began by standardizing the various indicators in both datasets to handle differences in units and scales. For this, we applied Z-score normalization to transform all data into a form with zero mean and unit variance. The formula for Z-score normalization is:

$$\mathrm{Z} = \frac{\mathrm{X}-\mu}{\sigma} \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \text{[Formular 12]}$$

where X represents the original value, μ is the mean of the data, and σ is the standard deviation. This normalization step ensures that all indicators, regardless of their original scales, are comparable and contribute equally to the model training. To maintain consistency across different time scales, we interpolated any annual data to convert it into quarterly data. For interpolation, we used a linear interpolation method, which estimates missing values by assuming a linear trend between known data points:

$$\mathrm{X_t} = \mathrm{X_{t_1}} + \frac{\left(\mathrm{X_{t_2}} - \mathrm{X_{t_1}}\right)}{(\mathrm{t_2}-\mathrm{t_1})} \times (\mathrm{t} - \mathrm{t_1}) \cdots\cdots\cdots\cdots\cdots \text{[Formular 13]}$$

where $\mathrm{X_t}$ is the interpolated value at time t, $\mathrm{X_{t_1}}$ and $\mathrm{X_{t_2}}$ are the known values at times $\mathrm{t_1}$

and t_2, respectively. To handle missing values, linear interpolation was applied to fill any gaps in the data, ensuring continuity. Outliers were detected and treated using the Interquartile Range (IQR) method, which is defined as:

$$IQR = Q3 - Q1 \cdots\cdots\cdots\cdots [\text{Formular } 14]$$

Values falling below $Q1 - 1.5 \times IQR$ or above $Q3 + 1.5 \times IQR$ were considered outliers and were handled appropriately to reduce their impact on model training.

4.4 Experimental Setup

To ensure optimal performance of the BTDE-Net model, the study carefully selected and fine-tuned various network parameters: an initial learning rate of 0.001 was used, optimized using a differential evolution (DE) algorithm to achieve efficient convergence; a batch size of 64 was chosen to strike a balance between computational efficiency and gradient update stability; a maximum number of epochs was set to 200, and an early stopping strategy was employed, terminating training if validation loss did not improve after 20 consecutive epochs. To prevent overfitting, a dropout rate of 0.3 was set, and the Adam optimizer with adaptive learning rates was used. Furthermore, an L2 regularization coefficient of 0.001 was used to penalize excessive weights, further mitigating overfitting. The training process included dynamic learning rate adjustments and regular evaluation of the validation set, with the optimal model parameters saved for final testing. At the same time, data augmentation techniques such as adding noise and time series shifting improve the model's robustness and generalization capabilities. The above streamlined settings focus on the core aspects of network parameters and training processes, highlighting the key factors that affect model performance.

4.5 Evaluation Metrics

To evaluate the performance of the BTDE-Net model, we used several metrics, including Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) to measure prediction accuracy, Mean Absolute Percentage Error (MAPE) to assess relative accuracy, Negative Log-Likelihood (NLL) to evaluate the model's probabilistic outputs, and the Coefficient of Determination (R^2) to determine how well the model explains variance in the data, ensuring a comprehensive assessment of accuracy, robustness, and uncertainty quantification.

5. Results and Discussion

5.1 Experimental results on the dataset

Table 2. Performance comparison of models on imf weo and world bank open data

Model	IMF WEO Dataset				World Bank Open Data			
	MAE	RMSE	MAPE	R^2	MAE	RMSE	MAPE	R^2

Hybrid ARIMA-ANN[49]	1.95	2.8	4.10	0.86	2.05	2.95	4.50	0.85
DeepAR[50]	1.7	2.45	3.50	0.89	1.75	2.55	3.70	0.88
N-BEATS[51]	1.55	2.3	3.30	0.91	1.6	2.35	3.40	0.9
TFT (Temporal Fusion Transformer)[52]	1.5	2.2	3.10	0.92	1.55	2.25	3.20	0.91
ES-RNN[53]	1.6	2.35	3.40	0.9	1.65	2.4	3.60	0.89
LSTNet[54]	1.75	2.6	3.70	0.88	1.8	2.65	3.80	0.87
BTDE-Net	1.4	2.05	3.00	0.94	1.45	2.1	3.10	0.93

