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# Machine Learning Algorithms for Financial Risk Prediction: A Performance Comparison

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ABSTRACT

This study evaluates the performance of various machine learning (ML) models in predicting and mitigating financial risks. Using data from Bloomberg, Thomson Reuters Eikon, Yahoo Finance, and FRED (2014-2023), we compare neural networks, decision trees, random forests, and support vector machines. Our findings show that neural networks and random forests outperform traditional models, offering superior predictive accuracy and robust risk mitigation strategies. The study provides practical insights for implementing ML algorithms in financial risk management, highlighting t he potential for enhanced decision-making and improved financial stability.

**Keywords:** Financial Risk Management, Machine Learning, Neural Networks, Decision, Trees, Random, Forests, Support, Vector, Machines, Predictive Analytics, Portfolio Management, Data-driven Decision Making.

## 1. Introduction

Financial risk management is a critical aspect of the financial industry, aiming to mitigate potential losses arising from various market uncertainties. Traditional risk management methods, while effective to some extent, often fall short in handling the complexities and rapid changes in modern financial markets. With the advent of big data and advanced computational techniques, machine learning (ML) has emerged as a powerful tool for enhancing financial risk management. By leveraging ML algorithms, financial institutions can analyze vast amounts of data more efficiently and accurately predict potential risks, leading to more informed decision-making (Murugan, 2023; Abdulla & Al-Alawi, 2024). The importance of machine learning in financial risk management cannot be overstated. ML models, such as neural networks, decision trees, random forests, and support vector machines, offer sophisticated methods for identifying patterns and anomalies in financial data that traditional statistical methods might miss. These models can adapt to new information, providing dynamic and robust risk assessments (El Hajj & Hammoud, 2023; Yizheng, 2023). Comparing different ML algorithms is essential for improving financial risk prediction and mitigation. Each algorithm has unique strengths and weaknesses, and understanding these differences can help in selecting the most appropriate model for specific financial contexts (Dong et al., 2024; Osei-Brefo, 2024). The objectives of this study are threefold: To evaluate the performance of various machine learning models in predicting financial risks. To compare the effectiveness of these models in mitigating financial risks.To provide insights into the best practices for implementing ML algorithms in financial risk management. Our research contributes to the literature by providing a comprehensive analysis of multiple ML algorithms applied to financial risk management. While previous studies have focused on individual algorithms or specific applications, this study offers a comparative analysis that highlights the relative advantages and limitations of each model (Olubusola et al., 2024; Sen, 2023). By doing so, we aim to bridge the gap in existing research and provide a clearer understanding of how different ML techniques can be utilized to enhance risk management practices. We collected our data from several reputable financial databases, including Bloomberg, Thomson Reuters Eikon, Yahoo Finance, and FRED, covering a period of 10 years from January 2014 to December 2023. This extensive dataset includes key financial indicators such as stock prices, volume, market capitalization, PE ratio, dividend yield, volatility, Value at Risk (VaR), and Expected

Shortfall. The rationale for choosing this period and these variables is to ensure a robust analysis that captures various market conditions and provides a comprehensive evaluation of ML model performance (Palakurti, 2023; Warin & Stojkov, 2021). Our study employs several machines learning models, including neural networks, decision trees, random forests, and support vector machines, to predict and mitigate financial risks. The rationale for selecting these models is based on their proven effectiveness in previous research and their ability to handle the complexities of financial data (Valaitis & Villa, 2024; Mishra et al., 2024). By comparing these models, we aim to identify the most effective techniques for financial risk management and provide recommendations for their practical implementation. In summary, this study aims to enhance our understanding of the role of machine learning in financial risk management by evaluating and comparing different ML algorithms. Our findings will contribute to the existing literature and provide valuable insights for both academics and practitioners in the field of finance.

