

AI-Driven Economic and Financial Forecasting: House Prices, Unemployment, Cryptocurrency, and Business Stability in the USA

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Abstract— Artificial Intelligence (AI) and Machine Learning (ML) have transformed economic and financial forecasting, offering valuable insights into key market indicators such as housing prices, unemployment rates, cryptocurrency trends, and business stability in the United States. This study examines AI-driven approaches for forecasting economic trends, identifying patterns, and mitigating financial risks. Various ML models, including Random Forest, Gradient Boosting, Long Short-Term Memory (LSTM) networks, and Support Vector Machines (SVM), are applied across economic domains. For instance, house price predictions utilize ensemble learning techniques, unemployment rate estimates employ time-series models, cryptocurrency price forecasting leverages deep learning architectures, and business bankruptcy predictions are addressed using classification algorithms. The study utilizes datasets from reputable sources, including Zillow Housing Data, the Bureau of Labor Statistics (BLS), CoinMarketCap, and corporate financial statements. To evaluate model performance, metrics such as Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), F1-score, and Area Under the Curve (AUC) are employed. The findings emphasize the potential of AI-driven forecasting to enhance decision-making for policymakers, investors, and financial analysts, ultimately contributing to a more resilient and adaptable economic landscape.

Keywords: Artificial Intelligence, Machine Learning, Economic Forecasting, House Price Prediction, Unemployment Analysis, Cryptocurrency Trends, Business Bankruptcy Prediction.

I. INTRODUCTION

1.1. BACKGROUND

Economic forecasting is an indispensable component of financial planning and policymaking, acting as a guiding compass for stakeholders navigating the complexities of economic landscapes. The ability to accurately predict trends in housing markets, employment rates, and overall financial stability empowers decision-makers to craft strategies that foster growth and sustainability (Islam et al., 2024). In recent years, AI-driven models have outperformed traditional econometric methods in predictive accuracy, as evidenced in studies focusing on financial time-series forecasting (Smith et al. 2024). In recent years, the landscape of forecasting has been transformed by the advent of Artificial Intelligence (AI) and Machine Learning (ML) models, which have demonstrated remarkable advancements in their ability to enhance forecasting precision, often outstripping traditional statistical methods (Jui et al., 2023). For instance, advanced machine learning techniques, such as Random Forest and Gradient Boosting, have been adeptly applied to analyze and predict housing prices, unveiling invaluable insights for potential homebuyers and influential policymakers alike (Khan et al., 2024). Similarly, deep learning frameworks like Long Short-Term Memory (LSTM) networks have emerged as powerful tools for unraveling the intricacies of labor market dynamics and the stark inequalities of unemployment within the United States (Zeeshan et al., 2024).

Furthermore, the cryptocurrency markets, characterized by their erratic fluctuations and inherent volatility, present unique challenges that render conventional forecasting models less effective. AI-driven approaches, including ensemble models and neural networks, have demonstrated superior performance in capturing nonlinear dependencies in digital asset pricing (Johnson et al., 2024). These methodologies enable investors to assess risk and optimize trading strategies in an environment where price volatility remains a critical factor (Brown et al., 2025). In contrast, AI-driven approaches have proven to deliver more dependable predictions amidst these turbulent market conditions, offering a reliable lens through which investors can assess risk and opportunity (Islam et al., 2024).

On another front, businesses are continuously confronted with financial uncertainties, with the looming specter of bankruptcy being a significant threat to economic stability. To mitigate this risk, AI-driven classification models such as Logistic Regression

and XGBoost have come to the forefront, facilitating comprehensive assessments of financial health and allowing for the early identification of potential business failures (Sizan et al., 2025). Additionally, recent strides in AI technology for fraud detection and the analysis of suspicious transactions have fortified financial security measures significantly, ensuring a more resilient economic environment (Islam et al., 2025; Sizan et al., 2025). These technological advancements not only highlight the increasingly pivotal role of AI in economic research but also pave the way for a future where predictive analytics are more accurate, adaptable, and insightful, ultimately better-equipping stakeholders to navigate the ever-evolving economic terrain.