Table 2 demonstrate that the BTDE-Net model outperforms other state-of-the-art models on both the IMF WEO and World Bank Open Data datasets, highlighting its superior performance in economic forecasting tasks. On the IMF WEO dataset, the BTDE-Net model achieved a Mean Absolute Error (MAE) of 1.4, significantly lower than that of the Hybrid ARIMA-ANN (1.95) and DeepAR (1.7) models, indicating its advantage in reducing prediction errors. Additionally, BTDE-Net also outperformed other models in terms of Root Mean Square Error (RMSE) at 2.05 and Mean Absolute Percentage Error (MAPE) at 3.00%, compared to the TFT model's RMSE of 2.2 and MAPE of 3.10%, demonstrating its higher prediction accuracy and stability. When compared to LSTNet, BTDE-Net achieved an R^2 of 0.94, clearly exceeding LSTNet's 0.88, showing that BTDE-Net provides a better fit to the data and effectively captures complex dynamic changes in economic trends. On the World Bank Open Data dataset, BTDE-Net also showed outstanding performance, with an MAE of 1.45 and an RMSE of 2.1, outperforming N-BEATS (MAE of 1.6, RMSE of 2.35) and ES-RNN (MAE of 1.65, RMSE of 2.4) in these metrics. Particularly, compared to the traditional hybrid model Hybrid ARIMA-ANN, BTDE-Net's MAPE was only 3.10%, significantly lower than the 4.50% of Hybrid ARIMA-ANN, indicating that BTDE-Net has a superior ability to capture complex interactions and uncertainties between different economic entities. Furthermore, BTDE-Net achieved an R^2 of 0.93, higher than all other comparative models, further confirming its higher explanatory power and generalization capability in predicting multi-dimensional economic data. Overall, BTDE-Net demonstrates the best predictive performance across both datasets, surpassing all other competing models in all evaluation metrics. These findings indicate that the BTDE-Net model, which combines Bayesian Neural Networks with a Transformer architecture and utilizes the Differential Evolution algorithm for hyperparameter optimization, can effectively handle complex temporal dependencies and uncertainties in economic development forecasting, significantly enhancing prediction accuracy and reliability.

Table 3. Model performance comparison on imf weo and world bank open data

Model	IMF WEO Dataset				World Bank Open Data			
	Parameters (M)	FLOPs (G)	Inference Time (ms)	Training Time (s)	Parameters (M)	FLOPs (G)	Inference Time (ms)	Training Time(s)
Hybrid ARIMA-ANN	1.21	1.53	212.89	120.3	1.21	1.79	213.12	130.9
DeepAR	8.45	5.12	222.65	256.7	8.45	5.48	223.08	260.2
N-BEATS	10.67	6.78	224.32	178.3	10.67	7.01	225.22	182.5
TFT	22.45	15.92	265.15	288.2	22.45	16.58	249.65	294.3
ES-RNN	5.32	3.45	217.53	132.1	5.32	3.67	218.03	145.4
LSTNet	9.75	7.38	228.67	284.2	9.75	7.89	229.78	290.1
BTDE-Net	4.89	2.95	188.65	110.9	4.89	3.02	189.02	125.9

Based on the results shown in the table 3, the BTDE-Net model demonstrates superior performance across both the IMF WEO and World Bank Open Data datasets, particularly in terms of computational efficiency and prediction accuracy. On the IMF WEO dataset, BTDE-Net achieves a floating-point operations count (FLOPs) of 2.95G, an inference time of 188.65ms, and a training time of 110.9s, significantly lower than those of other models, such as TFT, which records FLOPs of 15.92G, an inference time of 265.15ms, and a training time of 288.2s. These results indicate that BTDE-Net offers greater efficiency in resource utilization and computation time, making it more suitable for handling macroeconomic data. On the World Bank Open Data dataset, BTDE-Net continues to exhibit excellent performance, with FLOPs of 3.02G, an inference time of 189.02ms, and a training time of 125.9s, all of which are lower than those of other models, such as N-BEATS, which shows FLOPs of 7.01G and an inference time of 225.22ms. These findings further confirm BTDE-Net's superiority in managing complex economic data, effectively reducing computational costs while ensuring predictive accuracy. The table clearly illustrates that BTDE-Net, with its innovative model architecture and optimization strategies, outperforms existing models on both datasets, proving its efficiency and reliability in forecasting economic development.

