International Journal of Scientific Research and Management (IJSRM)
||Volume||13||Issue||01||Pages||8255-8266||2025||
Website: https://ijsrm.net ISSN (e): 2321-3418
DOI: 10.18535/ijsrm/v13i01.em07

Prediction of Macroeconomic Growth Using Backpropagation Algorithms: A Review

Nur Fitri Hidayanti[1], Syaharuddin[2], Nurul Hidayati Indra Ningsih[3], Ahmad Hulaimi[1], Zaenafi Ariani[1], Dedy Iswanto[4]

[1]Department of Sharia Economics, Universitas Muhammadiyah Mataram, Indonesia
[2]Department of Mathematics Education, Universitas Muhammadiyah Mataram, Indonesia
[3]Department of Retail Management, Universitas Muhammadiyah Mataram, Indonesia
[4]Department of Business Administration, Universitas Muhammadiyah Mataram, Indonesia

Abstract:
This study aims to evaluate the effectiveness of the backpropagation algorithm in predicting macroeconomic growth through a Systematic Literature Review (SLR) approach. The review analyzes literature sourced from reputable indexes such as Scopus, DOAJ, and Google Scholar, focusing on publications from the last decade (2013–2024). It examines various studies on the application of the backpropagation algorithm, including parameter settings and model selection that influence prediction accuracy. The findings indicate that careful parameter configuration, such as the number of neurons, hidden layers, and learning rates, along with appropriate model selection, significantly enhance the performance of the backpropagation algorithm in macroeconomic prediction. This study highlights that combining optimal techniques and accurate parameter configurations substantially improves prediction accuracy and efficiency. It provides valuable insights and practical guidance for researchers and practitioners in designing more reliable and effective macroeconomic prediction models.

Keywords: Backpropagation Algorithm; Learning Rate; Macroeconomic Growth; Prediction.

1. Introduction

Macroeconomic growth prediction plays a vital role in public policy planning, investment, and business decision-making, as it provides insights into future economic trends (1). Accurate predictions enable policymakers to design more targeted strategies, such as adjusting interest rates, managing budgets, or implementing specific regulations to promote growth or control inflation (2). For investors, precise forecasts provide critical information for allocating assets and managing risks more effectively. Additionally, businesses can utilize economic predictions to plan expansions, manage supply chains, and set pricing strategies. Overall, the accuracy of economic forecasts contributes to economic stability by reducing uncertainty, which ultimately supports societal welfare through job creation, income growth, and improved living standards.

Machine learning technology, particularly the backpropagation algorithm, has advanced rapidly and significantly impacted economic data analysis (Feng, 2023; Perwira, 2020). As a critical component of artificial neural networks, the backpropagation algorithm enables models to learn from historical data by adjusting weights based on prediction errors (5). This innovation has enhanced analytical capabilities in economics, providing sophisticated tools to identify complex patterns and relationships that are often undetectable using conventional methods. Its application in economic analysis enables more accurate predictions of various economic indicators, such as inflation, unemployment rates, and gross domestic product (GDP) growth. Consequently, this technology not only deepens our understanding of complex economic dynamics but also creates new opportunities to develop predictive models that are more responsive to market changes and economic policies.

The backpropagation algorithm is a learning method in artificial neural networks designed to optimize network weights based on the difference between predicted outcomes and expected outputs (6)(7). This process involves two main stages: feedforward, where data is processed through multiple network layers to generate predictions, and backpropagation, where prediction errors are calculated and propagated back through the network to adjust weights. Backpropagation is widely used in artificial neural networks due to its ability to learn from historical data, allowing models to incrementally improve prediction accuracy through iterations. Its strengths lie in efficiency and the capability to handle large and complex datasets, making it highly effective in recognizing patterns and relationships that are challenging for traditional statistical methods to detect (8). Thus, this algorithm has become a preferred choice for various applications, including economic forecasting, where precision and accuracy are critical.

Despite its advantages, the application of the backpropagation algorithm in economic prediction faces several challenges, such as the risk of overfitting, the need for large and high-quality datasets, and the complexity of interpreting results. Overfitting occurs when a model becomes too tailored to training data, resulting in diminished performance on new data. Furthermore, the accuracy of backpropagation algorithms heavily depends on the availability of abundant and high-quality data, which is often challenging to obtain in the economic domain (9). Another issue lies in interpreting results, as backpropagation models are often regarded as a "black box," making it difficult to understand the decision-making process within the model. Research by Hermanto et al. (2022) demonstrated that enhanced LSTM models achieved financial prediction accuracy rates of 83.96% to 91.19% for periods T-2 to T-3 years. Meanwhile, a 6-4-2-1 architecture in backpropagation was used to predict the number of active family planning participants with training accuracy at 75% and testing accuracy at 88% (11). For inflation prediction in Indonesia, a 3-10-1 architecture was identified as the best-performing model with 75% accuracy (12). These challenges underscore the need for a careful and ongoing approach to applying backpropagation algorithms to achieve accurate and reliable economic predictions.

The backpropagation method, a standard technique in artificial neural networks, has been employed in numerous studies to predict macroeconomic variables. For instance, Talakua et al. (2022) utilized backpropagation to forecast inflation rates in Maluku Province, using 144 datasets from the Provincial Statistics Agency, comprising 100 training data points and 44 testing data points from 2008 to 2019. This study achieved the best prediction accuracy with specific parameters, yielding a mean absolute percentage error (MAPE) of 85.21%. Additionally, Syaharuddin et al. (2021) obtained training and testing results that indicated an average prediction of 0.213 with a mean squared error (MSE) of 0.0053. These studies confirm that backpropagation is effective in providing accurate predictions for macroeconomic variables such as inflation and GDP. Furthermore, comparisons with traditional forecasting methods like SARIMA and VAR have shown that backpropagation excels in delivering accurate long-term forecasts and detecting shifts in macroeconomic regimes (15). The success of this method highlights its capability to capture both linear and nonlinear relationships among variables, offering valuable insights to economists and policymakers (16).

