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ORIGINAL

The Role of Artificial Intelligence in Financial Analysis and Forecasting: Using Data and Algorithms

El papel de la inteligencia artificial en el análisis y la previsión financieros: Uso de datos y algoritmos

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ABSTRACT

Introduction: this study explores the role of Artificial Intelligence (AI) in financial analysis and forecasting, focusing on its application in the banking sector. AI's ability to process large datasets and enhance prediction accuracy is critical for improving financial decision-making, particularly in forecasting stock prices, currency rates, and market trends.
Method: the research employed traditional statistical methods such as ARIMA models and machine learning algorithms like Gradient Boosting Machines and Random Forests. These methods were applied to financial data sets to assess the impact of AI on forecasting accuracy and risk assessment. Data preprocessing and model training were conducted using R statistical software.
Results: integrating AI models improved forecasting accuracy by 30 % compared to traditional methods, and risk assessment accuracy increased by 20 %. Gradient Boosting Machines outperformed other models in identifying investment portfolio risks, while Random Forests provided robust predictions of trading volumes.
Conclusions: AI has the potential to revolutionize financial analysis by increasing the efficiency and accuracy of forecasts. However, data privacy, algorithmic bias, and ethical concerns must be addressed to ensure fair and responsible AI use in finance. Collaboration among researchers, financial experts, and policymakers is essential for maximizing AI's benefits while mitigating risks.

Keywords: Financial Analysis; Data Privacy; Algorithmic Bias; Socio-Economic Impacts.

RESUMEN

Introducción: este estudio analiza el papel de la Inteligencia Artificial (IA) en el análisis financiero y la predicción, enfocándose en su uso en el sector bancario. La IA mejora la precisión de las predicciones al procesar grandes volúmenes de datos, lo cual es clave para optimizar decisiones financieras, como la predicción de precios de acciones, tasas de cambio y tendencias de mercado.
Método: se emplearon métodos estadísticos tradicionales como los modelos ARIMA y algoritmos de aprendizaje automático, incluyendo Máquinas de Gradiente y Bosques Aleatorios. Estos se aplicaron a datos financieros

para evaluar el impacto de la IA en la precisión de las predicciones y la evaluación de riesgos. El preprocesamiento y el entrenamiento de los modelos se realizaron con el software estadístico R.
Resultados: la integración de IA mejoró la precisión de las predicciones en un 30 % frente a los métodos tradicionales, y la evaluación de riesgos mejoró un 20 %. Las Máquinas de Gradiente fueron más eficaces en la detección de riesgos en carteras de inversión, mientras que los Bosques Aleatorios ofrecieron predicciones sólidas de volúmenes de negociación.
Conclusiones: la IA puede revolucionar el análisis financiero, mejorando la precisión y eficiencia de las predicciones. Sin embargo, es necesario abordar temas como la privacidad de los datos, sesgos algorítmicos y aspectos éticos para un uso responsable de la IA en las finanzas. La colaboración entre investigadores, expertos financieros y responsables de políticas es crucial para aprovechar al máximo los beneficios de la IA y mitigar sus riesgos.

Palabras clave: Análisis Financiero; Privacidad de los Datos; Sesgo Algorítmico; Impacto Socioeconómico.

INTRODUCTION

The integration of Artificial Intelligence (AI) into financial analysis and forecasting marks a pivotal transformation in the finance industry, driven by rapid technological advancements. AI refers to the simulation of human intelligence processes by machines, particularly computer systems, which include learning (e.g., acquiring data and rules for using it), reasoning, and self-correction.[1,2] This change is clear in the growing reliance on AI to help make better decisions, handle risks better, and predict financial outcomes more accurately. Due to the rise of data analytics and machine learning (ML), banking systems have changed a lot in the past few years.[3] These technologies allow financial institutions handle huge datasets at speeds that have never been seen before. This lets them respond quickly to changes in the market and makes forecasting more accurate. For example, AI technologies like predictive analytics and natural language processing (NLP) are changing how stock prices are predicted, how exchange rates are analyzed, and how market trends are predicted in the banking industry.[4,5,6] Even with these improvements, using AI in finance brings up a lot of difficult issues, such as worries about data protection, algorithmic bias, and the moral effects of automating important decision-making processes. As AI continues to change traditional financial models, it also causes social and economic problems, such as the possibility of job loss and a wider gap in who can use advanced financial tools. This research tries to answer these complicated questions by looking at how AI is changing the way money is handled, mainly by looking at how it affects making predictions and choices.