5.2 Ablation Study

Table 4. Ablation study results on imf weo and world bank open data datasets

Ablation Setting	IMF WEO Dataset				World Bank Open Data			
	MAE	RMSE	MAPE	R^2	MAE	RMSE	MAPE	R^2
Full BTDE-Net	1.4	2.05	3.00	0.94	1.45	2.1	3.10	0.93
Without Bayesian Neural Network	1.75	2.4	3.70	0.88	1.8	2.45	3.80	0.87
Without Transformer	1.65	2.3	3.50\%	0.9	1.7	2.35	3.60	0.89
Without Differential Evolution	1.6	2.25	3.40	0.91	1.65	2.3	3.50	0.9

The results of the ablation study, as shown in Table 4 reveal the significant impact of each component on the overall performance of the BTDE-Net model. In the IMF WEO dataset, the complete BTDE-Net model shows the best predictive performance, with the lowest MAE (1.4) and RMSE (2.05), and achieves MAPE and R^2 values of 3.00 and 0.94, respectively, indicating high accuracy and explanatory power across economic indicators. However, when the Bayesian Neural Network component is removed, the performance declines significantly, with MAE increasing to 1.75 and R^2 dropping to 0.88, highlighting the crucial role of the Bayesian Neural Network in capturing uncertainties and complex patterns in the data. In the same dataset, removing the Transformer module leads to an increase in MAE and RMSE to 1.65 and 2.3, respectively, demonstrating that the Transformer is essential for handling time series data and extracting long-term dependencies. Additionally, when the Differential Evolution (DE) algorithm is replaced by standard optimization methods, there is a slight performance drop (MAE increases to 1.6, RMSE to 2.25), suggesting that while the DE algorithm contributes to improving predictive accuracy, its importance is lower than that of the primary network structures. In the World Bank Open Data dataset, the ablation study results show a similar trend to those observed in the IMF WEO dataset. The complete BTDE-Net model maintains the best performance, with MAE and RMSE at 1.45 and 2.1, respectively, while the model's performance declines when any component is removed. Notably, removing the Bayesian Neural Network results in the most substantial performance degradation (MAE increases to 1.8, R^2 drops to 0.87), confirming the importance of this component in capturing data complexity. Overall, these ablation study results indicate that each component of the BTDE-Net model contributes significantly to enhancing its predictive accuracy and adaptability. The Bayesian Neural Network and Transformer modules play critical roles in capturing complex patterns and uncertainties in time series data, while the Differential Evolution algorithm provides additional optimization benefits, albeit with a relatively smaller impact.