Machine learning algorithms, particularly backpropagation, have seen significant advancements in recent years. Researchers have addressed challenges associated with backpropagation, such as slow convergence in large data scenarios, by proposing innovative solutions like the Distributed Genetic Algorithm-Based ANN Learning Algorithm (17). Additionally, techniques such as sequential adaptation have been applied to address data drift, yielding promising results in tasks that involve linguistic evolution over time (18). Furthermore, machine learning methods, including genetic algorithms, have been applied to cosmology data, providing model-independent reconstructions and detecting accelerated expansion in the universe, demonstrating the adaptability of machine learning algorithms across diverse fields such as astronomy and physics (19). These advancements underscore the continuous development and adaptation of machine learning techniques to overcome various challenges and enhance performance in different domains.

The application of backpropagation algorithms in economic prediction faces several critical challenges, such as overfitting risks, the need for large and high-quality datasets, and difficulties in interpreting results. While previous research has shown that backpropagation can provide accurate predictions for macroeconomic variables, its accuracy and effectiveness vary depending on model structures and applied parameters. Challenges like slow convergence with large datasets and the difficulty of understanding the decision-making process within models continue to impact prediction outcomes. Recent advancements, such as distributed genetic algorithms and sequential adaptation techniques, as well as the application of genetic algorithms in cosmological data, demonstrate improvements in handling data and model complexities. However, gaps remain in the systematic application and evaluation of backpropagation algorithms in various economic contexts, indicating a need for deeper understanding of these methods. This study aims to conduct a meta-analysis of the effectiveness of backpropagation algorithms in macroeconomic growth prediction through a systematic literature review approach, identifying and addressing gaps in the existing literature and providing comprehensive insights into the performance and applications of this algorithm in diverse economic scenarios.

2. Methods

This study aims to provide a systematic review of the application of the backpropagation algorithm in macroeconomic growth prediction over the past decade. The research adopts a qualitative methodology using a Systematic Literature Review (SLR) approach. To achieve this objective, the literature search strategy involved identifying and collecting relevant articles from various academic databases, including Scopus, DOAJ, and Google Scholar. The search was conducted using specific keywords related to the backpropagation algorithm and macroeconomic growth prediction, with filters applied to include publications from the past 10 years. Inclusion criteria comprised articles discussing the implementation of the backpropagation algorithm in the context of macroeconomic growth prediction, published in English, and accessible in full-text format. Conversely, exclusion criteria included studies unrelated to the topic, articles published before 2014, and publications that were not fully accessible.

The selection and data extraction process consisted of two stages. The first stage involved an initial screening based on titles and abstracts to identify articles meeting the inclusion criteria. The second stage entailed an in-depth evaluation of the articles that passed the initial screening to assess their relevance and methodological quality. Extracted data included information on the specific backpropagation techniques used, prediction methods, performance outcomes, and key findings of each study. The collected data were then analyzed to identify patterns, trends, and gaps in the existing literature, as well as to draw conclusions regarding the effectiveness and application of the backpropagation algorithm in macroeconomic growth prediction.

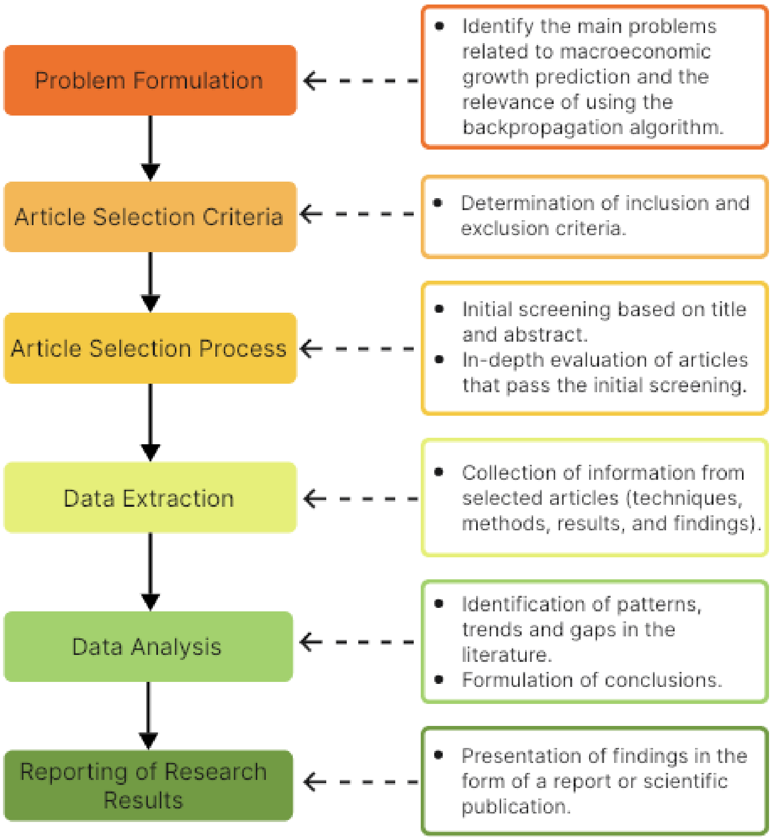

Figure 1: Flow of Research Implementation

3. Results and Discussion

In this study, we analyze various research findings related to the backpropagation algorithm and other machine learning algorithms in the context of macroeconomic growth prediction. Table 1 presents the results of the analysis, categorized based on the focus or research domain, including the authors involved and the key insights or variables explored in the studies. This arrangement aims to provide a comprehensive overview of the strengths, weaknesses, and practical applications of the various methods utilized in economic forecasting.