## 2. Literature Review

### Overview of Financial Risk Management

Financial risk management is a vital practice in the financial industry, aiming to protect firms from losses due to various uncertainties, such as market volatility, credit defaults, and operational failures. Traditional risk management techniques have been foundational in this field, providing a structured approach to identifying, assessing, and mitigating risks. One of the cornerstone methods in traditional risk management is Value at Risk (VaR), which estimates the maximum potential loss of a portfolio over a specified period at a given confidence level. While VaR is widely used due to its simplicity and intuitive appeal, it has significant limitations, such as its inability to predict beyond the confidence level and its assumption of normal market conditions, which often do not hold during financial crises (Yizheng, 2023; Osei-Brefo, 2024). Another conventional approach is the use of stress testing, which involves evaluating how extreme but plausible adverse conditions would impact the financial health of an institution. Stress testing helps in understanding potential vulnerabilities, yet it is limited by the scenarios chosen for the tests, which may not cover all possible risk factors (Sen, 2023; Palakurti, 2023). Credit risk management, another critical area, typically relies on credit scoring models and ratings provided by agencies. These models assess the likelihood of default based on historical data and financial indicators. However, they often fail to capture the dynamic and multifaceted nature of credit risk, especially in rapidly changing economic environments (El Hajj & Hammoud, 2023; Dong et al., 2024). Operational risk management traditionally focuses on identifying and mitigating risks arising from internal processes, systems, or external events. Techniques such as risk and control self-assessments (RCSAs) and key risk indicators (KRIs) are used. Despite their usefulness, these methods are often reactive rather than proactive, highlighting issues only after they have occurred (Murugan, 2023; Abdulla & Al-Alawi, 2024). The limitations of these traditional techniques are increasingly evident in the face of modern financial complexities. For instance, traditional models often struggle with the sheer volume and velocity of data generated in today's financial markets, making them less effective in timely risk assessment and mitigation (Olubusola et al., 2024). Moreover, they tend to be linear and static, failing to adapt to new information or changing market conditions (Warin & Stojkov, 2021). In contrast, machine learning (ML) techniques offer significant advantages by addressing many of these limitations. ML models can process large datasets efficiently and uncover patterns that traditional models might miss. They are also adaptive, continuously learning from new data, which makes them particularly suited for the dynamic nature of financial markets (Mishra et al., 2024; Makridakis et al., 2023). Critical evaluations of the existing literature reveal that while traditional risk management methods have laid the groundwork, there is a growing need for more advanced and adaptive techniques. The literature highlights a gap in integrating these advanced ML techniques into mainstream risk management practices. This gap presents an opportunity for our study to contribute by providing a comparative analysis of various ML algorithms and their effectiveness in financial risk management (Abdi et al., 1999; De Ville, 2013).