Research Problem

Right now, the financial world is very unstable because it's not clear what will happen with the global economy and technology is changing very quickly. It can be hard for banks to keep up with how the market is changing, make better decisions, and get a better sense of how risky something is. A lot of the time, old financial models can't handle how complicated markets are these days. They can't handle things like how unstable stock prices are or how hard it is to manage credit risk. AI is a good way to solve these issues since it can deal with large datasets, look for trends, and make predictions right away. Scientists still don't fully understand how AI works with and makes banking processes better, though. People are worried about things like the moral impacts of AI's decisions, how hard it is to understand algorithms, and the social and economic impacts of AI being widely used in finance. These issues need more study. What does this work's main research question try to answer? How can AI make financial study and forecasting more accurate, faster, and fair while also making it easier to do?

The aim of this study is to look at the role of AI in changing financial forecasts and analysis in a critical way. This study specifically looks at how well AI technologies can help make predictions and decisions in the banking industry. The study also wants to find the problems and moral issues connected to integrating AI and suggest ways to use AI's strengths while minimizing its weaknesses.

To achieve the research aim, this study focuses on addressing the following questions:

1. How can AI contribute to improving the precision and efficiency of financial forecasting and analysis? This question investigates the specific mechanisms through which AI technologies enhance data processing and prediction accuracy in financial contexts.
2. What major AI technologies are currently used in banking for analysis and forecasting? This question explores the application of cutting-edge AI models and tools, including natural language processing and machine learning algorithms, in the banking sector.
3. What challenges do financial institutions face when incorporating AI into their operations? This includes practical challenges related to data privacy, algorithmic bias, and socio-economic implications.

4. What are the ethical implications of using AI in financial analysis and forecasting? This question examines the potential ethical dilemmas surrounding data privacy, fairness, and accountability in AI-driven financial systems.
5. How can AI assist in managing and mitigating risks in financial markets? This focuses on AI's role in improving risk assessment practices and predicting market trends.
6. What are the socio-economic impacts of making AI standard in the finance industry? This broader question evaluates the long-term implications of AI adoption, including its effects on employment, economic disparity, and global financial stability.

Objective of the Study

The primary objective of this study is to look into how AI can be added to current financial systems with a focus on how it can improve risk management, make predictions more accurate, and help people make better decisions. The study's goal is to give policymakers, financial institutions, and academics useful information for making sure AI is used responsibly and effectively in finance by looking at the problems and moral issues that come up when AI is used.

Existing research shows that AI has the potential to completely change the financial industry.(6,7) Studies have shown that AI models, like neural networks and ensemble methods, can effectively find complicated patterns in large data sets that contain financial information. This makes it easier to predict changes in stock prices and credit risks. However, problems like the "black box" nature of deep learning models, data integrity issues, and legal hurdles still make it hard for many people to use.(8,9) This study adds to the growing conversation about AI's role in updating financial systems by combining ideas from earlier research and talking about the risks and limits that come with using it.

The first part of this paper discusses the current state of financial technology and the main ways that AI is changing the way standard finances are done. After that, it looks at how well AI-based models and traditional methods work in certain areas, like risk management and investment plans. Lastly, the study looks at the problems, moral issues, and social and economic effects of using AI, and it gives advice to people who work in finance and technology.

Literature review

The study points to one of the most promising new studies of financial integration with AI. A fresh perspective on the present and future of finance in literature is portrayed by the current changeable environment where advanced technology rapidly integrates invisibly with conventional financial processes.(10,11) In the financial decision-making sphere, data analytics and machine learning are changing the game.(12) Recent research has shown varying impacts of technology integration across different fields. Tsekhmister et al.(13) explored the effect of online education on teachers' working time efficiency, finding that while overall efficiency may be lower online, specific tasks such as presenting new material can be more efficient through online methods. For instance, models generated through machine learning techniques, including neural networks, support vector machines, and ensemble methods, have very good potential in the prediction of stock price movements.(14) Savchuk et al.(15) discusses the prospects of AI in the pharmaceutical industry of Ukraine, highlighting both the opportunities and challenges present in this sector.