5.3 Performance Evaluation of BTDE-Net on Macroeconomic Indicators

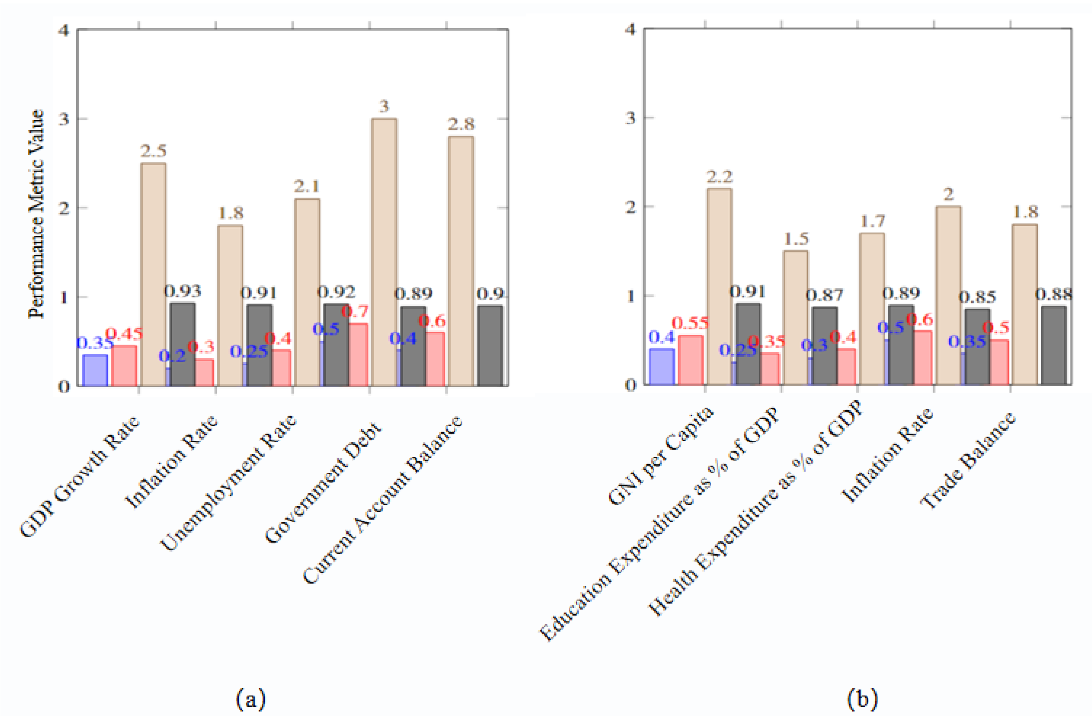

Figure 4. Performance of the BTDE-Net model across various economic indicators from (a) the IMF World Economic Outlook (WEO) dataset and (b) the World Bank Open Data dataset.

Figure 4 presents the performance metrics of the BTDE-Net model on various economic indicators from the IMF WEO and World Bank Open Data datasets. In the IMF WEO dataset, the BTDE-Net model demonstrates high predictive accuracy for GDP per capita growth, inflation rate, and unemployment rate, with a Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) of 0.35 and 0.45, respectively, for GDP per capita growth. These values are significantly lower than those for other economic indicators, indicating the model's effectiveness in capturing key macroeconomic trends. Additionally, the model achieves R^2 values of 0.93 for inflation rate and 0.91

for unemployment rate, suggesting a strong capability to accurately reflect these economic trends. However, the MAE for government debt and current account balance is relatively higher, at 0.5 and 0.4, respectively, reflecting the greater volatility of these variables and the challenges associated with predicting them. Overall, the BTDE-Net model exhibits robust predictive capabilities in the IMF WEO dataset, particularly for more stable macroeconomic indicators.In the World Bank Open Data dataset, the BTDE-Net model also shows excellent predictive performance, especially for public policy-related variables such as GNI per capita growth and GDP per capita growth, with MAE values of 0.40 and 0.29, respectively, demonstrating high accuracy. The RMSE values for inflation (consumer prices) and trade are slightly higher, at 0.50 and 0.60, but remain relatively low, indicating stable performance for these variables. Additionally, the R^2 values for all indicators are close to 1, with the R^2 for GNI per capita reaching 0.91, confirming the model's ability to capture variations in these economic indicators.The BTDE-Net model exhibits superior predictive performance across multiple complex economic indicators, particularly demonstrating strong capabilities when handling more stable and well-defined variables. The model also shows good adaptability and robustness in dealing with more volatile variables, affirming its effectiveness and reliability in forecasting digital economic development and providing valuable support for policymakers.

