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**Title:** The Role of Artificial Intelligence in Enhancing Predictive Accuracy of Economic Trends

**Related Studies**

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| **Study** | **Authors** | **Key Focus** | **Model/Approach** | **Key Result** | **Limitations** |
| Digital Economy Meets Artificial Intelligence: Forecasting Economic Conditions Based on Big Data Analytics |  | This paper explores the integration of artificial intelligence (AI) and big data analytics to improve economic modelling and forecasting in the context of the digital economy. It highlights the limitations of traditional economic models and demonstrates the advantages of AI-based methods in achieving accurate and comprehensive macroeconomic predictions. | A **Graph Neural Network (GNN)** is used to model the relationships and interactions between multiple economic factors. This network accounts for dynamic, weighted interconnections between variables.  An **LSTM (Long Short-Term Memory)** model is employed for economic forecasting. It leverages historical and current data to predict future economic trends, effectively integrating multimodal data inputs. | The proposed approach achieved significant improvement in economic forecasting accuracy. For instance, in stock prediction experiments, the Root Mean Squared Error (RMSE) reduced from 21.5% to 10.3% by incorporating relevant factors into the LSTM model.  The combined GNN and LSTM framework demonstrated its capability as a foundational tool for economic modelling, decision-making, and self-regulation in the digital economy. | The study relies on experimental validation with limited datasets, such as stock forecasting, which may not generalize to broader economic contexts.  The proposed model's performance is contingent on the quality and diversity of input data; limited or biased data could undermine its accuracy.  The authors did not compare their method extensively with other advanced neural network models or AI-based techniques.  Future enhancements are needed, including the development of real-world platforms and the integration of additional data analysis methods for improved accuracy. |
| Prediction Algorithm of Digital Economy Development Trend Based on Big Data |  | The study focuses on leveraging big data and artificial intelligence technologies to enhance economic trend prediction.  It specifically explores the use of interval data models to predict macroeconomic trends, which differs from traditional point data models. | **Interval Data Model:** The paper introduces an interval data model using the Hukuhara difference for stability in time-series data.  **Variable Selection Method:** Based on the mean square error (MSE) criterion, the model selects interval variables such as stock market indices, fund market data, futures transactions, and money market supply.  **Combined Model Structure:** Various combinations of financial indicators are evaluated to determine the optimal prediction models.  **Weighted Models:** Combines multiple models using equal weight, relative performance weight, and rank-based weight strategies. | The interval data model shows significant predictive capability for macroeconomic trends, outperforming traditional methods.  Predictions for China’s macroeconomic growth (2020-2023) suggest a stable and gradual development trajectory, with a GDP growth range of approximately 6.22–6.61%.  The combined model approach provided robust interval predictions, enhancing the accuracy and reliability of economic forecasts. | **Data Dependency:** The effectiveness of the prediction model heavily depends on the availability and reliability of interval financial data.  **Complexity of Unstructured Data:** Challenges remain in handling high-dimensional, unstructured data like text and images.  **Limited Talent Pool:** A shortage of professionals skilled in both economic and big data analytics impacts model development and maintenance.  **Model Instability:** The prediction model’s performance can be unstable, requiring manual adjustments and regular updates to adapt to new economic conditions. |