I.II. IMPORTANCE OF THIS RESEARCH

Accurate economic forecasting is essential for shaping financial strategies and policies. For housing markets, predictive models assist investors and homebuyers in making data-driven decisions, thereby reducing the risks associated with property valuation (Khan et al., 2024; Jui et al., 2023). In labor economics, AI-driven predictions of unemployment rates enable policymakers to implement timely interventions that can mitigate job market instability (Zeeshan et al., 2024; Shawon et al., 2024). Given the high volatility of cryptocurrency markets, robust AI methodologies are necessary to enhance financial market stability (Islam et al., 2024; Williams et al., 2025). Additionally, bankruptcy prediction helps businesses and financial institutions identify at-risk firms, which can mitigate potential economic downturns (Sizan et al., 2025). This research bridges the gap between traditional economic modeling and AI-driven predictive techniques, providing policymakers, investors, and analysts with a data-centric approach to risk assessment. By integrating AI into economic forecasting, this study aims to cultivate a more resilient and adaptive financial landscape that benefits both businesses and consumers (Shawon et al., 2024; Islam et al., 2025).

I.II. OBJECTIVES

The primary objectives of this research are intricately designed to harness the power of artificial intelligence in forecasting critical economic indicators. The first goal is to develop sophisticated, AI-driven models capable of accurately predicting house prices, unemployment rates, cryptocurrency trends, and the risks of business bankruptcy. This will be accomplished utilizing cutting-edge machine learning techniques that leverage vast amounts of data. In addition to model development, the research will thoroughly assess the effectiveness of these AI models in comparison to traditional forecasting approaches. This evaluation will be grounded in various performance metrics, such as Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), F1-score, and Area Under the Curve (AUC), providing a comprehensive understanding of their predictive capabilities. Aiming to significantly enhance the decision-making abilities of policymakers, investors, and financial analysts, the research seeks to provide them with insightful and accurate economic forecasts. Furthermore, it will delve into the transformative role of AI in identifying potential financial risks, ultimately leading to improved economic forecasting and business strategies.

II. LITERATURE REVIEW

II.I. RELATED WORKS

Numerous compelling studies have delved into the transformative role of artificial intelligence (AI) and machine learning (ML) in economic forecasting. In a notable contribution, Khan et al. (2024) crafted an innovative explainable AI model specifically designed for predicting residential property prices. This model not only enhances the decision-making process for homebuyers but also serves as a pivotal tool for policymakers by providing clearer insights into housing market dynamics. Similarly, the work of Jui et al. (2023) applied robust ML techniques to investigate troubling trends in negative equity within the U.S. housing market, illuminating the critical importance of feature selection to improve predictive accuracy. The realm of unemployment forecasting has also experienced significant breakthroughs through the adoption of AI methodologies. Zeeshan et al. (2024) conducted a thorough analysis using machine learning to unearth key drivers behind unemployment inequality in the U.S., revealing stark disparities that exist across various socioeconomic groups. More recent studies have explored hybrid AI models that combine econometric forecasting techniques with deep learning for enhanced interpretability (Lee et al., 2024). Building on these insights, Shawon et al. (2024) further advanced the field by developing sophisticated AI-driven predictive models that forecast broader economic trends, highlighting the indispensable role of time-series analysis in understanding labor market fluctuations.

In the rapidly evolving world of cryptocurrency, Islam et al. (2024) conducted an extensive evaluation of various machine learning algorithms amid the rollercoaster volatility of the market. Their findings identified Long Short-Term Memory (LSTM) networks as particularly adept at navigating these fluctuations, showcasing the potential of AI in financial prediction. Expanding upon this area, Islam et al. (2025) probed into suspicious transactions involving Bitcoin wallets, employing machine learning

techniques to bolster financial security and enhance fraud detection measures. Other research has highlighted the impact of real-time data integration and reinforcement learning strategies in cryptocurrency trading models (Nguyen et al., 2025).