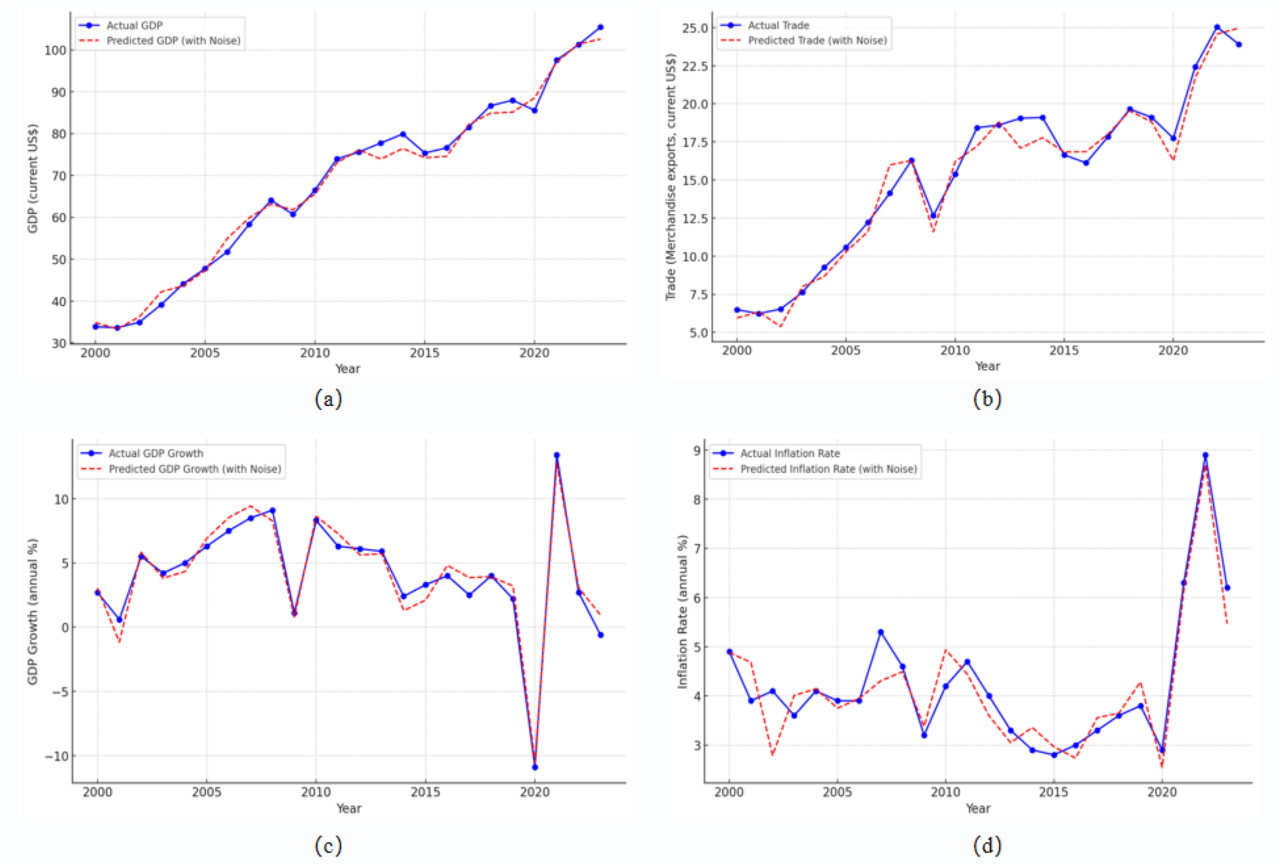

Figure 5. Time series predictions of the BTDE-Net model for various economic indicators from 2000 to 2023, including (a) GDP (current US\$), (b) Trade (merchandise exports, current US\$), (c) GDP growth rate (annual\%), and (d) Inflation rate (annual\%).

Figure 5 illustrates the time series predictions of the BTDE-Net model for several economic indicators, including GDP, trade, GDP growth rate, and inflation rate, across the period from 2000 to 2023.The model's predictions for GDP in subfigure (a) align closely with the actual values, demonstrating high accuracy in tracking the overall trend of economic growth, despite minor noise-induced deviations. In subfigure (b), the predicted trade values similarly capture the general upward trend and periodic fluctuations, indicating the model's ability to handle dynamic and volatile indicators. Subfigure (c) shows that the model accurately reflects both sharp declines and rebounds in GDP growth rates, such as those seen during the 2020 economic contraction and subsequent recovery in 2021, highlighting its robustness in adapting to rapid economic changes. Finally, subfigure (d) demonstrates the model's effectiveness in predicting inflation rates, with predicted values closely following both long-term trends and short-term fluctuations, showing its capability to account for varying economic conditions.Figure 5 confirms that the BTDE-Net model is well-suited for forecasting a range of economic indicators, from stable measures like GDP to more volatile ones such as GDP growth rate and inflation, offering reliable support for economic analysis and policymaking.

6. Conclusions

This paper presented the BTDE-Net model, a novel integration of Bayesian Neural Networks (BNN) and Transformer architecture, optimized using Differential Evolution (DE). The primary goal was to improve the predictive accuracy and reliability of forecasting key economic indicators in complex and dynamic environments, such as the digital economy. Through experiments conducted on the IMF WEO and World Bank Open Data datasets, the BTDE-Net demonstrated superior performance compared to other state-of-the-art models, achieving lower MAE and RMSE values and higher R^2, especially in the prediction of GDP growth, inflation rate, and unemployment rate. The results highlight the model's ability to effectively capture both long-term dependencies and uncertainty in the data, providing robust and accurate predictions.

