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LEVERAGING ARTIFICIAL INTELLIGENCE FOR FINANCIAL ANALYSIS AND FORECASTING

***Mitesh Kadakia**

Vice-Principal and Associate Professor, Badruka College of Commerce and Arts, Hyderabad.

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***Corresponding Author: Mitesh Kadakia**

Vice-Principal and Associate Professor, Badruka College of Commerce and Arts, Hyderabad.

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ABSTRACT

This paper investigates into the utilization of Artificial Intelligence (AI) towards strengthening accuracy and decision-making in financial analysis and prediction. The comparison made on four distinct models of prediction: ARIMA (Autoregressive Integrated Moving Average) Random Forest(RF). Support Vector Machines (SVM) and Long Short-Term Memory (LSTM) brings to light the predictions like stock prices, inflation rate, and interest rates. Performance criteria were set through upper-hand that AI models have when contrasted with the traditional approach to financial indicators as well as several factors in terms of decision such as speed and decision confidence risk. Results and analysıs indicate how the Al-powered models, and 1n this regard the MAE, RMSE, accuracy models which utilized LSTM algorithm provide a very superior accuracy over forecasting, allow quicker decisions compared to traditional ones, and perform much better for predicting risks relate to any finance. This research underscores the immense potential of AI to optimize financial Strategy reduce risks, and enable more effective decision-making in real-time financial markets.

KEYWORDS: Artificial Intelligence, Financial Analysis, Forecasting. Machine Learning, Deep Learning Artificial Decision-Making. Stock Price Prediction, Risk Prediction, Accuracy.

1. INTRODUCTION

For organizations to make wise decisions and reach their financıal objectives, financial forecasting and analysıs are crucıal tools. Busınesses can find opportunities. dangers, and areas io data and making accurate predictions about future financial performance.

A useful standard for assessing the effectiveness of various corporate divisions, plansor projectsis financial forecastıng. By contrasting actual outcomes with projected outcomes. busmness can learn a great deal about how effective their efforts are.

Deviation analysis, a potent tool in financial forecasting, draws attention to the difference between expected and actual outcomes Businesses can uncover areas tor optimisation and development by delving further into the underlying causes of these variations. Businesses may make well-informed decisions and improve their strategies for future success with the help of this data-driven strategy

Rapid and significant technological advancements have revolutionised a variety of industries, and the financial sector is no exception. One of the most important technological developments in finance, according to Kokina& Davenport (2017), is the introduction and use of artificial intelligence (AI). Artificial Intelligence (A1) is the replication of human intelligence in computers, which are carefully designed to analyse and interpret complex patterns in data, make decisions on their own. and learn from experiences. A paradigm shift has been sparked by the integration of Al into financial decision-making, which has improved productivity, accuracy, and profitability. This essay seeks to explore the significant influence that artificial intelligence has on financial decision-making, highlighting both the advantages and disadvantages of this technology. Traditional investment tactics, on the other hand, mostly depended on human intuition, which frequently resulted in skewed assessments and lost opportunities.

2. LITERATURE REVIEW

Faheem, Aslam, and Kakolu (2024) explored how financial forecasting has been transformed by artificial intelligence (AI), specifically in terms of enhancing risk assessment and decision-making procedures. Their research demonstrated the promise of predictive analytics driven by Al, which can improve risk assessment and facilitate wiser decision-making. Artificial intelligence (AI) models can evaluate enormous volumes of financial data in real time by utilising machine learning algorithms, neural networks, and big data analytics. This allows them to find insights that traditional methods might overlook. Financial firms can analyse credit risks, forecast market movements, and improve investment strategies thanks to these capabilities. Furthermore, Al models become more efficient in changing market situations as they learn and adapt over time. Notwithstanding its benefits, he study also covered the drawbacks of AI-enabled financial prediction, including issues with data security, interpretability of the modei, and moral dilemmas in automated decision-making. The authors came to the conclusion that artificial intelligence is essential to building a more robust and informed financial environment

Al-Surmi, Bashiri, and Koliousis (2022) examined how information technology (IT) and marketing strategies fit strategically and how this affects operational success. The researchers put up a novel paradigm for decision-making that combines IT and marketing tactics, based on a thorough examination of the literature. The study gathered data from 242 managers across a variety of businesses and using structural equation modelling (SEM) to validate the proposed links. The findings showed that organisational structure moderates he positive mediation of the connection between marketing strategy and performance by IT strategy. Additionally, the study presented an artificial neural network (ANN)-based Al-based decision-making model that outperformed conventional approaches. By experimentally examining the mediating effect of marketing strategy on IT strategy, performance, and operational decision-making, this research added to the body of literature.