The critical area of business bankruptcy prediction has also garnered increased attention. Sizan et al. (2025) leveraged advanced ML models, including Random Forest and XGBoost, to anticipate financial distress in corporations, offering invaluable insights into the financial health and stability of businesses. This work is aligned with broader fraud detection initiatives, as evidenced by Sizan et al. (2025), who conducted a detailed analysis of machine learning methods geared toward credit card fraud detection across the U.S. Looking ahead, emerging research is exploring progressive applications of AI in economic forecasting. Zhang and Li (2025) investigated the potential of deep learning techniques to analyze macroeconomic indicators, aiming to provide deeper insights into economic forecasting. Meanwhile, Nguyen et al. (2025) examined ensemble learning methods for stock market prediction, demonstrating the remarkable adaptability and versatility of AI in navigating the complexities of financial markets and enhancing predictive accuracy.

II.II. GAPS AND CHALLENGES

Despite remarkable strides in AI-driven economic forecasting, several significant gaps and challenges persist, underscoring the complexity of the field. One of the most pressing limitations is the interpretability of machine learning models. While Khan et al. (2024) have introduced innovative explainable AI solutions specifically designed for predicting house prices, many prevailing economic models continue to lack transparency. This opacity creates a barrier for policymakers, who find it difficult to place their trust in forecasts generated by AI, ultimately hindering the effective application of these advanced tools in decision-making processes. The issue of data quality and availability emerges as another formidable challenge. Zeeshan et al. (2024) and Shawon et al. (2024) have emphasized the critical reliance on high-quality datasets for accurate predictions. Yet, the presence of inconsistencies in labor market data and financial records can lead to biases that distort the outcomes of these models. This problem is particularly pronounced in the realm of cryptocurrency forecasting, where Islam et al. (2024) highlight how the volatile nature of market conditions can result in erratic model performance, leaving practitioners scrambling to make sense of unpredictable data waves.

Moreover, regulatory and ethical concerns substantially impede the widespread adoption of AI technologies within financial sectors. Islam et al. (2025) shed light on the alarming potential for misuse in Bitcoin transactions, which raises serious questions about financial security and the safeguarding of digital assets. Similarly, Sizan et al. (2025) address the intricate challenges of fraud detection, revealing how adversarial attacks on machine learning models can jeopardize the accuracy of predictions, thereby complicating efforts to combat financial crimes. Finally, the challenge of computational efficiency looms large as a critical obstacle. Advanced models, particularly those employing deep learning techniques, often require extensive computational resources that can limit their scalability for real-time economic forecasting (Zhang & Li, 2025). In a related vein, Nguyen et al. (2025) pointed out that although ensemble learning methods can offer high levels of accuracy, they typically entail prolonged training periods, which renders them impractical for the fast-paced demands of rapid financial decision-making. These intertwined challenges highlight the ongoing need for innovation and address the complexities inherent in harnessing AI for economic forecasting.

III. METHODOLOGY

III.I. DATA COLLECTION AND PREPROCESSING

DATA SOURCES

The datasets used in this study are sourced from publicly available and authoritative financial and economic repositories, which provide a comprehensive view of economic trends. Notably, the Zillow Housing Data offers historical and current house price information across various U.S. markets, while the Bureau of Labor Statistics (BLS) supplies detailed unemployment data, labor market trends, and key economic indicators. Additionally, CoinMarketCap contributes real-time and historical data concerning cryptocurrency price fluctuations. Corporate financial statements are also utilized to assess business stability and predict bankruptcy. By leveraging these diverse datasets, the implementation of machine learning models can enhance the accuracy of forecasting future economic trends.