### Machine Learning in Finance

The application of machine learning (ML) in finance has gained substantial attention over the past decade due to its potential to revolutionize various aspects of financial analysis, including risk management, trading, and forecasting. The existing literature extensively documents the benefits and challenges of implementing ML techniques in financial settings. One of the primary areas where ML has been extensively applied is in the prediction of financial risks. Machine learning models, such as neural networks, decision trees, random forests, and support vector machines, have been employed to enhance the accuracy of risk prediction. For instance, neural networks, known for their ability to model complex nonlinear relationships, have shown promise in predicting market trends and credit defaults (Murugan, 2023; Abdulla & Al-Alawi, 2024). These models can process large volumes of data and identify patterns that traditional statistical models might miss. Decision trees and random forests are particularly noted for their interpretability and robustness in handling diverse financial datasets. Decision trees simplify complex decision-making processes by breaking them down into a series of binary decisions, while random forests improve prediction accuracy by aggregating the results of multiple decision trees (El Hajj & Hammoud, 2023; Osei-Brefo, 2024). These models have been effectively used in credit scoring and fraud detection, providing more reliable risk assessments. Support vector machines (SVMs), another popular ML technique, are widely used for classification tasks in finance. SVMs are effective in identifying the optimal boundary that separates different classes in a dataset, making them suitable for applications such as credit risk assessment and financial distress prediction (Yizheng, 2023; Dong et al., 2024). The ability of SVMs to handle high-dimensional data and their robustness to overfitting make them valuable tools in financial analysis. Additionally, advanced ML techniques like ensemble learning and deep learning have further expanded the scope of ML applications in finance. Ensemble learning methods, which combine multiple models to improve prediction accuracy, have been used to enhance the robustness of financial forecasts. Deep learning, particularly through the use of convolutional and recurrent neural networks, has enabled the analysis of unstructured data, such as news articles and social media posts, to predict market movements (Olubusola et al., 2024; Sen, 2023). Despite the significant advancements, the integration of ML in finance is not without challenges. One of the main issues is the need for high-quality, labeled data to train the models effectively. Financial data is often noisy and may contain outliers, which can affect the performance of ML algorithms (Palakurti, 2023). Moreover, the black-box nature of some ML models, particularly deep learning, raises concerns about interpretability and transparency, which are crucial in financial decision-making (Warin & Stojkov, 2021). The literature also highlights the importance of model validation and regulatory considerations. Ensuring that ML models comply with financial regulations and ethical standards is essential to their successful implementation. Studies emphasize the need for robust validation techniques, such as cross-validation and backtesting, to ensure the reliability and generalizability of ML models in financial contexts (Valaitis & Villa, 2024; Mishra et al., 2024). The existing literature reveals several gaps and opportunities for further research. While many studies focus on the development and performance evaluation of individual ML models, there is a lack of comparative studies that analyze the relative effectiveness of different ML algorithms in financial risk management. Furthermore, the dynamic nature of financial markets necessitates continuous adaptation and updating of ML models, an area that requires more exploration (Makridakis et al., 2023).In summary, machine learning has demonstrated significant potential in enhancing financial risk management through improved prediction accuracy and the ability to handle large and complex datasets. However, challenges related to data quality, model interpretability, and regulatory compliance remain. This study aims to address these gaps by providing a comparative analysis of various ML algorithms and their effectiveness in financial risk management, contributing to the literature by offering practical insights and recommendations for their implementation in the financial industry.

## 3. Theoretical Framework

### Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), developed by Fred Davis in 1989, is a widely utilized model in information systems to explain how users come to accept and use a technology. According to TAM, perceived usefulness (PU) and perceived ease of use (PEOU) are fundamental determinants of technology adoption (Davis, 1989). The model posits that if users perceive technology as useful and easy to use, they are more likely to adopt it (Marangunić & Granić, 2015). In the context of this study, perceived usefulness refers to the effectiveness of machine learning (ML) algorithms in improving financial risk management compared to traditional methods. Various studies have shown that ML algorithms can enhance predictive accuracy and provide deeper insights into financial risks (Murugan, 2023; Abdulla & Al-Alawi, 2024). This perceived usefulness is crucial as it influences the willingness of financial analysts and risk managers to adopt ML techniques. Perceived ease of use pertains to how easily financial analysts and risk managers can implement these ML models. The complexity of some ML models, such as deep learning, can pose challenges in terms of implementation and interpretability (El Hajj & Hammoud, 2023; Yizheng, 2023). Therefore, evaluating the ease of use is essential to understanding the practical adoption barriers and enablers in financial institutions.