Bharadiya (2023) examined how machine learning (ML) has revolutionised business intelligence (BI) and how it affects decision-making. By facilitating more effective data gathering and preparation such as cleaning and feature engineering, machine learning has transformed business intelligence. Better forecasting, customer segmentation. demand prediction and preparation, such as data integration, cleaning and feature engineering, machine learning has and churn analysis are made possible by machine learning-powered predictive analytics. While natural language processing (NLPY improves sentiment analysis, text mining, and chatbots for better customer care, machine learning (ML) helps detect outliers, fraud, and operational anomalies Additionally, recommendation systems powered by machine learning provide tailored recommendations based on content-based and collaborative filtering strategies. Through sophisticated data visualisation, machine learning also makes interactive dashboards and real-time monitoring possible. Improved accuracy, quicker decision-making, improved customer experience, lower costs and a competitive edge are some advantages of ML in BI. But issues like ‣interpretability, ethics data quality. and talent gaps still exist. Future developments n machine learning, such as edge computing, augmented analytics, and moral AI practices. were also covered in the study

Paramesha, Rane, and Rane (2024) suggested a thorough framework for integrating Big Data, the Internet of Things (oT). and artificial intelligence (AD) to improve BI capabilities. The framework entails collecting data from Internet of Things devices, using Big Data technologies to analyse it, and applying Al to analyse it. Blockchain guarantees data accuracy and security, while edge computing lowers latency and permits real-time decision-making. BI apps like dynamic dashboards and automated workflows are powered by the insights that are produced. Key issues in the field were discovered by the study, which demonstrated how organisations may foresee future results, enhance operational procedures, and obtain a deeper knowledge by combining various technologies. In today's data-driven world, the authors stressed that integrating these technologies can set up companies for long-term growth and success by providing fresh chances for innovation and competitive advantage.

Adesina, Iyelolu, and Paul (2024) examined how predictive analytics may improve busines performance and strategic decision-making, The study examined the elements of predictive analytics such as data mining, machine learning, and statistical methods, and followed its development in tandem with advances in big data platforms, cloud computing, and artificial intelligence. By using predictive analytics, companies can improve their market share, profitability, and efficiency b, extracting actionable insights from raw data. Along with addressing issues like data privacy and ethical considerations, the report also covered new developments in Al, the Internet of Things (IoT), and real-time analytics. The authors came to the conclusion that in the present data-driven company environment using predictive analytics is crucial for long-term success and obtaining a competitive edge.

2. RESEARCH METHODOLOGY

2.1 Data Collection

Data was extracted from financial databases on stock market prices, interest rates inflation rates, and other economic indicators. In forecasting the stock market, daily closing prices of Apple Inc. (AAPL) were used. Over a period of 10 years, economic indicators like interest rates, inflation rates, and GDP growth rates from government reports and central bank publications were also gathered. Data were pre-cleaned for data cleansing and anamolies/missing value elimination prior to using the dataset for analysis.

2.2 Model Selection

Four models were selected in this study, namely ARIMA (Autoregressive Integrated Moving Average), Random Forest (RF), Support Vector Machines (SVM), and Long Short-Term Memory (LSTM), to forecast the financial indicators as these models are capable of handling different types of data patterns. In fact, one can distinguish between the traditional time series model ARIMA and machine learning models: Random Forest, SVM and LSTM used for complex relationships that could be nonlinear.

Using ARIMA as a baseline model, since ARIMA has been shown to be effective for time series data that consist mainly of univariate components.

Random Forest (RF), a tree-based ensemble learning model. was used for its ability to handle both regression and classification tasks, as well as its robustness in managing high-dimensional data.

Support Vector Machines (SVM), which are known to be strong in classification tasks and able to model complex decision boundaries, were used for predicting financial trends.

LSTM was selected because it can capture long-term dependencies in time-series data. very necessary for predicting stock prices and other financial forecasts based on the history of events and trends.

2.3 Model Implementation

Historical data was used in implementing and training the models selected. It split the data into a training set (80%) and test set (20%). The machine learning models used the training set to train their models, after which their prediction was tested using the test set. Feature engineering such as lag variables, moving averages, and technical indicators were added on the machine learning models (RF, SVM, and LSTM).

The ARIMA model has been fine-tuned using a grid search for optimal values of p, d, and c to fit the data well. For RF, SVM, and LSTM models, hyperparameters such as the number of trees to choose in Random Forest, the type of kernel to be used for SVM, and the number of layers and neurons to consider in LSTM were optimized using cross-validation in addition to grid search.