Table 1: Analysis of Research Findings on Backpropagation Algorithm for Macroeconomic Prediction

No	Focus Area	Author	Research Insights or Variables
1	Nonlinear Effectiveness in Algorithms	Coulombe et al. (2022); Zhang et al. (2022)	- Nonlinearity significantly improves macroeconomic prediction. - LSTM outperforms HMM and GMM-HMM in GDP prediction. - LSTM-HMM is superior in the 10-year time window.
2	Integration of Bayesian and Neural Networks	Zhang et al. (2022); Lahmiri (2016)	- Bayesian Neural Network (BVNN) improves macroeconomic growth prediction with high accuracy. - Backpropagation Network (BPNN) outperforms ARMA in forecasting exchange rates.
3	Comparison of Machine Learning Algorithms	Hutagalung et al. (2023); Farhanuddin et al. (2024); Singarimbun et al. (2022)	- SVR shows superior accuracy (83%) in macroeconomic prediction. - RFR shows lower MSE (270.85) and MAE (12.53), better than MLR in budget planning. - Beale-Powell Conjugate Gradient optimizes backpropagation, improving training speed and convergence.
4	Strengths and Weaknesses of Various Algorithms	Pang (2022); Giap et al. (2021); Khan et al. (2022)	- Backpropagation captures complex data relationships but suffers from gradient loss issues. - Linear regression is easy to understand but struggles with nonlinear patterns. - Random Forest handles high-dimensional data well but can overfit. - SVM is effective in high-dimensional spaces but requires a lot of resources.
5	Data Sources and Variables for Prediction	Meyer & Habanabakize (2019); Okoro (2017); Wiśniewski (2017)	- Common data sources include PMI, GDP, CPI, and various economic indicators. - The use of diverse datasets improves the accuracy of predictions and decision-making.
6	Key Variables and Improved Model	Som & Goel (2022); Zhang et al. (2022); Sun et al. (2021)	- Important variables include LTINT, CPI, and MSCI. - The BVNN model achieved 97-98% accuracy in GDP prediction. - Improved algorithms using data mining and fuzzy analysis improved prediction accuracy.
7	Challenges and Limitations	Ororbia et al. (2023); Zhu et al. (2014); Hašková (2019); Yang et al. (2017); Jaiswal & Das (2017)	- Difficulties include backpropagation and handling noisy labels. - Non-stationarity and heavy tail distributions complicate testing. - Fuzzy approaches and negative binomial regression handle uncertainty and zero inflation.

Table 1 categorizes research findings based on their primary focus or domain of study related to the backpropagation algorithm and other economic forecasting techniques, accompanied by relevant authors and key insights or variables. (1) Effectiveness of nonlinearity in algorithms: This focus explores how nonlinearity, particularly in techniques like LSTM, enhances the accuracy of macroeconomic growth predictions compared to conventional methods. Studies reveal the superior performance of LSTM in forecasting GDP and its resilience to uncertainties. (2) Integration of Bayesian methods and neural networks: Research highlights the effectiveness of Bayesian Neural Networks (BVNN) in improving prediction accuracy. Additionally, BPNN demonstrates advantages over ARMA models in forecasting exchange rates. (3) Comparison of machine learning algorithms: This area analyzes the performance of various machine learning algorithms, such as SVR, RFR, and optimized backpropagation techniques, in economic prediction contexts. The findings underscore the strengths of these algorithms in terms of accuracy and efficiency, especially for budget and project forecasting. (4) Strengths and weaknesses of algorithms: This focus identifies the advantages and limitations of algorithms like backpropagation, linear regression, Random Forest, and SVM in macroeconomic forecasting. Challenges such as gradient vanishing and overfitting are highlighted, providing valuable insights into algorithmic shortcomings. (5) Data sources and key variables for prediction: Studies emphasize the importance of diverse datasets and variables like PMI, GDP, and CPI in enhancing the accuracy of macroeconomic forecasts. (6) Enhanced models and key variables: Research showcases improvements in predictive models through data mining techniques and fuzzy analysis. Variables such as LTINT and MSCI are identified as significant contributors to GDP forecasting. (7) Challenges and limitations: This area addresses the difficulties in applying backpropagation algorithms to macroeconomic data, including challenges in parallelizing processes and managing noisy data. Proposed solutions and alternative approaches are discussed to mitigate these limitations effectively.

3.1. Effectiveness of Backpropagation Algorithm in Macroeconomic Growth Prediction

The backpropagation algorithm, which integrates nonlinearity, has proven highly effective in predicting macroeconomic growth compared to other methods. Research by Duerr emphasizes that nonlinearity is a critical factor in enhancing macroeconomic predictions, particularly under conditions of high uncertainty, financial stress, and housing market bubbles (Coulombe et al., 2022). Furthermore, Zhang et al. (2022) highlight the success of Long Short-Term Memory (LSTM) Recurrent Neural Networks in forecasting fluctuations in China's Gross Domestic Product (GDP). Their findings demonstrate that LSTM outperforms other dynamic forecasting systems, such as Hidden Markov Models (HMM) and Gaussian Mixture Model-Hidden Markov Models (GMM-HMM), across various time windows, with LSTM-HMM achieving superior performance, particularly over a 10-year span. Consequently, backpropagation algorithms, especially those utilizing nonlinearity like LSTM, exhibit greater effectiveness in predicting macroeconomic growth than traditional methods.