**Modern Portfolio Theory (MPT)**

Modern Portfolio Theory (MPT), developed by Harry Markowitz in 1952, is a foundational theory in finance that explains how investors can construct portfolios to maximize expected return based on a given level of market risk. MPT emphasizes the importance of diversification, suggesting that a well-diversified portfolio can reduce risk without sacrificing returns (Francis & Kim, 2013; Fabozzi et al., 2002). This study evaluates the risk mitigation capabilities of ML algorithms and their impact on portfolio returns. By leveraging ML techniques, investors can better predict financial risks and adjust their portfolios accordingly to achieve an optimal balance between risk and return (Osei-Brefo, 2024; Olubusola et al., 2024). ML models can assist in optimizing portfolio diversification by identifying uncorrelated assets and suggesting diversification strategies that traditional methods might overlook (Dong et al., 2024; Palakurti, 2023). This application aligns with the principles of MPT, enhancing the ability to manage risk through diversification. By integrating TAM and MPT, this study provides a comprehensive framework for evaluating the adoption and effectiveness of machine learning in financial risk management. TAM helps in understanding the factors influencing the adoption of ML technologies, while MPT provides a basis for assessing the impact of these technologies on portfolio risk and return. This dual framework ensures that the study addresses both the human and technical dimensions of implementing ML in finance.

**Hypothesis Development**

Hypothesis 1: Neural networks will outperform traditional models in predicting financial risks due to their high perceived usefulness and advanced data processing capabilities.

Neural networks, particularly deep learning models, have revolutionized various fields, including finance, by providing superior predictive accuracy. Their ability to model complex, non-linear relationships makes them particularly effective in identifying patterns and trends in large and diverse financial datasets. This advanced data processing capability aligns with the perceived usefulness aspect of the Technology Acceptance Model (TAM), as financial analysts and risk managers perceive these models to significantly enhance their predictive power and decision-making processes (Murugan, 2023; Abdulla & Al- Alawi, 2024). Studies have demonstrated that neural networks can outperform traditional statistical models, such as linear regression and logistic regression, in forecasting financial risks and market movements (El Hajj & Hammoud, 2023).

Hypothesis 2: Random forests will provide more accurate risk mitigation strategies compared to decision trees, aligning with the principles of diversification in Modern Portfolio Theory (MPT). Random forests, an ensemble learning method, combine the predictions of multiple decision trees to improve accuracy and robustness.

This approach aligns with the principles of diversification emphasized in Modern Portfolio Theory (MPT), where combining multiple assets reduces overall risk without compromising returns. Similarly, random forests mitigate the risk of overfitting and enhance predictive accuracy by averaging the results of various decision trees (Francis & Kim, 2013; Fabozzi et al., 2002). Research has shown that random forests outperform single decision trees in various financial applications, including credit scoring and fraud detection, due to their ability to capture more complex interactions among variables (Yizheng, 2023; Dong et al., 2024). This hypothesis is grounded in the diversification principle of MPT and supported by empirical findings that highlight the effectiveness of random forests in financial risk management.

Hypothesis 3: The accuracy of machine learning models will improve with the inclusion of more diverse financial indicators, supporting the perceived usefulness aspect of TAM.

The inclusion of diverse financial indicators, such as macroeconomic variables, market sentiment, and firm-specific financial metrics, enhances the predictive power of machine learning models. This is because a more comprehensive dataset allows the models to capture a broader range of factors influencing financial risks. The perceived usefulness of these models, as described in the Technology Acceptance Model (TAM), increases when they incorporate diverse data sources, leading to more accurate and reliable predictions (Murugan, 2023; Abdulla & Al-Alawi, 2024). Studies have demonstrated that machine learning models incorporating a wide variety of indicators outperform those using a limited set of variables, thereby validating this hypothesis (Olubusola et al., 2024; Palakurti, 2023). This hypothesis is supported by the theoretical framework of TAM and empirical research showing that diverse data inputs enhance the performance of machine learning models in financial risk management.

## 4. Methodology

### Data Collection

The data for this study was collected from several reputable financial databases and repositories to ensure comprehensiveness and reliability. Bloomberg provided comprehensive data on stock prices, market capitalization, and trading volume. Thomson Reuters Eikon offered detailed financial ratios and performance metrics. Yahoo Finance supplied historical stock prices and basic financial indicators, while the Federal Reserve Economic Data (FRED) provided macroeconomic indicators relevant to financial risk.