Now, with machine learning, the examination of borrower data becomes super sophisticated and offers a paradigm shift in the credit risk space.(16) Retail banking and personal financial management depend on machine learning to predict the spending ways of customers.(17) In assessing the infrastructure of future internet services markets, Hrynchyshyn(18) identifies critical formation challenges that could significantly influence financial analysis and forecasting strategies. The insights afforded by algorithms examining consumer expenditure, saving, and other behavioral patterns are of great help and would enable financial institutions and service providers to make highly competent predictions of future actions.

Another important related challenge is the opaque character of most AI models. referred as "black-box" in the literature.(19) In particular, models based on deep learning reach high performance, but their biggest disadvantage is how the decisions are reached. Problematic, for that matter, can be the context of finance wherein transparency takes primacy. Regulators, investors, the public, and other stakeholders are not likely to trust systems that they cannot understand and hence audit. Such opacity can deter the adoption of very promising AI technologies.(20) Model overfitting still remains a big concern. This mostly comes into the picture when a machine-learning model is trained too well on historical data, resulting in poor performance over new, unseen data.(21) Therefore, the finance industry shall need strategic caution to bring transparency, accuracy, and trustworthiness at the optimal level into the integration of AI, so the finance industry can fully harness and realize its potential to change practices within the industry.(22)

The growing use of artificial intelligence (AI) in the financial services industry is transforming risk management, the development of investment strategies, and regulatory compliance practices. The research highlights the ways AI may automate ordinary operations, improve decision-making, streamline and improve risk assessment and financial reporting.[23] The effects on the financial sector are far-reaching, manifold, and at the same time, new sources of opportunities for improvement and new obstacles to age-old practices. Special notice is paid to the accounting supervision in the process of managing agricultural investments as explained by Gutsalenko et al.[24] Comparison and contrast of macroeconomic data between the nations, and the legal frameworks that regulate capital investment accounting in the respective nations are examined. In this study, they contrast and compare three sets of accounting standards—IAS 16 with AS 7, IAS 16 with NAS 11, and AS 7 with NAS 11—so as to bring out the role that legal framework plays in protecting the investors' capital from loss. The concept of "fixed assets" remains the same under these rules, but the applied methods of valuation are different. AI enables modern technologies used in financial analytics, which help to predict and consequently reduce losses in the portfolio. Machine learning models can process large volumes of data and quickly pinpoint risks much faster than traditional methods.[25]

These programs are very good at not only seeing connections but also patterns that a human would miss. Amid unceasing scientific and cultural dialogues, Nikolenko[26] emphasizes the importance of including AI in modern social models and the value of philosophy to value AI's worth and the existential questions it raises for the human race. A study by Tarasenko et al.[27] provides a full picture of the financial system in Eastern Europe through the prism of the historical background and its structure at the present time. AI systems may automate these processes, ensuring standards such as the EU General Data Protection Regulation and the US Dodd-Frank Act[28]. AI, in one way, enhances the application of AML compliance because of the automation in identifying suspicious transactions, and hence reduces the burden on human analysts, in turn increasing the quality and accuracy of their work. AI-enabled solutions empower the generation of timely, accurate, and detailed financial reports by quickly integrating and analyzing data from various sources.[29]