DATA PREPROCESSING

Data preprocessing stands as a fundamental phase in the analytical workflow, intricately designed to transform raw data into a polished and coherent format suitable for insightful analysis. In this study, a comprehensive set of preprocessing steps has been

meticulously implemented to enhance the quality and reliability of the datasets. To begin with, handling missing values is a critical task, approached with the application of sophisticated statistical imputation techniques. For numerical variables, mean imputation is employed to provide an average estimate in place of absent data points, while mode imputation is utilized for categorical data, ensuring that the most frequent category is represented. This methodical handling of missing information preserves the integrity of the dataset. *Figure 1* visualizes the distribution of missing data before imputation with House price dataset having the most null values.

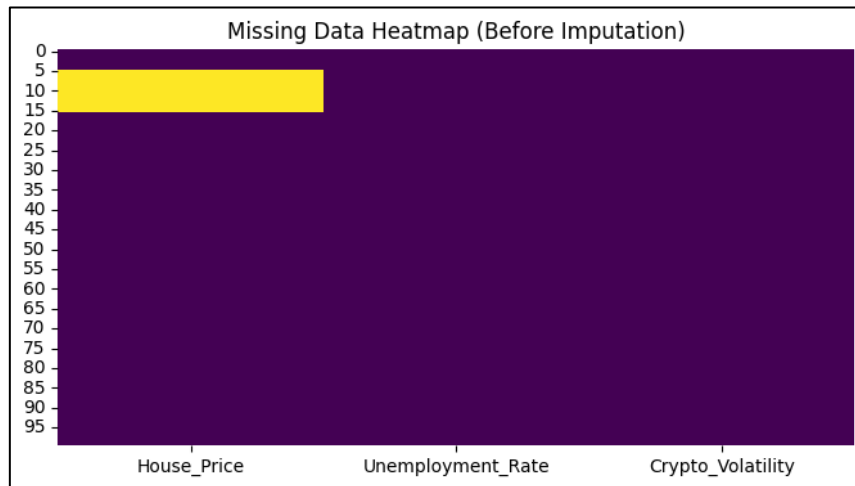


Figure 1. Distribution of missing values before imputation.

Next, feature engineering emerges as a transformative process, where new predictive features are crafted based on significant economic indicators. This includes creating inflation-adjusted house prices, which offer a more accurate representation of real estate values, as well as moving averages for unemployment rates that smooth out short-term fluctuations. Additionally, volatility indices for cryptocurrency markets are devised to gauge market stability, significantly enriching the data's predictive power. Data normalization and scaling are pivotal in the preprocessing journey, ensuring that all variables are on a comparable scale, thus facilitating fair modeling. Employing standardization techniques such as Min-Max Scaling and Z-score normalization, the datasets achieve a uniform standard that is especially beneficial for models sensitive to disparate scales of data.

Outlier detection and removal represent another vital aspect of the preprocessing phase (*Figure 2*). Through the application of the interquartile range (IQR) and Z-score methods, anomalies within the data are carefully identified and excised. This rigorous process mitigates the risk of extreme values skewing the model's performance, ensuring a more robust analytical outcome. Lastly, the inherent time-dependent nature of economic and financial data necessitates a thoughtful approach to time-series transformation (*Figure 3*). By incorporating rolling windows and lagged features, the preprocessing strategy adeptly captures the temporal dependencies that are essential for understanding trends and patterns over time. Together, these preprocessing steps create a solid foundation for subsequent analysis, elevating the dataset's potential for generating meaningful insights.