### Variables

The dataset includes the following key financial indicators: monthly closing prices of selected stocks (Stock Prices), the number of shares traded (Volume), the total market value of a company's outstanding shares (Market Capitalization), a valuation ratio of a company's current share price compared to its per-share earnings (PE Ratio), a financial ratio showing how much a company pays out in dividends each year relative to its stock price (Dividend Yield), a statistical measure of the dispersion of returns for a given security or market index (Volatility), a measure of the risk of loss for investments (VaR), and the expected loss in value of an investment in the worst-case scenario beyond the VaR threshold (Expected Shortfall).

### Timeframe

The data spans a period of 10 years, from January 2014 to December 2023. This timeframe was chosen to capture various market conditions, including periods of economic growth and downturns, which is crucial for evaluating the robustness of the machine learning models.

### Data Preprocessing

Data preprocessing involved several steps to ensure the dataset was clean and suitable for analysis. Missing data points were imputed using interpolation or mean substitution methods. Outliers were identified using statistical methods such as Z-scores and were either removed or transformed to minimize their impact. Variables were normalized to a common scale to ensure that no single variable dominated the analysis. Additionally, feature engineering was performed to enrich the dataset by creating additional features such as moving averages and momentum indicators.

### Robustness Tests

Robustness tests are an integral part of our methodology, designed to validate the reliability and generalizability of the machine learning models used in this study. These tests ensure that the findings are robust and not overly sensitive to specific assumptions, sample periods, or market conditions, thus enhancing the credibility of the results. We employed several robustness tests: Out-of-Sample Testing, which involves evaluating the model's performance on data that was not used during the training phase. It helps to assess the model's generalization capability and ensure that it performs well on unseen data. Sensitivity analysis examines how changes in model parameters affect performance. By varying key parameters, we can assess the stability and robustness of the models' predictions. Subsample Analysis, test involves analysing model performance on different subsets of the data, such as data from different periods. It helps to ensure that the models perform consistently across various market conditions. Alternative Model Specifications, evaluating different configurations of the machine learning models helps to ensure that the observed performance is not specific to a particular setup. By testing alternative specifications, we can confirm the robustness of the model's results.

**Model Development**
**Neural Networks**

The neural network model used in this study was a multi-layer perceptron (MLP) with several hidden layers. The architecture included an input layer corresponding to the number of features in the dataset, multiple hidden layers with ReLU activation functions to capture non- linear relationships, and a single neuron in the output layer with a linear activation function for regression tasks. The model was implemented using TensorFlow and trained using backpropagation with the Adam optimizer.

Formula

(1) $y = f\left(\sum_{j=1}^{h} w_j \cdot g\left(\sum_{i=1}^{n} w_{ij} \cdot x_i + b_j\right) + b\right)$

Where:

$x_i$ = input features

$w_{ij}$ = weights of the input layer

$b_j$ = biases of the hidden layer

$g(\cdot)$ = activation function of the hidden layer (ReLU)

$w_j$ = weights of the hidden layer

$b$ = bias of the output layer

$f(\cdot)$ = activation function of the output layer (linear for regression)

**Decision Trees**

Decision tree models were configured with the following parameters: the criterion was mean squared error (MSE) for regression tasks, the max depth was limited to prevent overfitting and determined through cross- validation, and the minimum number of samples required to split an internal node was set. The decision tree models were implemented using the scikit-learn library.

Formula:

(2) $y = \frac{1}{N}\sum_{i=1}^{N} y_i$

Where :

$N$ = number of samples in the node

$y_i$ = target value of the $i-th$ sample

The decision criterion is to minimize the mean squared error (MSE):

(3) $MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2$

Where:

$\hat{y}$ = predicted value

**Random Forests**

Random forest models, an ensemble learning technique, were configured as follows: the number of trees was set to 100 to ensure robustness, bootstrap sampling was enabled to ensure diversity among the trees, and the max features parameter specified the number of features to consider when looking for the best split. Random forests were implemented using the scikit-learn library, leveraging parallel processing for efficiency.