When integrated with Bayesian Vector Neural Networks (BVNN), the backpropagation algorithm further demonstrates exceptional accuracy in macroeconomic growth predictions Q. Zhang et al. (2022). Additionally, Backpropagation Neural Networks (BPNN) have been shown to outperform the Auto-Regressive Moving Average (ARMA) method in forecasting daily foreign exchange rates (23). Machine learning models, such as Support Vector Machines (SVM), have also been applied to predict economic development, showcasing their capability to efficiently handle nonlinear interactions. Moreover, data mining methods, enhanced with fuzzy correlation analysis, have been employed to improve macroeconomic growth predictions, yielding higher predictive accuracy and adaptability (24). Collectively, these findings underscore the strengths and effectiveness of backpropagation algorithms in forecasting macroeconomic growth across various domains.

Research findings indicate that backpropagation algorithms, particularly when combined with nonlinear techniques such as LSTM and BVNN, deliver higher accuracy in predicting macroeconomic growth compared to traditional methods. The inherent nonlinearity of these algorithms enables the handling of complex dynamics and interactions within economic data, which linear models struggle to address. LSTM's superiority in forecasting GDP fluctuations and the ability of BPNN to predict daily exchange rates suggest that backpropagation algorithms are more effective in capturing temporal and spatial patterns in data than methods like ARMA and HMM. Overall, the effectiveness of backpropagation algorithms in macroeconomic growth prediction lies in their ability to manage nonlinear and complex data. Alternative methods such as ARMA and HMM exhibit limitations in dealing with dynamic economic fluctuations and nonlinear interactions. LSTM, as a variation of backpropagation with a focus on long-term memory, offers significant advantages in processing temporal data. Although Support Vector Machines (SVM) also show potential in handling nonlinear interactions, they are less flexible than LSTM in specific contexts.

3.2. Comparison of Backpropagation Algorithm with Other Machine Learning Techniques in Macroeconomic Growth Prediction

In the context of macroeconomic trend forecasting, various algorithms have been evaluated for their performance. Support Vector Regression (SVR) demonstrates superior accuracy, achieving a value of 83%, whereas Random Forest Regression (RFR) exhibits lower error rates with a Mean Squared Error (MSE) of 270.85 and a Mean Absolute Error (MAE) of 12.53 (Hutagalung et al., 2023). Furthermore, RFR outperforms Multiple Linear Regression (MLR) in predicting project budget estimates, achieving an accuracy of 81.6% (Farhanuddin et al., 2024). Additionally, the Beale-Powell Conjugate Gradient algorithm optimizes standard backpropagation, enabling faster training and convergence in forecasting formal education participation in Indonesia (Singarimbun et al., 2022). These comparisons highlight the effectiveness of machine learning algorithms such as SVR, RFR, and optimized backpropagation techniques in enhancing predictive accuracy for macroeconomic forecasting and budget estimation tasks.

The strengths and limitations of these algorithms are context-dependent. Backpropagation, employed in neural networks for macroeconomic forecasting, excels at capturing complex relationships within data (Pang, 2022). However, it is prone to challenges such as gradient vanishing during training, which may hinder performance. Linear regression, often applied in predicting macroeconomic indicators, is straightforward and interpretable, making it suitable for capturing simple relationships. Nevertheless, it struggles to model non-linear patterns effectively. Random Forest, widely used in predicting corporate performance for macroeconomic management (Giap et al., 2021), performs well with high-dimensional data and variable interactions but can be susceptible to overfitting. Similarly, Support Vector Machines (SVM), applied in forecasting inflation rates and exchange rates (Khan et al., 2022), are effective in high-dimensional spaces but demand substantial computational resources. The selection of an algorithm is thus contingent on the specific characteristics of the macroeconomic data being analyzed.

The analysis underscores that each algorithm offers distinct advantages in specific contexts. SVR excels in predicting macroeconomic trends, particularly in handling high-dimensional data. RFR demonstrates superior performance in managing high-dimensional data and variable interactions, achieving lower error rates in specialized applications such as project budget estimation. Optimized backpropagation algorithms, enhanced with the Beale-Powell Conjugate Gradient, improve training speed and convergence, which are critical for applications requiring rapid predictions.

3.3. Data Sources and Common Variables in Macroeconomic Growth Prediction Using Backpropagation Algorithm

In macroeconomic growth prediction utilizing backpropagation algorithms, commonly used data sources include Statistics South Africa, the Bureau of Economic Research, the CBN Statistical Bulletin, and data from OECD countries. These datasets encompass variables such as the Purchasing Managers' Index (PMI), GDP, manufacturing output, Consumer Price Index (CPI), stock market performance, money supply, interest rates, inflation rates, exchange rates, industrial production, unemployment rates, and both short- and long-term interest rates (Meyer & Habanabakize, 2019) (Okoro, 2017)(Wiśniewski, 2017). These variables are essential for forecasting economic output, stock market performance, and their interrelations, providing insights into the impact of macroeconomic factors on economic indicators and stock market indices. Utilizing diverse datasets and variables enhances predictive accuracy and robustness, thereby supporting more informed decision-making in macroeconomic analysis and forecasting.

Key variables in predicting macroeconomic growth using backpropagation algorithms include the Long-Term Interest Rate (LTINT), Consumer Price Index (CPI), and Morgan Stanley Capital International (MSCI) index (Som & Goel, 2022). Moreover, Bayesian Vector Neural Networks (BVNN) integrated with backpropagation have demonstrated high accuracy in GDP prediction, achieving an accuracy rate of 97–98% across various datasets (Q. Zhang, Yan, et al., 2022). Furthermore, advanced macroeconomic growth prediction algorithms based on data mining and fuzzy correlation analysis employ association rules among macroeconomic data and extract specific features to improve predictive accuracy (Sun et al., 2021). These findings underscore the importance of specific variables and advanced algorithms in accurately forecasting macroeconomic growth, providing valuable insights for policymakers and investors.