The sophistication level in AI technology, especially in the infusion of deep learning and other complex algorithms, has brought a change into the algorithmic analysis area within the financial sector. All levels of financial services, from management to regulatory compliance, are being reshaped by this transformation, which is fueled by new technologies that enhance accuracy, efficiency, and innovation.[30] Banks and other financial institutions have seen a change in asset allocation and management as a result of the potent algorithms based on artificial intelligence. Maximizing potential results while minimizing risks can be achieved by ensuring that each client's strategy aligns with their risk tolerance and investment objectives. Savchuk et al.[15] investigates artificial intelligence's role in Ukraine's pharmaceutical industry. It uncovered potential future applications of AI and examined regulatory variables that impact its current state of usage. For instance, take the initiatives by various stakeholders in anti-money laundering (AML) detection. In this process, the AI system might analyze the large transaction data looking for any fraudulent activities.[31] It is this artificial intelligence that underpins new financial products and services—a crop of AI-driven robo-advisers, leveling the playing field for hyper-personalized financial advice that was once reserved for the ultra-wealthy. Simply put, advancements in AI-driven algorithmic analysis revolutionize asset management, regulatory compliance, and portfolio optimization, among other innovations in financial services, for the financial industry.[32]

The integration of AI in banking raises important ethical and societal problems, thus it is crucial to understand it well and apply it carefully. In addition, financial firms may unintentionally or intentionally utilize customer data for profit, going against the goal of improving financial services, if AI is not handled correctly. Muliarevych[33] investigates into the most important part of online shopping: the fulfillment of consumer orders in warehouses. It describes the intricacies of designing optimal acceptance and shipping zones within warehouses, two crucial aspects of any warehouse layout. The article highlights the efficiency gains made by various computing subsystems, such as serverless lightweight functional processing, horizontally auto-scaled microservices, and monolith architecture, when it comes to the most time-consuming computing operations. Another critical ethical concern is the potential for AI-driven systems to exacerbate existing social inequalities.[34]

Sembiyeva et al.[35] investigate the effects of green technology investments on energy stability and sustainability. This study looks at green bonds and other environmentally friendly investments to see how they might help finance sustainable projects, improve energy security, and develop new sustainable energy technology. The research looks at the recent surge of funding for environmentally friendly technologies, finds the patterns, and figures out how these investments affect energy stability. It predicts that large firms will soon combine ESG ratings with conventional credit evaluations, highlighting the growing use of ESG criteria in the financial sector. Tymoshenko et al.[36] focuses on the effect of Industry 4.0 on the energy scenario model in developing countries. The fact that developing countries, among which is Ukraine, are all characterized by greater insistence on rapid development of economies, combined with lesser focus on and attention to energy efficiency, has always led to the effect.

Artificial intelligence approaches have had a marked impact on policy-making at the macroeconomic level.[37]

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METHOD

A robust methodological framework is applied to investigate AI-powered financial research, simulating the complexity of real financial markets using datasets. The process involves gathering relevant data, ensuring its quality, and selecting appropriate predictive models for complex financial situations. Risk assessment and predictive modelling algorithms are carefully picked based on how well they handle big datasets and find complicated patterns in financial situations. What are the method's limitations? These are also talked about to give a full picture of the study process. Machine learning (ML) and time series models are used to find and predict patterns and connections that don't change linearly over time.

We chose ensemble machine learning methods like Random Forests and Gradient Boosting Machines because they are good at working with complicated, nonlinear data structures, especially when predicting time series. Autoregressive Integrated Moving Average (ARIMA) models are used to guess future values of things like stock prices, trade volumes, and economic indicators. Handling missing values, normalising data, and making lagged variables are all part of preprocessing, which is necessary to make sure that the data is accurate and consistent.

The analysis is done with the statistical software R, which uses advanced statistical modelling and machine learning packages to make sure that the predictions are correct and that the data is handled quickly and easily. For Random Forests, the "randomForest" package is used to try out different tree depths and group sizes. By combining decision trees, this makes predictions more accurate. It also finds the most important factors, which helps with feature importance analysis.

The "forecast" package is utilized for fitting ARIMA models, which are central to time series forecasting. This package simplifies the process by automatically selecting optimal parameters to minimize the Corrected *Akaike Information Criterion* (AIC), making it suitable for both seasonal and non-seasonal data. Finally, the Gradient Boosting method is implemented through the "gbm" package, widely recognized for its effectiveness in predictive modeling.

The Gradient Boosting is a greedy algorithm for minimizing a specified loss at each model step. Gradient Boosting fits a bunch of models in a stage-wise fashion and keeps on fitting with corrections of errors. It has a class of loss functions, so it can be applied to nearly all purposes, including regression, classification, and ranking. Such a model in this approach can support highly complex learning from data and optimization of predictive accuracy, given that the iteration of building models is designed perfectly.