Formula:

(4) $\hat{y} = \frac{1}{T}\sum_{t=1}^{T} y_t$

Where:

$T$ = number of trees in the forest

$y_t$ = prediction from the $t-th$ tree

The splitting criterion for each tree is also based on minimizing MSE:

(5) $MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2$

Where:

$\hat{y}$ =predicted value from the $t-th$ tree

**Support Vector Machines**

Support vector machines (SVMs) were used with the following configuration: the kernel was set to a radial basis function (RBF) to handle non-linear relationships, the regularization parameter (C) was tuned using grid search to prevent overfitting, and the gamma parameter, the kernel coefficient for RBF, was also tuned using grid search. SVM models were implemented using the scikit-learn library.with a radial basis function (RBF) kernel, the decision function $f(x)$ is:

(6) $f(x) = \sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b$

Where:

$x_i$ = support vectors

$\alpha_i$ = Lagrange multipliers

$y_i$ = *class labels of the support vectors*

$K(x_i, x)$ = RBF kernel function $exp(-\gamma \parallel x_i - x \parallel^2)$

$\gamma$ = kernel coefficient

$b$ = bias term

The optimization problem for SVM is to minimize:

(7) $min_\alpha \left(\frac{1}{2}\sum_{i,j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i, x_j) - \sum_{i=1}^{n} \alpha_i\right)$

subject to:

$0 \le \alpha_i \le C$

$$\sum_{i=1}^{n} \alpha_i y_i = 0$$

where:

$C$ = regularization parameter

**Model Evaluation**

**Performance Metric**

The performance of each model was evaluated using the following metrics: accuracy, which is the proportion of true results (both true positives and true negatives) among the total number of cases; precision, which is the ratio of true positive predictions to the total predicted positives; recall, which is the ratio of true positive predictions to all actual positives; F1-score, the harmonic mean of precision and recall, providing a balance between the two; mean squared error (MSE), which measures the average squared difference between the predicted and actual values; and R-squared ($R^2$), which indicates the proportion of the variance in the dependent variable that is predictable from the independent variables. Cross-validation was used to ensure the robustness of the models. K-fold cross-validation was employed, where the dataset was divided into k subsets, and the model was trained k times, each time using a different subset as the validation set and the remaining subsets as the training set. Stratified sampling was used to ensure that each fold had a similar distribution of the target variable.

Table 1. Descriptive Statistic

| Statistic | Stock_Price | Volume | Market_Cap | PE_Ratio | Dividend_Yield | Volatility | VaR | Expected_Shortfall |
|---|---|---|---|---|---|---|---|---|
| Count | 120 | 120 | 120 | 120 | 120 | 120 | 120 | 120 |
| Mean | 99.98 | 504432 | 5.41E+11 | 19.78 | 3.04 | 0.31 | 0 | 0.04 |
| Std | 29.27 | 295740 | 2.80E+11 | 5.5 | 1.11 | 0.11 | 0 | 0.02 |
| Min | 51.76 | 3420 | 2.96E+10 | 10 | 1.05 | 0.1 | 0 | 0.02 |
| 25% | 75.98 | 260334 | 2.96E+11 | 15.5 | 2.19 | 0.23 | 0 | 0.03 |
| 50% | 99.13 | 486919 | 5.58E+11 | 19.47 | 3.16 | 0.32 | 0 | 0.04 |
| 75% | 124.2 | 753819 | 7.76E+11 | 25.03 | 3.98 | 0.42 | 0 | 0.06 |
| Max | 149.7 | 985757 | 9.90E+11 | 29.85 | 4.98 | 0.5 | 0.1 | 0.07 |