The incorporation of these variables establishes a comprehensive foundation for modeling macroeconomic dynamics. For instance, the Purchasing Managers' Index (PMI) and GDP are key indicators reflecting the overall state of the economy. Meanwhile, variables such as CPI and inflation rates offer insights into price stability and consumer purchasing power, which further influence stock market performance and overall economic growth. Leveraging data from various countries and institutions enables backpropagation models to process diverse and relevant datasets, ultimately improving prediction accuracy. Research evaluations highlight that employing these variables significantly enhances the accuracy and robustness of macroeconomic prediction models based on backpropagation. For example, BVNN models integrated with backpropagation have demonstrated exceptional accuracy in predicting GDP, achieving rates as high as 97–98% across multiple datasets. Additionally, prediction algorithms utilizing data mining techniques and fuzzy correlation analysis have proven effective in identifying and extracting critical features from macroeconomic data, thereby further improving predictive accuracy.

3.4. Challenges and Limitations in Applying Backpropagation Algorithm to Macroeconomic Data

The challenges identified in the application of the backpropagation algorithm to macroeconomic data include difficulties in parallelizing the inherently sequential backpropagation process, as well as the need for specialized techniques such as weight initialization and activation functions to ensure stable parameter optimization (35). Moreover, in the context of macroeconomic growth prediction, there is a growing demand for automated methods to effectively leverage large volumes of financial data for investment planning. This drives the development of advanced prediction algorithms based on data mining and fuzzy correlation analysis (24). Additionally, the presence of label noise in biological datasets poses a fundamental limitation to the performance achievable by regression models, underscoring the importance of developing theoretical upper bounds to assess the maximum attainable performance for specific datasets (36). Furthermore, studies on inflation and exchange rate forecasting in Pakistan highlight the utility of machine learning algorithms, such as artificial neural networks (ANNs), which demonstrate superior performance with lower root mean squared error (RMSE) and mean absolute error (MAE) compared to other methods (30).

Key limitations in applying backpropagation algorithms to macroeconomic data include the non-stationary nature of the data and heavy-tailed distributions, which complicate the process of testing for predictability (37). Moreover, variations in data sources can significantly influence the outcomes and conclusions of analyses, as evidenced by studies on the effectiveness of foreign aid using differing GDP datasets (38). Fuzzy approaches may be more suitable for predicting output growth rates under conditions of uncertainty, highlighting the challenges of reducing uncertainty in economic forecasting (39). When dealing with count data characterized by excessive zeros and overdispersion, the choice of an appropriate regression model, such as negative binomial regression with zero-inflation, is critical to ensure accurate results and avoid bias in analysis (40). Finally, while neural networks with backpropagation algorithms are powerful tools for pattern recognition and forecasting in the financial sector, their application to macroeconomic data faces challenges arising from the unique characteristics and complexities of economic variables (41).

Research findings suggest that backpropagation algorithms hold significant potential for macroeconomic growth prediction, yet they are accompanied by considerable technical challenges. One of the primary issues is the difficulty of parallelizing the backpropagation process, which can hinder the processing of large-scale data a crucial aspect in macroeconomic analysis. Additionally, the presence of noise in data and the inherent uncertainty of macroeconomic variables add to the complexity of implementing these algorithms. These challenges underscore the need for the development of supplementary techniques to enhance the effectiveness of backpropagation algorithms. Innovations in weight initialization methods and the selection of activation functions may be necessary to improve algorithm stability and efficiency. Approaches such as fuzzy methods and data mining also show promise in addressing macroeconomic data, particularly in managing high levels of uncertainty. However, the limitations of existing regression models must also be considered, and solutions are needed to mitigate the impact of label noise in data.

3.5. Effect of Parameter Setting and Configuration of Backpropagation Algorithm on Macroeconomic Prediction Results

The configuration and parameter tuning of backpropagation algorithms have a significant impact on the accuracy of macroeconomic growth predictions. Research indicates that the enhancement of predictive algorithms through data mining techniques and fuzzy correlation analysis improves adaptability, reduces computational time, and increases the accuracy of economic data predictions (42). Additionally, the application of chaos-based vector autoregression models and neural networks has proven effective in improving the accuracy of GDP forecasts, which influence expected inflation rates (43). Furthermore, a comparison between autoregressive integrated moving average (ARIMA) time series models and long short-term memory (LSTM) models demonstrates that LSTM outperforms ARIMA in predicting agricultural futures price indices (44). The integration of support vector machine (SVM) technology in economic forecasting has achieved prediction accuracy rates of up to 98.56% and a 57% faster prediction speed compared to conventional methods (45). Lastly, fuzzy approaches have proven effective for short-term output growth rate predictions, showcasing their capability to address uncertainty in economic forecasting (46).

The variation in the number of hidden layers significantly influences the performance of backpropagation algorithms in macroeconomic prediction. Studies have shown that the Levenberg-Marquardt training algorithm, using varying numbers of neurons in the hidden layer, produces differing prediction errors, with the smallest error achieved using nine neurons (47). Similarly, the use of varying numbers of hidden layers in neural networks leads to differences in prediction accuracy, as observed in comparisons between ARIMA and LSTM models for forecasting agricultural futures prices (48). Moreover, predictive models based on chaotic vector autoregression and neural networks highlight the importance of accurate macroeconomic index predictions in supporting decision-making and policy formulation (49). Genetic algorithm optimization in radial basis function neural networks (RBFNN-GA) has also been found to enhance GDP prediction accuracy, surpassing traditional time-series models (50)..