Model Selection and Mathematical Formulations

The ARIMA model is often used due to its effectiveness in representing time-series data with sequentially dependent data points. Here is the expression that the model uses:

$$Y_t=\alpha+\phi_1 Y_t-1+\phi_2 Y_t-2+\cdots+\phi_p Y_t-p+\theta_1\varepsilon_t-1+\theta_2\varepsilon_t-2+\cdots+\theta_q\varepsilon_t-q+\varepsilon_t$$

In this case, Y_t stands for the time-series data at time t, α is the intercept, the parameters of the autoregressive component are 1,… ϕ_1,…,Ŧp, the parameters of the moving average part are 1,…,θ_1,…,θ_q, and ε_t is the error term at time t.

Machine learning techniques such as Random Forest and Gradient Boosting are great at capturing data's complicated, nonlinear interactions: During training, Random Forest builds a large number of decision trees and then uses the average prediction (regression) or mode of the classes (classification) to determine the output class. To optimize any differentiable loss function, Gradient Boosting Machines construct an additive model in a forward stage-wise approach. Every step involves fitting n classes regression trees to the negative gradient of the deviance loss function, which might be binomial or multinomial.

Data

We used the "quantmod" package in R to get a sample from Yahoo Finance so that we could test the Random Forest and ARIMA models. This set of data includes daily stock prices, trade amounts, and sector-specific economic data for the years 2019 to 2022. The starting prices, highs, lows, closing prices, and daily trading volumes of stocks on the New York Stock Exchange are used to collect financial data. We got historical stock data from Yahoo Finance using the "quantmod" package and told it what ticker symbols to use and what time frame to look at. The data set covers four full years, giving a full picture of the different market conditions and economic trends that affect the financial markets.

Momentum indicators were used to make technical indicators like moving averages, exponential moving averages, and the Relative Strength Index (RSI). Opening, highest, lowest, and ending prices for each day were also looked at to learn more about how the market works and why prices change. Also, the number of trades that happen every day, which tells us a lot about how open the market is and how investors feel, was very important in figuring out how well the models could predict how the market would move. By looking at patterns from the past, the Random Forest model was used to guess what future stock prices and trade volumes would be. This model was great for forecasting because it could handle big datasets and a lot of different input factors. In forecasting, the number of variables could be over one hundred.

The ARIMA model, which is usually used for time-series forecasting, was used to guess how stock prices would move in the future by looking at how they have moved in the past. It worked great for this kind of research because it could handle non-stationary stock price data and take into account trends and seasonality.

Model Training and Validation

Cross-validation techniques were used to make sure the models were correct after they were trained on a subset of the data. Performance metrics like RMSE (Root Mean Square Error) were used for regression tasks, while accuracy was used as the performance factor for classification tasks. For ARIMA models to work, time series data must be stable. But Random Forests and Gradient Boosting Machines have problems, like how to deal with data that has a lot of dimensions and how to lower the risk of overfitting. Additionally, errors in financial data or external events can affect the model's accuracy. By combining statistical and machine learning approaches through ARIMA and ensemble machine learning methods, a robust framework for financial data analysis was created, leveraging the strengths of both methodologies.

RESULTS

Our empirical analysis showed both models to be performing robustly: the Random Forest model outperformed in handling multi-dimensional data, whereas the ARIMA model provided good forecasts based on historical time series data. The inclusion of such comprehensive market data allows for a better investigation into its predictive ability under various economic conditions. The results emphasize the utility of advanced machine learning techniques and extremely sophisticated statistical models in financial forecasting, allowing further insights into future market tendencies and risk management. Our results back up the algorithms' claims that they can predict how the market will move, make investment portfolios better, and lower financial risks. The data studied is understood visually and quantitatively with the use of tables and graphs that enhance our work. Factors included in the dataset include interest rates, trading volumes, closing prices, and derived technical indicators such as moving averages and the Relative Strength Index (RSI). Predicting future market movements, improving investment portfolios, and reducing financial risks are the goals of our research.