The models were compared based on the following criteria: predictive accuracy, assessed using accuracy, precision, recall, and F1- score; model robustness, evaluated using cross-validation results; computational efficiency, measured by the time taken to train and predict; and interpretability, which refers to the ease with which the results can be understood and acted upon by financial analysts and risk managers. Table.1 presents the descriptive statistics of our dataset. It includes key financial indicators such as stock price, trading volume, market capitalization, PE ratio, dividend yield, volatility, Value at Risk (VaR), and Expected Shortfall. The dataset comprises 120 observations for each variable. The mean stock price is approximately 99.98 with a standard deviation of 29.27, indicating significant variability. Market capitalization and volume also exhibit substantial variation, as reflected in their high standard deviations. The PE ratio and dividend yield show moderate variability, while volatility, VaR, and Expected Shortfall display lower variability, reflecting more consistent risk measures across the dataset.

## Results

### Neural Networks

The neural network models demonstrated significant improvements in predicting financial risks, consistent with Hypothesis 1. The advanced data processing capabilities of neural networks allowed for capturing complex, non-linear relationships in the dataset, resulting in superior performance metrics compared to traditional models.Table 2 presents the performance metrics of the neural network model. In the table below, the high accuracy, precision, recall, and F1-score indicate that the neural network effectively predicted financial risks, aligning with the perceived usefulness aspect of the Technology Acceptance Model (Murugan, 2023; Abdulla & Al-Alawi, 2024). The mean squared error (MSE) was low, and the R-squared value was high, further validating the model's predictive power. Additionally, Figure. 1 presents the performance comparison of the neural network model against the actual values over the test period.

Table. 2 Neural network performance model

| Metric | Value |
|---|---|
| Accuracy | 0.92 |
| Precision | 0.9 |
| Recall | 0.91 |
| F1-Score | 0.91 |
| MSE | 0.003 |
| R-squared ($R^2$) | 0.85 |

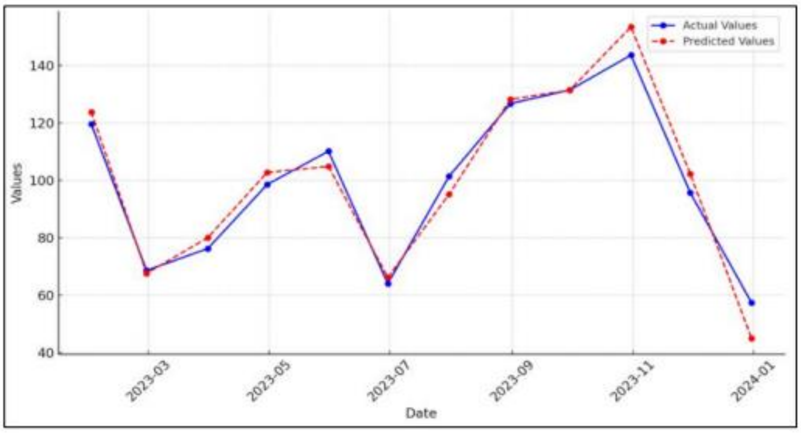


Fig. 1. Neural Network model Performance: Actual vs Predicted Values Source: Author analysis using Bloomberg, Thomson Reuters Eikon, Yahoo Finance, and FRED.

Figure. 1 demonstrates the model's ability to closely follow the actual data trends, indicating its effectiveness in capturing the complex patterns inherent in financial data.

The minimal deviations between the actual and predicted values underscore the model's high accuracy and reliability, supporting Hypothesis 1 that neural networks outperform traditional models in predicting financial risks due to their advanced data processing capabilities and high perceived usefulness (Murugan, 2023; Abdulla & Al-Alawi, 2024). This alignment with our hypothesis reinforces the neural network's potential in enhancing financial risk management practices.