The contributions of this research lie in the innovative integration of BNN and Transformer, which allowed for uncertainty quantification and improved temporal data modeling, alongside the DE algorithm that optimized hyperparameters efficiently. These advancements contribute significantly to the field of economic forecasting by offering a more reliable model for predicting complex economic trends. However, the model's reliance on high-quality data makes it sensitive to data noise or missing values, which could affect its accuracy in real-world applications. Additionally, the high computational cost, particularly for large datasets, may limit the model's scalability in real-time applications, requiring further optimization for practical deployment.

Future work will focus on addressing these limitations by exploring data imputation techniques and noise reduction methods to make the model more robust in handling incomplete or noisy datasets. Additionally, optimizing the computational efficiency of BTDE-Net, potentially through model compression or more efficient training algorithms, will help reduce the processing burden, making it suitable for real-time forecasting. Enhancing the model's adaptability to evolving economic conditions through online learning approaches could further improve its responsiveness. Applying the model to other domains that require complex temporal forecasting, such as environmental and social policy, will also be considered as a natural extension of this research, offering broader applications beyond the economic field.

Acknowledgements

This article received no financial or funding support.

Conflicts of Interest

The author confirms that there are no conflicts of interest.

References

[1] Ding, C., Liu, C., Zheng, C. and Li, F. Digital economy, technological innovation and high-quality economic development: based on spatial effect and mediation effect. Sustainability, 2021, 14(1), 216.

[2] Weber, R.H. WTO law and cross-border data flows for digital trade. In: Research Handbook on Digital Trade. Cheltenham: Edward Elgar Publishing, 2023, 73-89.

[3] Pînzaru, F., Zbuchea, A. and Viţelar, A. Digital transformation trends reshaping companies, 635-646.

[4] World Health Organization. Evidence as a catalyst for policy and societal change: towards more equitable, resilient and sustainable global health. Meeting report of the WHO Global Evidence-to-Policy Summit, 15–17 November 2021. Geneva: World Health Organization, 2022.

[5] Masoura, M. and Malefaki, S. Evolution of the Digital Economy and Society Index in the European Union: a socioeconomic perspective. TalTech Journal of European Studies, 2023, 13(2).

[6] Li, Q., Chen, H., Chen, Y., Xiao, T. and Wang, L. Digital economy, financing constraints, and corporate innovation. Pacific-Basin Finance Journal, 2023, 80, 102081.

[7] World Economic Outlook. Divergences. World Economic Outlook, 2023.

[8] Liu, Z., Liu, J. and Osmani, M. Integration of digital economy and circular economy: current status and future directions. Sustainability, 2021, 13(13), 7217.

[9] Niu, Y., Ying, L., Yang, J., Bao, M. and Sivaparthipan, C. Organizational business intelligence and decision making using big data analytics. Information Processing & Management, 2021, 58(6), 102725.

[10] Anwar, S.T. The sharing economy and collaborative consumption: strategic issues and global entrepreneurial opportunities. Journal of International Entrepreneurship, 2023, 21(1), 60-88.

[11] Subramaniam, M. How smart products create connected customers. MIT Sloan Management Review, 2022, 64(1), 33-37.

[12] Ivancic, R. and Ott, S. Machine Economicus–Business Forecast 4.0-methods to predict short-, medium-and long-term futures. Marketing Review St. Gallen, 2020, 37(3), 20-31.

[13] Abbad, M., Magboul, I.H.M. and AlQeisi, K. Determinants and outcomes of e-business adoption among

manufacturing SMEs: insights from a developing country. Journal of Science and Technology Policy Management, 2022, 13(2), 456-484.

[14] Andres, A.R., Otero, A. and Amavilah, V.H. Using deep learning neural networks to predict the knowledge economy index for developing and emerging economies. Expert Systems with Applications, 2021, 184, 115514.