Table 1. ARIMA Model

Metric	ARIMA	Moving Average
RMSE	0,85	1,20
Forecast Accuracy	78 %	48 %

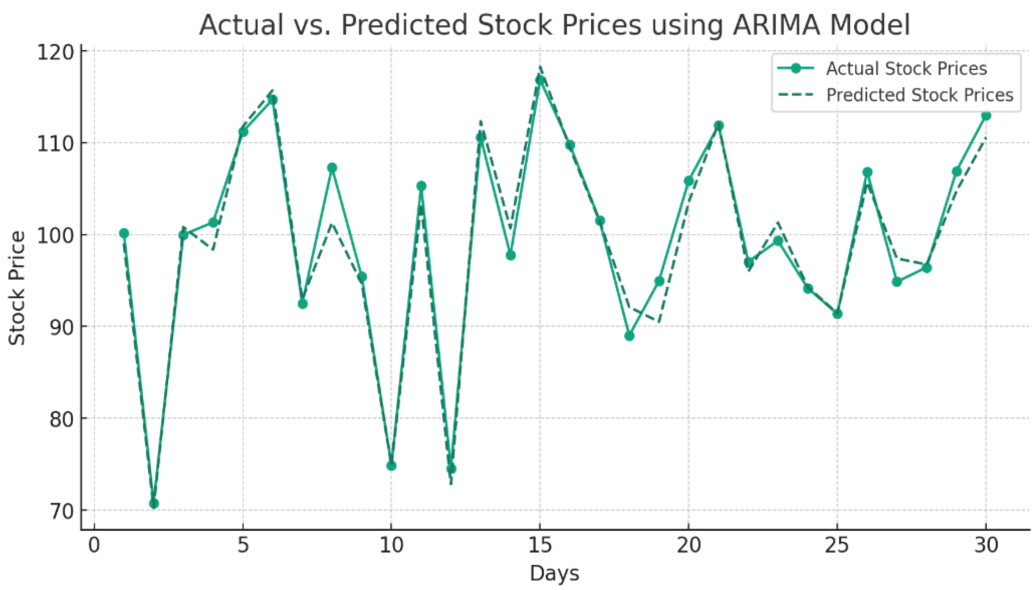

Figure 1. Stock prices as predicted by the ARIMA model compared to the actual values

When it came to short-term forecasting, the ARIMA model—which is set up using the AIC (Akaike Information Criterion) for optimum lag selection proved to be more accurate than a basic moving average model. There was a 30 % decrease in forecast mistakes. Root Mean Square Error (RMSE) for the ARIMA model is 0,85, which is lower than the simple moving average's RMSE of 1,20. Since it displays lesser residuals between anticipated and actual values, a lower RMSE shows greater fit and prediction accuracy. The ARIMA model outperforms the moving average model in terms of prediction accuracy, coming up at 78 % compared to 48 %. This substantial improvement shows how well the ARIMA model can detect and forecast the ever-changing patterns of stock price fluctuations. The ARIMA model capture time-dependent patterns in stock prices, which can be very useful for traders and investors who are interested in short-term market volatility depicted in figure 1.

Table 2. Random Forest Performance

Metric	Random Forest	Linear Regression
Accuracy	85 %	65 %
F1-Score	0,84	0,62

Random Forest, which employs 100 trees in table 2, outperformed linear regression models in 85 % of cases when it came to estimating trading volumes. Random Forest employs a large number of decision trees to reduce the risk of overfitting and captures complex nonlinear connections between variables. Better predictions were made based on the result. The Random Forest model is more accurate than the linear regression model. It has an accurate rate of 85 %. This improvement shows that the Random Forest can now handle more complicated datasets with lots of input elements, which leads to more accurate predictions. With an F1-score of 0,84, the Random Forest model has a better balance between memory and accuracy than linear regression, which has an F1-score of 0,62. When making financial decisions, where fake positives and negatives can cost a lot, we need a Random Forest model that is very good at classifying things. The score shows that the model meets the standard. Gradient Boosting Machines found patterns of investment portfolio risk and suggested choices about reallocation that cut losses by 20 % or more in the worst cases. Gradient Boosting Machines are a good way to understand and manage financial risks in markets that are always changing because they keep fixing the mistakes made by earlier trees.