2.4 Evaluation Metrics

Three such measures have been used to evaluate the performance of each model: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Accuracy. The measure of average magnitude of errors generated in the predictions using MAE reflects how far the predicted values are from their actual values. RMSE gives the square root of the average squared differences between predicted and actual values, which penalizes larger errors more critically and is particularly useful in financial forecasting. Accuracy measures the percentage of correct predictions made by the model, giving an overall measure of how successful the model was at making predictions. These metrics were calculated for each model, and then the results were compared to determine which model produced the most accurate and reliable predictions.

Decision-Making Analysis

In order to assess the effect of Al models on decision-making, an evaluation was carried ou with four major parameters: Decision Accuracy, Time Taken for Prediction, Decision

Confidence and risk Prediction Accuracy. The accuracy of the decisions made by each model was calculated as a percentage of correct predictions compared to the actual market movements, and Time Taken for Prediction was an indication of the efficiency of the model in producing predictions. which is of paramount importance in high-speed financial markets. Decision Confidence measured the I confidence of each model in itS predictions, thus indicating how reliable the model is for making high-stakes decisions, and Risk Prediction Accuracy measured how well each model can predict financial risks, such as market downturns or volatility. These factors were important in determining how AI models affect the speed, reliability, and effectiveness of financial decision-making in real time scenarios.

3. Data Analysis

Table 1 Analysis of error statistics of forecasting errors opens up the significant differences between the four models, namely: ARIMA, RF, SVM, and LSTM, since their mean absolute errors have variations in them. On the basis of MAE criteria, LSTM shows the best performance results with a MAE of 0.06 units, meaning that its predictions are always closer to the target value Moreover, its lowest RMSE of 0.08 shows that LSTM is less prone to big errors besides making higher predictive accuracy than the other models. In contrast, ARIMA showed the highest MAE of 0.12 and the highest RMSE of 0.15, indicating less reliability in it and relatively more errors ir prediction. In terms of overall accuracy, LSTM is again ahead with an impressive 95% and outperforms Random Forest (91%) and SVM (89%), which also perform well but not as effectively as LSTM. ARIMA has the lowest accuracy at 85%, failing to keep up with the precision of machine learning models, especially in the capturing of complex patterns. Overall, the results indicate that though traditional models like ARIMA are valid, machine learning models, especially LSTM, are superior in terms of accuracy and more appropriate for financial forecasting tasks, which can give more reliable and consistent predictions

The table indicates that the LSTM outperforms all the other models 1n terms of forecasting. as it results in the highest accuracy and lowest error metrics. hence taking the highest reliability and accuracy measurements. Random Forest comes close with strong performances but with errors greater than that of LSTM. SVM gives 8ood performance. though with the inability to minimize error and accuracy. ARIMA performs the weakest, with higher errors and lower accuracy. indicating that traditional models struggle compared to machine learning approaches 1n this context.

Table 3 Performance metrics of various AI models for decision making in financial forecasting ARIMA Random Forest SVM Long Short-Term Memory Accuracy Mean Absolute Percentage Error Confidence Time-to-Prediction LSTM is a highly accurate model and the most confident model, ensuring very precise prediction, but requires the longest amount of time. It turns out that the fastest model in the list above is Random Forest, which not only has achieved great decision

accuracy. confidence, but also speed of execution, while S VM is efficient in terms of accuracy and confidence but a little slower and also less effective as a predictor for risks compared with Random Forest. Traditional model ARIMA delivers the lowest performance in terms of decision accuracy confidence, and risk prediction. Hence, it is not ideal for fast and dynamic financial decision- making. Overall, LSTM provides the best accuracy and confidence, but Random Forest provides an optimal combination of speed and reliability in real-time financial forecasting.

4. CONCLUSION

This study reveals the transformative impact of artificial intelligence in financial analysis and forecasting. In particular, it focuses on accuracy and enhancing decision-making ability. It presents a comparison between several AI models: ARIMA, Random Forest, Support Vector Machines. and Long Short-Term Memory (LSTM). Indeed, machine learning and deep learning techniques are much better than ARIMA in forecasting financial indicators like stock prices, inflation rates,. and interest rates. Findings indicate that LSTM, in particular, outstrips the rest with regard to accuracy. decision-making confidence, and risk prediction performance. These enable valuable decisions in real-time financial settings. The study, therefore, not only emphasizes the accuracy of the forecasting but also how decision factors, such as speed of prediction, confidence levels, and capabilities for risk management, affect decision-making. Results from the study indicated a significant enhancement both in terms of predictions' quality as well as efficiency of decision through the implementation of Al into the financial forecasting activity, ultimately more informed and timelier reliable financial strategies.

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