[15] Zohuri, B. and Rahmani, F.M. Artificial intelligence driven resiliency with machine learning and deep learning components. International Journal of Nanotechnology & Nanomedicine, 2019, 4(2), 1-8.

[16] Bousqaoui, H., Slimani, I. and Achchab, S. Comparative analysis of short-term demand predicting models using ARIMA and deep learning. International Journal of Electrical and Computer Engineering, 2021, 11(4), 3319.

[17] Ni, J. and Xu, Y. Forecasting the dynamic correlation of stock indices based on deep learning method. Computational Economics, 2023, 61(1), 35-55.

[18] Lakshminarayanan, S.K. and McCrae, J.P. A comparative study of SVM and LSTM deep learning algorithms for stock market prediction, 446-457.

[19] Nosratabadi, S., Mosavi, A., Duan, P., Ghamisi, P., Filip, F., Band, S.S., Reuter, U., Gama, J. and Gandomi, A.H. Data science in economics: comprehensive review of advanced machine learning and deep learning methods. Mathematics, 2020, 8(10), 1799.

[20] Ozbayoglu, A.M., Gudelek, M.U. and Sezer, O.B. Deep learning for financial applications: a survey. Applied Soft Computing, 2020, 93, 106384.

[21] Helbing, D. Societal, economic, ethical and legal challenges of the digital revolution: from big data to deep learning, artificial intelligence, and manipulative technologies. In: Towards Digital Enlightenment: Essays on the Dark and Light Sides of the Digital Revolution. Cham: Springer, 2018, 47-72.

[22] Khalil, K., Eldash, O., Kumar, A. and Bayoumi, M. Economic LSTM approach for recurrent neural networks. IEEE Transactions on Circuits and Systems II: Express Briefs, 2019, 66(11), 1885-1889.

[23] Wang, S., Wang, Q. and Zhao, J. Deep neural networks for choice analysis: extracting complete economic information for interpretation. Transportation Research Part C: Emerging Technologies, 2020, 118, 102701.

[24] Park, S. and Yang, J.-S. Interpretable deep learning LSTM model for intelligent economic decision-making. Knowledge-Based Systems, 2022, 248, 108907.

[25] Bhuiyan, M.A., Dinçer, H., Yüksel, S., Mikhaylov, A., Danish, M.S.S., Pinter, G., Uyeh, D.D. and Stepanova, D. Economic indicators and bioenergy supply in developed economies: QROF-DEMATEL and random forest models. Energy Reports, 2022, 8, 561-570.

[26] Smith, M. and Alvarez, F. Predicting firm-level bankruptcy in the Spanish economy using extreme gradient boosting. Computational Economics, 2022, 59(1), 263-295.

[27] Buckmann, M. and Joseph, A. An interpretable machine learning workflow, 2022.

[28] Vinuesa, R. and Sirmacek, B. Interpretable deep-learning models to help achieve the Sustainable Development Goals. Nature Machine Intelligence, 2021, 3(11), 926-926.

[29] Liu, W., Suzuki, Y. and Du, S. Forecasting the stock price of listed innovative SMEs using machine learning methods based on Bayesian optimization: evidence from China. Computational Economics, 2024, 63(5), 2035-2068.

[30] Oloyede, A.A., Faruk, N., Noma, N., Tebepah, E. and Nwaulune, A.K. Measuring the impact of the digital economy in developing countries: a systematic review and meta-analysis. Heliyon, 2023, 9(7).

[31] Kurz, H.D. On machine ages: causes, forms and effects of technological change. In: The Routledge Handbook of Smart Technologies. London: Routledge, 2022, 56-76.

[32] Brynjolfsson, E., Rock, D. and Syverson, C. Artificial intelligence and the modern productivity paradox: a clash of expectations and statistics. Cambridge, MA: National Bureau of Economic Research, 2017.

[33] Agrawal, A., Gans, J. and Goldfarb, A. Prediction machines, updated and expanded: the simple economics of artificial intelligence. Boston, MA: Harvard Business Press, 2022.

[34] Adesina, A.A., Iyelolu, T.V. and Paul, P.O. Leveraging predictive analytics for strategic decision-making: enhancing business performance through data-driven insights. World Journal of Advanced Research and Reviews, 2024, 22(3), 1927-1934.