| Enhancing Financial Forecasting Accuracy Through AI-Driven Predictive Analytics Models |  | The paper explores how AI-powered predictive analytics can improve financial forecasting accuracy. It examines the application of machine learning (ML), deep learning (DL), and big data analytics to enhance risk assessment, decision-making, and investment strategies. | •  The study employs AI models such as neural networks, decision trees, support vector machines (SVM), and deep learning techniques like Long Short-Term Memory (LSTM) networks.  •  Traditional forecasting models (ARIMA, SARIMA, and econometric models) are compared with AI-driven models.  •  Experiments were conducted under different market conditions (stable, volatile, and mixed) to assess AI models' adaptability and performance. | •  AI-driven predictive analytics significantly outperforms traditional models, especially in volatile and mixed market conditions.  •  AI models provide better adaptability, risk assessment, and predictive accuracy, making them valuable for financial institutions.  •  The study highlights AI's role in improving investment strategies, risk management, economic policy-making, and corporate financial planning. | •  **Data Quality and Availability:** AI models depend on high-quality data, and inconsistencies can affect accuracy.  •  **Interpretability of AI Models:** Deep learning models often function as "black boxes," making it difficult for financial analysts to understand their decisions.  •  **Computational Resources:** AI models require significant computing power, which can be costly for some firms. |
| HOW CAN AI PREDICT ECONOMIC TRENDS IN THE MONEY CYCLE? |  | The paper explores the application of artificial intelligence (AI) in economic forecasting, particularly within the framework of the Cycle of Money theory. It examines how AI-driven models can enhance economic predictions by analyzing enforcement and escape savings dynamics​ | The study employs AI-driven neural networks to analyze historical and real-time economic data. These models integrate macroeconomic indicators, sentiment analysis, and enforcement/escape savings concepts to improve the accuracy of economic predictions. Techniques such as back-testing, cross-validation, and performance metrics (e.g., MAE, RMSE) are used to validate the models​ | The implementation of AI in economic forecasting has led to an improvement in prediction accuracy, ranging from 15% to 95% in Big Data analytics. AI has enhanced decision-making in monetary policy and optimized enforcement savings, leading to more efficient financial systems​ | AI models struggle with the unpredictable nature of economic events, such as geopolitical crises and shifts in consumer behavior. Additionally, data biases, overreliance on historical data, and the exclusion of qualitative human insights limit the effectiveness of AI-driven forecasts. Cultural resistance to AI adoption and infrastructure challenges further hinder implementation, especially in developing nations​ |
| THE ROLE OF AI IN PREDICTIVE ANALYTICS FOR MARKET TRENDS AND CONSUMER DEMAND |  | The paper discusses the role of Artificial Intelligence (AI) in predictive analytics for market trends and consumer demand. It highlights AI's ability to process vast datasets, recognize patterns, and forecast demand with greater accuracy, ultimately helping businesses optimize marketing strategies, inventory management, and risk mitigation. | The study examines various AI techniques, including machine learning models (supervised, unsupervised, and deep learning), natural language processing (NLP), real-time data analysis, and AI-powered recommendation systems. It also explores AI's integration in dynamic pricing, personalized marketing, and risk management. | AI-driven predictive analytics significantly improves market trend forecasting, enhances personalized marketing, optimizes inventory and supply chain management, and aids in risk assessment. Case studies from retail, healthcare, finance, manufacturing, energy, and transportation demonstrate AI's practical benefits, such as Walmart's demand forecasting and Uber's dynamic pricing. | Challenges include data privacy concerns, algorithmic biases, ethical transparency, and the need for high-quality data. Additionally, AI models may struggle with unpredictable economic and consumer behavior shifts, and their effectiveness depends on businesses’ ability to interpret and act on AI-generated insights. |
| Artificial Intelligence Applied to Stock Market Trading: A Review |  | **Portfolio Optimization** – Using AI to optimize asset selection and risk management.  **Stock Market Prediction** – Applying AI for price trend forecasting.  **Financial Sentiment Analysis** – Using AI to analyze market sentiment from news and social media.  **Combination Approaches** – Integrating multiple AI techniques for better decision-making. | **Portfolio Optimization:** AI-driven optimization models include heuristic methods, multi-objective approaches, and deep learning techniques for asset selection.  **Stock Market Prediction:** AI models such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), and ensemble learning methods are used for financial forecasting.  **Sentiment Analysis:** Natural Language Processing (NLP) techniques, lexicon-based sentiment analysis, and deep learning models assess the impact of news and social media on stock prices.  **Hybrid AI Models:** The study highlights the increasing trend of combining AI techniques for improved trading strategies. | 1.AI significantly enhances stock market forecasting accuracy compared to traditional statistical methods.  2.Deep learning models, such as LSTM and CNNs, outperform older machine learning techniques in stock price prediction.  3.Sentiment analysis from social media and news articles provides valuable insights for market trend predictions.  4.Hybrid models combining multiple AI techniques show superior performance over single-method approaches. | **Data Challenges:** AI models require large, high-quality datasets, and noisy or biased data can reduce prediction accuracy.  **Model Complexity:** Deep learning models are often "black boxes," making them difficult to interpret for financial analysts.  **Computational Requirements:** Advanced AI models require significant computing power, which may be a limitation for smaller financial firms.  **Generalizability:** AI models trained on historical data may struggle to adapt to unforeseen market events or crises. |
| Machine learning in financial forecasting: A U.S. review: Exploring the advancements, challenges, and implications of AI-driven predictions in financial markets" |  | 1.Reviews AI and ML applications in U.S. financial forecasting.    2.Explores advancements, challenges, and regulatory implications of AI in finance. | 1.Conducts a systematic literature review of studies from 2010–2024.    2.Examines various ML techniques, including deep learning, reinforcement learning, and hybrid models.    3.Investigates regulatory concerns and ethical considerations. | 1.AI and ML significantly enhance financial forecasting accuracy through deep learning and reinforcement learning techniques.    2.Hybrid models combining multiple algorithms outperform single AI models.    3.Ethical issues, data biases, and model interpretability remain major concerns.    4.AI-driven predictions improve decision-making but require transparency to gain stakeholder trust. | 1.Data quality issues and bias impact AI accuracy.    2.Lack of explainability in AI decisions limits trust in financial predictions.    3.AI-based models struggle to account for unpredictable market events (e.g., economic crises, geopolitical risks).    4.Calls for improved regulatory frameworks and AI transparency. |
| The role of artificial intelligence in the decision-making process: a study on the financial analysis and movement forecasting of the world’s largest stock exchanges" |  | 1.Investigates the role and effectiveness of AI in forecasting stock market movements.    2.Examines AI models’ predictive capabilities compared to traditional market performance. | 1.Uses an empirical and experimental study with four AI-based models: Artificial Neural Networks (ANN), k-Nearest Neighbors (KNN), Naïve Bayes (NB), and Random Forest (RF).    2.Tests model performance with 34 global stock indices and 9 technical indicators.    3.Employs accuracy and F1-score as performance metrics. | 1.All AI models outperformed the market average, contradicting the weak Efficient Market Hypothesis (EMH).    2.RF demonstrated the highest accuracy (72.74%) compared to ANN, KNN, and NB.    3.The ability of AI to optimize parameters and time windows improved forecasting accuracy.    4.Suggests AI can enhance financial decision-making by identifying market inefficiencies. | 1.Limited scope of technical indicators; only a subset was used.    2.Data set was restricted to pre-2019, excluding effects of recent financial crises (e.g., COVID-19, Russia-Ukraine war).    3.Did not explicitly categorize stock markets into developed vs. developing economies.    4.AI models were not optimized for time-series forecasting; suggested use of Long Short-Term Memory (LSTM) in future research. |
| REVIEW OF AI TECHNIQUES IN FINANCIAL FORECASTING: APPLICATIONS IN STOCK MARKET ANALYSIS |  | 1.Discusses the scope and limitations of AI in financial forecasting.    2.Evaluates AI’s impact on stock market predictions and its integration challenges. | 1.Reviews AI-based stock market forecasting using models such as LSTM and Support Vector Machines (SVM).    2.Investigates the role of AI in portfolio optimization and trend analysis. | 1.AI improves prediction accuracy but still struggles with real-world financial complexities.    2AI models can incorporate structured (financial statements) and unstructured data (news, social media sentiment) for decision-making. | 1.AI models depend on high-quality data; poor data quality leads to errors.    2.Market volatility and external economic factors reduce AI prediction accuracy.    3.AI models require frequent updates due to the dynamic nature of financial markets. |
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