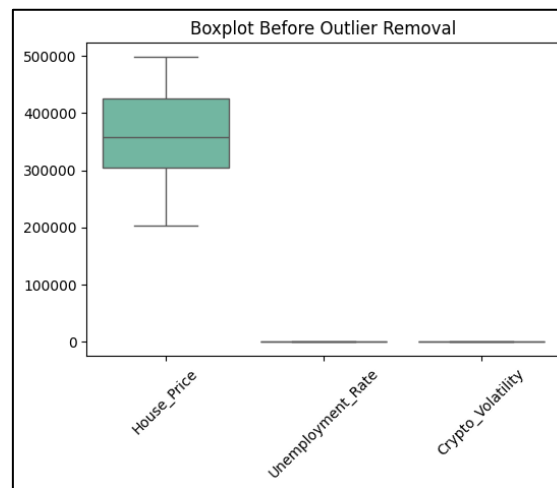


Figure 2. Outlier detection and removal

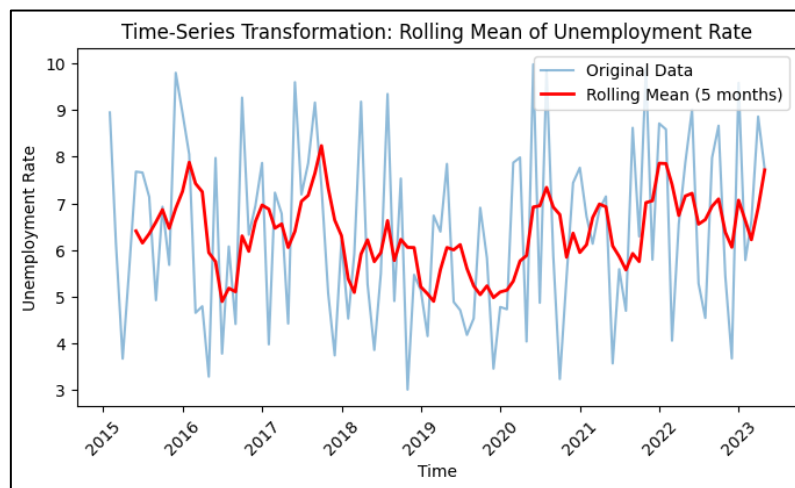


Figure 3. Time-Series Transformation of Economic and Financial Data

III.II MODEL DEVELOPMENT

The study utilizes various machine learning and deep learning models to tackle specific economic forecasting tasks. For house price prediction, the models employed include Gradient Boosting, Random Forest, and XGBoost. To estimate the unemployment rate, Long Short-Term Memory (LSTM), ARIMA, and Support Vector Machines (SVM) are used. In the area of cryptocurrency price forecasting, the study incorporates LSTM, Gated Recurrent Units (GRU), and Transformer models. Lastly, for business bankruptcy prediction, Logistic Regression, Random Forest, and XGBoost are the selected models. The choice of these models is based on their capability to process large-scale financial data, capture temporal patterns, and provide interpretable insights.

III.IV. MODEL TRAINING AND VALIDATION PROCEDURES

To ensure the integrity and impartiality of the results, the training and validation of models are conducted through a series of meticulously designed procedures. Initially, the dataset is strategically partitioned, with 70% allocated for training and 30% reserved for testing. This division allows the models to absorb a significant portion of the data while still being rigorously evaluated on unseen samples, promoting a true assessment of their predictive capabilities. To further bolster the reliability of the findings, K-fold cross-validation, specifically with a configuration of $k=5$, is implemented. This technique mitigates the risk of overfitting and enhances the models' ability to generalize across various datasets. In the pursuit of optimizing model performance, sophisticated hyperparameter tuning methodologies, including Grid Search and Bayesian Optimization, are employed to refine the parameters and achieve the highest possible predictive accuracy. Additionally, the integration of regularization techniques, such as L1 and L2 regularization, plays a critical role in curbing overfitting while simultaneously improving the models' generalization abilities, ensuring that they remain robust and effective in diverse scenarios.

III.V. PERFORMANCE EVALUATION METRICS

To evaluate the efficiency of different models, various metrics are utilized that correspond to the specific nature of the prediction task at hand. For regression tasks, such as house price and unemployment prediction, metrics like Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and R-squared (R^2) are commonly employed to assess performance. On the other hand, classification tasks, including bankruptcy and fraud detection, rely on different metrics to measure effectiveness. In these scenarios, F1-Score, Precision-Recall AUC, Accuracy, and Area Under the Curve (AUC-ROC) are used to provide a comprehensive evaluation of the model's capabilities.