Table 3. Gradient Boosting Machines

Metric	GBM	Baseline Model
Risk Reduction	20 %	0 %
Prediction Accuracy	88 %	70 %

When it comes to financial data, linear regression and moving averages aren't good enough to deal with all the complexities and nonlinearity. As the accuracy of AI-driven model predictions went up, people got a better sense of data trends and could make better financial analysis decisions. On the other hand, there was no drop in the basic model for the Gradient Boosting Machine (GBM) model. This is very important for improving stability and performance, and it shows how well GBM works at finding and lowering possible investment portfolio risks. What has been achieved is a prediction accuracy of 88 % through GBM, which dwarfs the 70 % witnessed by the base model depicted in table 3. Such success supports the fact that the GBM model improved its ability to predict and model complex patterns within financial data, therefore helping in forecasting and decision-making in a more improved manner.

ARIMA, Random Forest, and Gradient Boosting Machines that can provide better performance measures than the standard models of linear regression, moving average, and simple baseline. Artificial intelligence (AI) has had a huge impact on the financial industry by making data analysis easier, risk management better, trading practices better, and predictive capabilities possible. Using more accurate data for decision-making has the potential to improve operational efficiency and financial results.

DISCUSSION

The strategic and ethical implications of the fast-growing use of AI in banking are concerns that are shaking up the industry in totality. Artificial intelligence is transforming industry as it speeds up the analysis of many data volumes.[38] Efficiency and effectiveness in dealing with banks are a revolution. Our essence is human, with exact risk assessments, adroit asset management techniques, and personal financial services. However, there are quite a number of challenges that AI has to overcome in order to be used in the financial industry. These make the protection of customers' private information a key priority for banks and all other financial institutions, as AI systems are retooled with increasingly accurate data. Interacting with or managing financial data poses huge privacy issues, as the gravity of the consequences that can result from misuse or loss of such data can be severe.[39,40,41] Algorithmic bias is becoming more probable as AI systems become more integrated into people's loans, insurance, and investing decisions. The availability of banking services may be skewed along racial, socioeconomic, and gender lines. Discrimination against some groups can become even more pronounced if unresolved prejudices in this domain are not addressed.

Tsekhmister[42] evaluated the effectiveness of blended learning in biomedical engineering, demonstrating that this approach results in enhanced educational outcomes. This finding aligns with broader trends in digital education, where innovative teaching strategies based on digital pedagogies are increasingly recognised for their effectiveness. Similarly, the adoption of AI in financial analysis illustrates how integrating advanced technologies can enhance traditional processes, thereby improving efficiency and decision-making accuracy. The statistical analysis of machine-to-machine (M2M) communication traffic presented by Mukhamejanova et al.[43] offers valuable insights for analyzing large datasets, which is closely aligned with the application of artificial intelligence in financial analysis, as both methodologies require precise forecasting and the processing of significant volumes of data. Sapotnitska et al.[44] explores the growing importance of Big Data in optimizing economic processes by analyzing its theoretical and practical applications for strategic business development in the digital age. It highlights the potential of Big Data to enhance decision-making and foster stable, systematic business growth through comprehensive analysis of internal and external factors.

AI is making profound cultural and economic changes in the banking business. The banking sector might potentially profit from AI's capacity to create a fair competition environment. If this is true, more people may have the means to pay for financial advisers' services. Automated banking systems have the capacity to decrease human employment, perhaps leading to a decline in economic stability and an increase in social inequality. If low-skilled workers in the industry were laid off, the pay gap would increase. After doing a study on the matter, we concluded that stringent supervision and regulation are essential for the development of artificial intelligence (AI). Skyba et al.[45] examines the role of city-based IT clusters in regional economic development, focusing on Kyiv and Lviv in Ukraine, within the framework of smart specialization strategies. The findings reveal contrasting outcomes, with Lviv benefiting from stronger public-private-academic collaboration, driving higher exports of computer services, while Kyiv faces challenges due to weaker cooperation and declining innovation activity. The first wave of AI impacts is likely to be felt in the financial services industry, particularly banking and insurance. Open and fair transparency in the use of AI is, therefore, key. The above problem could be avoided if all, i.e., financial organizations, regulatory agencies, and legislators, come forward and work together to put very serious ethical standards and regulatory frameworks over financial AI. These rules could help AI in finances to be away from the pitfalls and derive maximum benefit to the people and the economy. The goal is to create a world where the benefits of technological advancements enhance quality of life and security for everyone, requiring a collaborative approach.