[35] Urbinati, A., Bogers, M., Chiesa, V. and Frattini, F. Creating and capturing value from Big Data: a multiple-case study analysis of provider companies. Technovation, 2019, 84, 21-36.

[36] Spiliotis, E., Makridakis, S., Semenoglou, A.-A. and Assimakopoulos, V. Comparison of statistical and machine learning methods for daily SKU demand forecasting. Operational Research, 2022, 22(3), 3037-3061.

[37] Kenney, M., Rouvinen, P., Seppälä, T. and Zysman, J. Platforms and industrial change. Industry and Innovation, 2019, 26(8), 871-879.

[38] Guo, B., Liu, Y., Liu, S., Yu, Z. and Zhou, X. CrowdHMT: crowd intelligence with the deep fusion of human, machine, and IoT. IEEE Internet of Things Journal, 2022, 9(24), 24822-24842.

[39] Ernst, E., Merola, R. and Samaan, D. Economics of artificial intelligence: implications for the future of work. IZA Journal of Labor Policy, 2019, 9(1), 1-35.

[40] Lee, I. and Shin, Y.J. Machine learning for enterprises: applications, algorithm selection, and challenges. Business Horizons, 2020, 63(2), 157-170.

[41] García, D. and Kristjanpoller, W. An adaptive forecasting approach for copper price volatility through hybrid and non-hybrid models. Applied Soft Computing, 2019, 74, 466-478.

[42] Zheng, Y., Xu, Z. and Xiao, A. Deep learning in economics: a systematic and critical review. Artificial Intelligence Review, 2023, 56(9), 9497-9539.

[43] Storm, H., Baylis, K. and Heckelei, T. Machine learning in agricultural and applied economics. European Review of Agricultural Economics, 2020, 47(3), 849-892.

[44] Nuccio, M. and Guerzoni, M. Big data: hell or heaven? Digital platforms and market power in the data-driven economy. Competition & Change, 2019, 23(3), 312-328.

[45] Sarker, I.H. Data science and analytics: an overview from data-driven smart computing, decision-making and applications perspective. SN Computer Science, 2021, 2(5), 377.

[46] Zakhidov, G. Economic indicators: tools for analyzing market trends and predicting future performance. International Multidisciplinary Journal of Universal Scientific Prospectives, 2024, 2(3), 23-29.

[47] Chanias, S., Myers, M.D. and Hess, T. Digital transformation strategy making in pre-digital organizations: the case of a financial services provider. The Journal of Strategic Information Systems, 2019, 28(1), 17-33.

[48] Brunetti, F., Matt, D.T., Bonfanti, A., De Longhi, A., Pedrini, G. and Orzes, G. Digital transformation challenges: strategies emerging from a multi-stakeholder approach. The TQM Journal, 2020, 32(4), 697-724.

[49] Büyükşahin, Ü.Ç. and Ertekin, Ş. Improving forecasting accuracy of time series data using a new ARIMA-ANN hybrid method and empirical mode decomposition. Neurocomputing, 2019, 361, 151-163.

[50] Huang, F., Lin, M. and Khattak, S.I. From uncertainty to sustainable decision-making: a novel MIDAS–AM–DeepAR-based prediction model for e-commerce industry development. Sustainability, 2024, 16(14), 6029.

[51] Wang, X., Li, C., Yi, C., Xu, X., Wang, J. and Zhang, Y. EcoForecast: an interpretable data-driven approach for

short-term macroeconomic forecasting using N-BEATS neural network. Engineering Applications of Artificial Intelligence, 2022, 114, 105072.

[52] Han, Y., Tian, Y., Yu, L. and Gao, Y. Economic system forecasting based on temporal fusion transformers: multi-dimensional evaluation and cross-model comparative analysis. Neurocomputing, 2023, 552, 126500.

[53] Redd, A., Khin, K. and Marini, A. Fast ES-RNN: a GPU implementation of the ES-RNN algorithm. arXiv preprint arXiv:1907.03329, 2019.

[54] Sambiani, K., Lare, Y., Zanguina, A. and Narra, S. Use of socio-economic, climatic, and land use land cover patterns in solid waste forecasting with integrated gradient LSTNet based model in Lomé, Togo. Applied Artificial Intelligence, 2024, 38(1), 2387504.