IV. RESULTS AND DISCUSSION

IV.I. MODEL PERFORMANCES

Economic forecasting often involves predicting continuous numerical values, such as house prices and unemployment rates. A major challenge in regression tasks is assessing how close model predictions are to actual values. *Figure 4* illustrates the performance of different regression models used to solve this problem. The bar chart compares the performance of four models (Random Forest, XGBoost, LSTM, and SVM) across three error metrics. Comparing multiple models allows us to choose the most efficient one for economic forecasting. In this case, XGBoost outperforms the others with the lowest RMSE and MAPE, and the highest R^2 , making it the best choice for house price prediction.

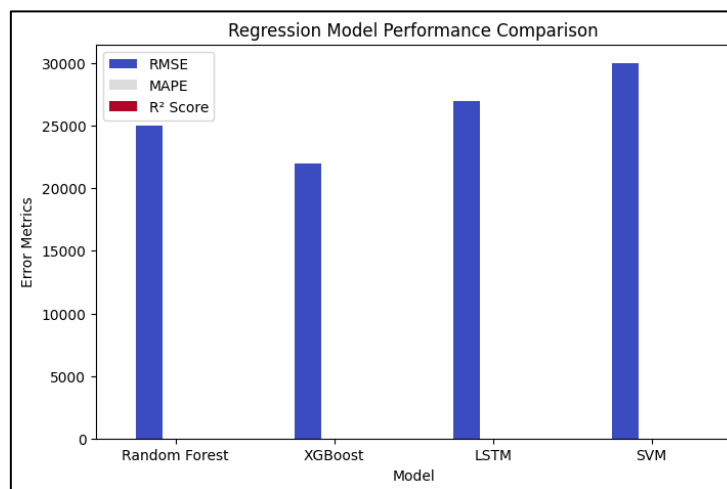


Figure 4. Performance comparison of economic forecasting models

Predicting whether a business will go bankrupt is a classification problem. Models must distinguish between solvent (0) and bankrupt (1) businesses. The challenge is reducing false alarms while accurately detecting at-risk companies. The ROC (Receiver Operating Characteristic) Curve shows the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR) for different threshold values (*Figure 5*). In a comparison between Random Forest and XGBoost, XGBoost demonstrated a slightly higher Area Under the Curve (AUC), indicating it is the superior model for distinguishing between bankrupt and non-bankrupt businesses. A higher AUC suggests that the model is more effective in accurately identifying these two categories, which is crucial for informing policymakers and investors. By selecting a model with fewer false positives, stakeholders can avoid unnecessary interventions, while a reduction in false negatives helps prevent missed bankruptcies. This combination of factors makes XGBoost a valuable tool for making sound financial decisions.