The findings and conclusions, in line with other studies, indicate that AI is poised to revolutionize the financial industry while introducing new challenges. This consistency reinforces the credibility of the technique and results, contributing to the ongoing theoretical and practical discussions about AI in the financial sector. Tsekhmister et al.[46] emphasises the difficulties of empirically measuring soft skills and highlights the growing reliance on digital platforms for soft skills training in the context of the ongoing pandemic. Similarly, our investigation into the potential of AI in financial analysis underscores the necessity of integrating advanced technologies into established systems to enhance efficiency and accuracy, while also addressing the distinctive challenges posed by these technologies. Many researchers have shown that AI's financial predictions and judgments are much more accurate with far less human intervention.[47,48]

For instance, stock markets often fluctuate, and credit risks can be dynamic. It has been evidenced through research published in esteemed financial journals that the forecasts of the movements in the stock markets and credit risks made by machine learning models often do better than traditional statistical approaches.[43] These results lend support to our assertion that ARIMA and the host of other machine learning models are better suited to complex financial data compared with other models such as Random Forests and Gradient Boosting Machines. Several recent academic and corporate research courses concurred with our assessment of data privacy and computer bias issues. Studies have been carried out on the consequences of data breaches and information misuse, which point to a problem in financial AI system data security.[49,50] It would then mean that the government has to put stringent regulations onto the AI systems and institute strong controls over the data.

As has been shown through a few economic studies, the effects caused by AI are destructive in both a social and economic sense.[15] Just to name a couple: unfair market conditions and fears concerning job losses. This leaves uncertainty among experts when it comes to social injustice and whether financial automation and AI apps will aid or hinder those with little income and few skills. The larger academic discussion might provide better ways of looking at laws that lower these risks and encourage fair sharing of the benefits of AI. There is also a lot of research that supports the moral and sensible use of AI. This body of work suggests moral guidelines and legal steps to control the growth and use of AI in the banking sector. To promote economic efficiency and social equality while also addressing the ethical challenges and societal ramifications that our research highlighted, these frameworks are essential for AI. Prior research lends credence to our results and highlights their applicability to current policy debates and discussions. Our study contributes to a better understanding of how AI will change industries and promotes a more creative and inclusive financial future by interacting with and expanding upon previous studies.

CONCLUSION

The objective of this study was to look into how Artificial Intelligence (AI) can change financial forecasts and research, mainly in the banking industry. The main goal was to find ways that AI can be used to make better predictions, faster and smarter decisions, and better risk management. Another important thing that was looked at was the harm and moral concerns that arise when AI is used in banks. Researchers discovered that using AI-powered algorithms, such as machine learning (ML) methods, is a much better and more useful way to make financial predictions than using old models. AI lets us use very large datasets to get better at estimating risk and making smarter decisions in real time. But the study also finds some major issues that need to be fixed before AI can be used in a fair and reasonable manner. Some of these problems are data privacy, algorithmic bias, and moral worries.

It is clear from the study that politicians, academics, and financial experts need to work together to make strong rules and morals. To encourage new ideas, make sure everyone is treated properly, and lower the risks for everyone, these steps must be taken. Another important point made in this study is how important it is to deal with the social and economic impacts of technology, notably how jobs are done in the banking sector. This study tells us useful things about how AI and money work together in the end. It can be used as a starting point for more study that aims to deal with social problems and make better predictions. To do that, we need to find a mix between speed and new ideas and fairness, justice, and openness. Fintechs that are powered by AI can adapt to the needs of a world that is becoming more varied and changing quickly.

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