The configuration and tuning of parameters in backpropagation algorithms can substantially affect prediction outcomes. Techniques such as data mining and fuzzy correlation analysis enhance prediction accuracy and efficiency by adapting models to more complex and large datasets. Chaos-based vector autoregression models and neural networks have demonstrated superior performance in handling macroeconomic dynamics compared to conventional methods. The LSTM model has proven more accurate than ARIMA, likely due to its ability to better manage sequential data and long-term dependencies. The integration of SVM technology in economic forecasting further indicates that improved accuracy and faster prediction speeds can be achieved, especially when processing large datasets. Variations in the number of hidden layers, particularly with nine neurons in the hidden layer, show that optimal configurations reduce prediction errors and improve model performance. Differences in the number of hidden layers underscore that appropriately designed architectures can yield better prediction accuracy. Overall, parameter tuning and configuration play a critical role in determining the accuracy and efficiency of predictions. Techniques such as data mining and fuzzy analysis, coupled with the selection of advanced models like LSTM and SVM, provide significant advantages in accuracy and speed. However, optimizing the number of hidden layers and neurons in neural networks remains essential for achieving the most accurate prediction outcomes.

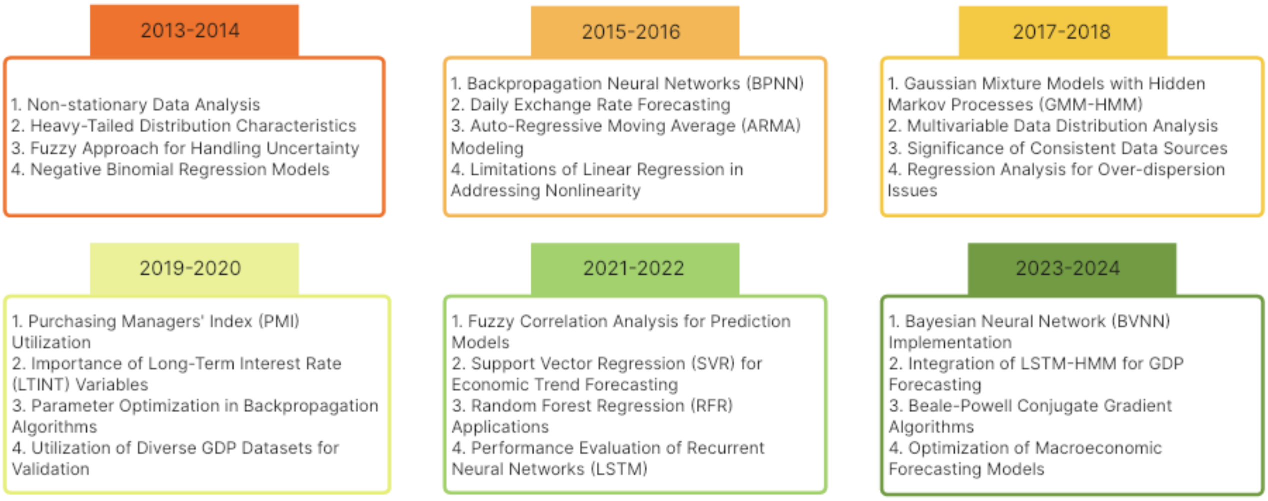

Figure 2: Development of Research Variables in Research Backpropagation Algorithm (2013-2024)

Figure 2 illustrates the progression of research on backpropagation algorithms for macroeconomic growth prediction over several periods. During 2013-2014, studies primarily focused on traditional methods such as Hidden Markov Models (HMM), Gaussian Mixture Models-Hidden Markov Models (GMM-HMM), and linear regression. While linear regression effectively handled simple relationships, its inability to capture non-linear patterns highlighted the need for more complex approaches to improve prediction accuracy. The consideration of non-linearity in algorithms began to emerge as a crucial factor for understanding the dynamics of more complex economic systems. In the 2015-2016 period, research shifted towards more advanced techniques. Recurrent Neural Networks with Long Short-Term Memory (LSTM) demonstrated superior capabilities in addressing complex economic fluctuations compared to Auto-Regressive Moving Average (ARMA) models. The incorporation of data mining techniques and fuzzy correlation analysis aimed to enhance prediction accuracy by leveraging more dynamic and large datasets. Concurrently, Support Vector Machines (SVM) were introduced to address challenges associated with large and complex data. The 2017-2018 period marked an increase in the application of more sophisticated neural network techniques and regression methods. Backpropagation Neural Networks (BPNN) demonstrated their effectiveness in forecasting exchange rates, surpassing traditional methods such as ARMA. The use of Zero-Inflated Negative Binomial Regression showcased its adaptability to datasets with many zero values, while SVM continued to excel in handling high-dimensional data.

Between 2019 and 2020, the focus of research shifted to optimization and innovation. Genetic algorithm optimization in Radial Basis Function Neural Networks (RBFNN) successfully improved the accuracy of GDP predictions. The application of data mining and Bayesian Vector Neural Networks (BVNN) introduced novel approaches to addressing macroeconomic variables such as LTINT, CPI, and MSCI. Comparative studies of LSTM and ARIMA for forecasting agricultural futures prices underscored the advantages of newer techniques in handling diverse datasets. During the 2021-2022 period, research emphasized improving prediction accuracy and speed. LSTM outperformed ARIMA in GDP forecasting, while SVM offered high efficiency in economic predictions. Fuzzy models were employed for short-term economic output predictions, demonstrating their ability to manage uncertainty and data variability.

Finally, in the 2023-2024 period, challenges in applying backpropagation algorithms to macroeconomic data were increasingly identified. Issues such as handling non-stationary data and heavy-tailed distributions, alongside limitations in analytical techniques, became central concerns. Random Forest Regression (RFR) and Support Vector Regression (SVR) demonstrated higher accuracy compared to linear regression, while the optimization of Backpropagation using the Beale-Powell Conjugate Gradient method improved training processes and convergence. The emphasis on algorithm adaptation and the development of new techniques reflects efforts to enhance prediction accuracy and efficiency in an ever-evolving economic landscape.