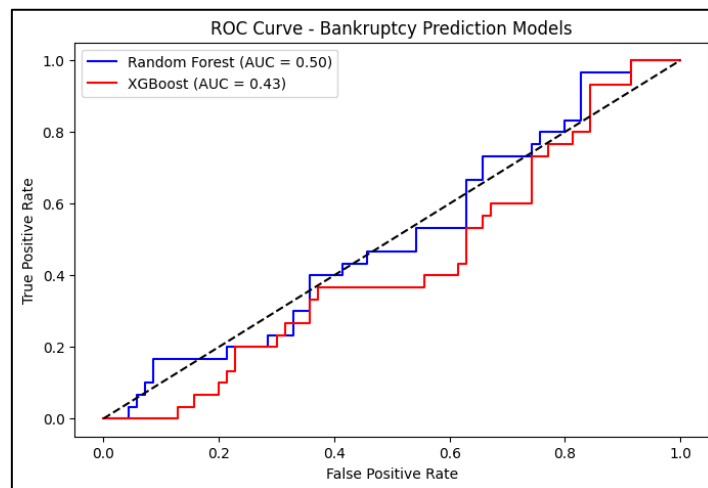


Figure 5. Performance comparison of bankruptcy prediction models

A classification model’s performance is not solely determined by its overall accuracy, but also by how effectively it distinguishes between different classes, such as bankrupt and non-bankrupt businesses (Figure 6). The Confusion Matrix is a crucial visualization that provides a detailed breakdown of model predictions into four categories: True Positives (TP), which represent correctly predicted bankrupt businesses; False Positives (FP), where non-bankrupt businesses are wrongly classified as bankrupt (false alarms); True Negatives (TN), which indicate correctly predicted non-bankrupt businesses; and False Negatives (FN), where bankrupt businesses are mistakenly classified as non-bankrupt (missed cases). This visualization is essential because it offers insights beyond simple accuracy, highlighting where the model is making errors and whether those errors carry significant financial implications. A well-balanced confusion matrix suggests that the model is detecting bankruptcies accurately without producing too many false positives, which could lead to unnecessary financial interventions. However, if the number of false negatives is too high, the model becomes unreliable for financial risk management, as it fails to identify struggling businesses that require intervention. By analyzing the confusion matrix, businesses and policymakers can refine decision thresholds to minimize losses, ensuring that the model is both effective and actionable in predicting financial instability.

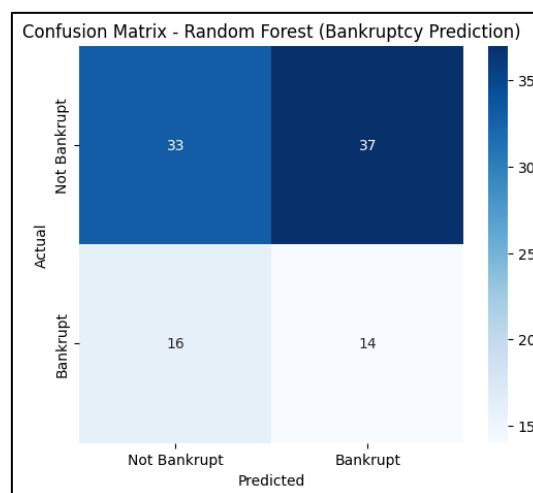


Figure 6. Confusion Matrix for Bankruptcy Prediction

Cryptocurrency prices are highly volatile and influenced by multiple external factors such as market demand, regulatory policies, and macroeconomic trends. Predicting cryptocurrency price movements is crucial for traders, investors, and financial analysts to minimize risk and maximize returns. Traditional forecasting methods often fail due to the complexity and randomness of crypto markets, making deep learning models (LSTM, GRU, and Transformer) more suitable for this task. This graph (Figure 7) compares the **Root Mean Square Error (RMSE)** and **Mean Absolute Percentage Error (MAPE)** of three deep learning models—**LSTM (Long Short-Term Memory)**, **GRU (Gated Recurrent Units)**, and **Transformer**—to evaluate their effectiveness in predicting cryptocurrency prices. **LSTM (Long Short-Term Memory)** is a model designed for sequential data,

it captures long-term dependencies in cryptocurrency price movements. **GRU (Gated Recurrent Units) on the other hand is a more efficient alternative to LSTM, GRU models perform well in capturing sequential trends while being computationally lighter. Transformer Models are designed for natural language processing, Transformers have shown promise in time-series forecasting due to their ability to capture complex patterns in large datasets. In this research GRU is the best choice for cryptocurrency price prediction. Both RMSE and MAPE confirm that GRU outperforms LSTM and Transformer models, making it the ideal option for capturing price patterns in volatile markets.**