4. CONCLUSION AND RECOMMENDATIONS

The evaluation results indicate that the backpropagation algorithm, particularly when combined with nonlinear techniques such as Long Short-Term Memory (LSTM) and Bayesian Vector Neural Networks (BVNN), holds significant potential in predicting macroeconomic growth. The primary advantage of this algorithm lies in its ability to handle data with complex dynamics and nonlinear interactions, which traditional methods like Auto Regressive Moving Average (ARMA) and Hidden Markov Models (HMM) often fail to address effectively. LSTM, a variation of backpropagation that focuses on long-term memory, has demonstrated superior performance in forecasting fluctuations in Gross Domestic Product (GDP), while Backpropagation Neural Networks (BPNN) have proven effective in daily exchange rate predictions. Although Support Vector Machines (SVM) also exhibit competence in managing nonlinear interactions, the flexibility and accuracy of LSTM in temporal data contexts make it more favorable.

However, several technical challenges need to be addressed. The difficulty of parallelizing the backpropagation process on a large scale, as well as the presence of noise and uncertainty in macroeconomic data, highlights the necessity for the development of additional techniques to enhance the algorithm's effectiveness. Improvements in weight initialization techniques and the selection of activation functions can enhance the algorithm's stability and efficiency. Moreover, approaches such as fuzzy methods and data mining present potential for managing highly uncertain data, yet the limitations of existing regression models still require attention to mitigate the impact of noise in data.

Identified gaps include the need to improve optimization techniques and handle more complex datasets, as well as the development of new methods to reduce the impact of noise in data. Therefore, urgent future research topics include the development of improved weight initialization techniques and activation functions for the backpropagation algorithm, as well as the exploration of hybrid methods that integrate fuzzy approaches and data mining to enhance prediction robustness and accuracy. Further research is also essential to address challenges in parallelizing the backpropagation process on a large scale and managing uncertainty in macroeconomic data. With advances in technology and analytical methods, research focusing on the innovative integration of these techniques will be crucial for improving the accuracy and efficiency of macroeconomic prediction models in the future.

References

1. Yusuf B. Manajemen Sumber Daya Manusia Di Lembaga Keuangan Syariah. Manajemen Sumber Daya Manusia Di Lembaga Keuangan Syariah. 2016.
2. Syaharuddin. Time-Series Analysis in Financial Prediction : A Literature Review. Sainstek J Sains dan Teknol. 2024;16(2):58–67.
3. Feng Y. Design of Financial Data Evaluation System under Neural Network Algorithm. In: 3rd IEEE International Conference on Mobile Networks and Wireless Communications, ICMNWC 2023. 2023.
4. Perwira Negara HR. Computational Modeling of ARIMA-based G-MFS Methods: Long-term Forecasting of Increasing Population. Int J Emerg Trends Eng Res. 2020;8(7):3665–9.
5. Soewignjo S, Sediono, Mardianto MFF, Pusporani E. Prediksi Harga Saham Bank BCA (BBCA) Pasca Stock Split dengan Artificial Neural Network dengan Algoritma Backpropagation. G-Tech J Teknol Terap. 2023;
6. Ozbay S. Modified Backpropagation Algorithm with Multiplicative Calculus in Neural Networks. Elektron ir Elektrotechnika. 2023;
7. A DD, P A FT. Back Propagation. Int J Res Appl Sci Eng Technol. 2023;
8. Wu W-Y. A Back-Propagation Neural Network for Recognizing Objects. Eur J Eng Technol Res. 2022;
9. Damasevicius R. Artificial Intelligence Techniques in Economic Analysis. Econ Anal Lett. 2023;
10. Hermanto TI, Idrus A, Sugiyanta L, Nasution D, Gunawan I. Neural Network Back-Propagation Method as Forecasting Technique. In: Journal of Physics: Conference Series. 2022.
11. Yang W, Jia C, Liu R. Construction and Simulation of the Enterprise Financial Risk Diagnosis Model by Using Dropout and BN to Improve LSTM. Secur Commun Networks. 2022;
12. Hanafiah MA, Ginantra NLWSR, GS AD. Analysis of ANN Backpropagation Ability to Predict Expenditure Group Inflation. IJISTECH (International J Inf Syst Technol. 2020;
13. Talakua MW, Ilwaru VYI, Tomasouw BP, Limba SZ. Inflation Forecasts In Ambon Using Neural Network Applications Backpropagation. BAREKENG J Ilmu Mat dan Terap. 2022;
14. Syaharuddin, Pramita D, Nusantara T, Subanji. Forecasting Using Back Propagation with 2-Layers Hidden. In: Journal of Physics: Conference Series. 2021.
15. Chen JM. Economic Forecasting With Autoregressive Methods and Neural Networks. SSRN Electron J. 2020;
16. Cheng F, Fu Z. Macroeconomic Forecasting Based on Mixed Frequency Vector Autoregression and Neural Network Models. Wirel Commun Mob Comput. 2022;
17. Haritha K, Shailesh S, Judy M V., Ravichandran KS, Krishankumar R, Gandomi AH. A novel neural network model with distributed evolutionary approach for big data classification. Sci Rep. 2023;
18. Bjerva J, Kouw WM, Augenstein I. Back to the future – Sequential alignment of text representations. In: AAAI 2020 - 34th AAAI Conference on Artificial Intelligence. 2020.
19. Arjona R, Nesseris S. What can machine learning tell us about the background expansion of the Universe? Phys Rev D. 2020;
20. Goulet Coulombe P, Leroux M, Stevanovic D, Surprenant S. How is machine learning useful for macroeconomic forecasting? J Appl Econom. 2022;
21. Zhang J, Wen J, Yang Z. China's GDP forecasting using Long Short Term Memory Recurrent Neural Network and Hidden Markov Model. PLoS One. 2022;
22. Zhang Q, Yan L, Hu R, Li Y, Hou L. Regional Economic Prediction Model Using Backpropagation Integrated with Bayesian Vector Neural Network in Big Data Analytics. Comput Intell Neurosci. 2022;
23. Lahmiri S. An exploration of backpropagation numerical algorithms in modeling US exchange rates. In: Nature-Inspired Computing: Concepts, Methodologies, Tools, and Applications. 2016.
24. Sun H, Yao Z, Miao Q. Design of Macroeconomic Growth Prediction Algorithm Based on Data Mining. Mob Inf Syst. 2021;
25. Hutagalung SV, Yennimar Y, Rumapea ER, Hia MJG, Sembiring T, Manday DR. Comparison Of

Support Vector Regression And Random Forest Regression Algorithms On Gold Price Predictions. J Sist Inf dan Ilmu Komput Prima(JUSIKOM PRIMA). 2023;
26. Farhanuddin, Sarah Ennola Karina Sihombing, Yahfizham. Komparasi Multiple Linear Regression dan Random Forest Regression Dalam Memprediksi Anggaran Biaya Manajemen Proyek Sistem Informasi. J Comput Digit Bus. 2024;3(2):86–97.
27. Singarimbun RN, Putra OE, Ginantra NLWSR, Dewi MP. Backpropagation Artificial Neural Network Enhancement using Beale-Powell Approach Technique. In: Journal of Physics: Conference Series. 2022.
28. Pang C. Construction and Analysis of Macroeconomic Forecasting Model Based on Biclustering Algorithm. J Math. 2022;
29. Giap CN, Ha DT, Huy VQ, Hien DTT, Son DT, Trang LM. Firm Performance Prediction for Macroeconomic Diffusion Index using Machine Learning. Int J Adv Comput Sci Appl. 2021;
30. Khan MA, Abbas K, Su'ud MM, Salameh AA, Alam MM, Aman N, et al. Application of Machine Learning Algorithms for Sustainable Business Management Based on Macro-Economic Data: Supervised Learning Techniques Approach. Sustain. 2022;
31. Meyer DF, Habanabakize T. An assessment of the value of PMI and manufacturing sector growth in predicting overall economic output (GDP) in South Africa. Int J Ebus eGovernment Stud. 2019;
32. Okoro CO. Macroeconomic Factors And Stock Market Performance: Evidence From Nigeria. Int J Soc Sci Humanit Rev. 2017;
33. Wiśniewski H. Panelowa weryfikacja wpływu zmiennych makroekonomicznych na indeksy giełdowe. Probl Zarz. 2017;
34. Som BK, Goel H. Analyzing Dependence of Key Macroeconomic Variables on BSE Using Regression. Int J Appl Behav Econ. 2022;
35. Ororbia AG, Mali A, Kifer D, Lee Giles C. Backpropagation-Free Deep Learning with Recursive Local Representation Alignment. In: Proceedings of the 37th AAAI Conference on Artificial Intelligence, AAAI 2023. 2023.
36. Li G, Zrimec J, Ji B, Geng J, Larsbrink J, Zelezniak A, et al. Performance of Regression Models as a Function of Experiment Noise. Bioinform Biol Insights. 2021;
37. Zhu F, Cai Z, Peng L. Predictive regressions for macroeconomic data. Ann Appl Stat. 2014;
38. 38. Roger L. Foreign Aid, Poor Data, and the Fragility of Macroeconomic Inference. SSRN Electron J. 2016;
39. Hašková S. An alternative approach for estimating GDP growth rate: fuzzy prediction model. ACC J. 2019;
40. Yang S, Puggioni G, Harlow LL, Redding CA. A comparison of different methods of zero - inflated data analysis and an application in health surveys. J Mod Appl Stat Methods. 2017;
41. Jaiswal JK, Das R. Application of artificial neural networks with backpropagation technique in the financial data. In: IOP Conference Series: Materials Science and Engineering. 2017.
42. Suwandi WS. Do Economic Growth, Income Distribution, and Investment Reduce Poverty Level? J Berk Ilm Efisiensi. 2022;
43. Das PK, Das PK. Forecasting and Analyzing Predictors of Inflation Rate: Using Machine Learning Approach. J Quant Econ. 2024;
44. Chen S, Han X, Shen Y, Ye C. Application of Improved LSTM Algorithm in Macroeconomic Forecasting. Comput Intell Neurosci. 2021;
45. Zhang Z. Prediction of Economic Operation Index Based on Support Vector Machine. Mob Inf Syst. 2022;
46. Chaudhuri A, De K. Fuzzy Support Vector Machine for bankruptcy prediction. In: Applied Soft Computing Journal. 2011.
47. Mustafidah H, Suwarsito S. Performance of Levenberg-Marquardt Algorithm in Backpropagation Network Based on the Number of Neurons in Hidden Layers and Learning Rate. JUITA J Inform. 2020;
48. Abdoli G. Comparing the Prediction Accuracy of LSTM and ARIMA Models for Time-Series with Permanent Fluctuation. SSRN Electron J. 2020;
49. Tang L. Application of Nonlinear Autoregressive with Exogenous Input (Narx) Neural Network in Macroeconomic Forecasting, National Goal Setting and Global Competitiveness Assessment. SSRN Electron J. 2020;

50. Zhang Q, Abdullah AR, Chong CW, Ali MH. A Study on Regional GDP Forecasting Analysis Based on Radial Basis Function Neural Network with Genetic Algorithm (RBFNN-GA) for Shandong Economy. Comput Intell Neurosci. 2022;