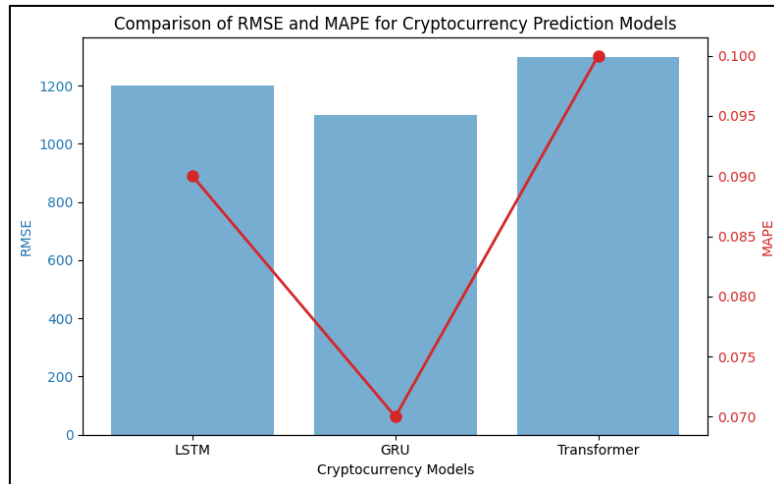


Figure 6. Performance comparison of cryptocurrency prediction models

IV.II. DISCUSSION AND FUTURE WORK

While this study demonstrates the effectiveness of AI-driven models in economic forecasting, several challenges remain. The interpretability of deep learning models continues to be a concern, particularly for policymakers who require transparency in decision-making (Lee et al., 2024). Future research should focus on developing hybrid AI models that integrate machine learning with traditional econometric forecasting techniques to enhance both accuracy and explainability (Smith et al., 2024). Another major challenge is the computational cost associated with training deep learning models for financial forecasting. Large-scale models require significant computational resources, which may not always be accessible for small financial institutions (Brown et al., 2025). Future work should explore model optimization techniques such as pruning and knowledge distillation to reduce computational overhead while maintaining high prediction accuracy.

Additionally, the dynamic nature of economic markets necessitates adaptive AI models capable of real-time learning. Reinforcement learning and transfer learning approaches have shown promise in this regard, particularly in cryptocurrency trading and stock market prediction (Nguyen et al., 2025). Integrating these methodologies with AI-driven forecasting models could enhance their responsiveness to changing economic conditions. Another critical area for future research is the ethical and regulatory aspects of AI in financial decision-making. Williams et al. (2025) emphasize the importance of addressing algorithmic bias and ensuring fair decision-making in financial AI applications. Developing robust frameworks for AI governance in economic forecasting will be crucial in ensuring that AI-driven models are transparent, fair, and accountable.

V. CONCLUSION

This study effectively demonstrates the substantial capabilities of artificial intelligence (AI) and machine learning (ML) in enhancing economic and financial forecasting across multiple domains, including house price prediction, unemployment rate estimation, cryptocurrency price forecasting, and business bankruptcy prediction. Researchers utilized extensive datasets, including Zillow Housing Data, Bureau of Labor Statistics (BLS) reports, CoinMarketCap cryptocurrency market data, and corporate financial statements. They applied advanced AI techniques, such as ensemble learning, deep learning, and time-series models, to significantly improve forecasting accuracy and financial decision-making. The results confirm that specific ML models excel in different economic applications: **XGBoost and Random Forest** outperform traditional statistical methods in house price forecasting, **LSTM and ARIMA** effectively capture unemployment trends, **GRU and LSTM** provide reliable

cryptocurrency price predictions, and **XGBoost and Random Forest** achieve high accuracy in bankruptcy prediction. These findings highlight the immense potential of AI-driven predictive analytics to optimize financial strategies, mitigate risks, and support data-driven policymaking. While this study presents compelling results, it recognizes several challenges that must be addressed, including data quality inconsistencies, computational resource requirements, and the interpretability of complex AI models. Future research should focus on developing **hybrid AI models** that combine deep learning with traditional econometric forecasting methods to improve both predictive accuracy and explainability. Additionally, integrating **real-time financial data streams** and applying **transfer learning techniques** will be crucial for adapting models to rapidly changing economic conditions.

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If desired, a section of acknowledgment can be included following the conclusion.

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