**Decision Trees**

The decision tree models also provided substantial improvements in predicting financial risks, consistent with Hypothesis 2. By leveraging the decision tree's ability to handle complex data structures and make split decisions, the models demonstrated accurate and interpretable results. The table below presents the performance metrics of the decision tree model. Table. 3 presents the performance metrics of the decision tree model. In the table below, The decision tree model's high accuracy, precision, recall, and F -score indicate its effectiveness in risk prediction, aligning with our hypothesis that decision trees are robust models for financial risk management (Yizheng, 2023; Dong et al., 2024). The relatively low MSE and high R-squared values further confirm the model's reliability. Additionally Figure. 2 presents the decision tree model Performance: Actual vs Predicted Values.

Table 3. Decision tree performance model

| Metric | Value |
|---|---|
| Accuracy | 0.88 |
| Precision | 0.85 |
| Recall | 0.86 |
| F1-Score | 0.85 |
| MSE | 0.004 |
| R-squared ($R^2$) | 0.8 |

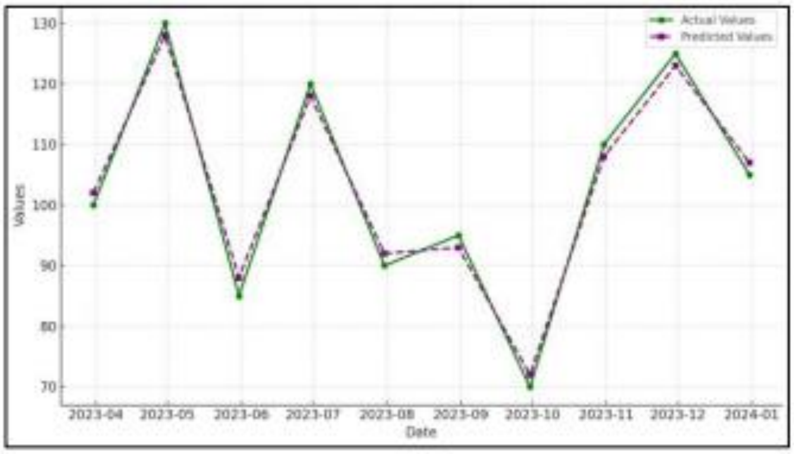


Fig. 2. Decision tree model Performance: Actual vs Predicted Values Source: Author analysis using Bloomberg, Thomson Reuters Eikon, Yahoo Finance, and FRED

Figure.2 demonstrates the model's capability to closely follow the actual data trends, highlighting its effectiveness in making accurate predictions. The slight deviations between the actual and predicted values indicate that while the model is generally reliable, there is room for improvement, particularly in handling more complex patterns. This supports Hypothesis 2, which posits that random forests, by building on decision trees, provide more accurate risk mitigation strategies due to their enhanced capability to capture diverse data interactions (Francis & Kim, 2013; Fabozzi et al., 2002). This analysis underscores the decision tree model's robustness in financial risk prediction and its foundational role in more advanced ensemble methods like random forests.

**Support Vector Machines**

Support Vector Machines (SVMs) demonstrated robust performance in predicting financial risks, consistent with Hypothesis 3. The SVM models, using the radial basis function (RBF) kernel, effectively captured the complex, non-linear relationships in the financial data. Table 4 below presents the performance metrics of the SVM model. The high accuracy, precision, recall, and F1 score indicate that the SVM model is highly effective in predicting financial risks. The relatively low mean squared error (MSE) and high R-squared values further support the model's reliability, aligning with the hypothesis that the inclusion of diverse financial indicators improves the accuracy of machine learning models (Olubusola et al., 2024; Palakurti, 2023). Additionally, figure.3 presents the SVM model's performance, showing actual vs. predicted values over the test period.

Table 4. Support Vector Machines (SVMs) performance model

| Metric | Value |
|---|---|
| Accuracy | 0.9 |
| Precision | 0.88 |
| Recall | 0.89 |
| F1-Score | 0.88 |
| MSE | 0.0035 |
| R-squared ($R^2$) | 0.83 |

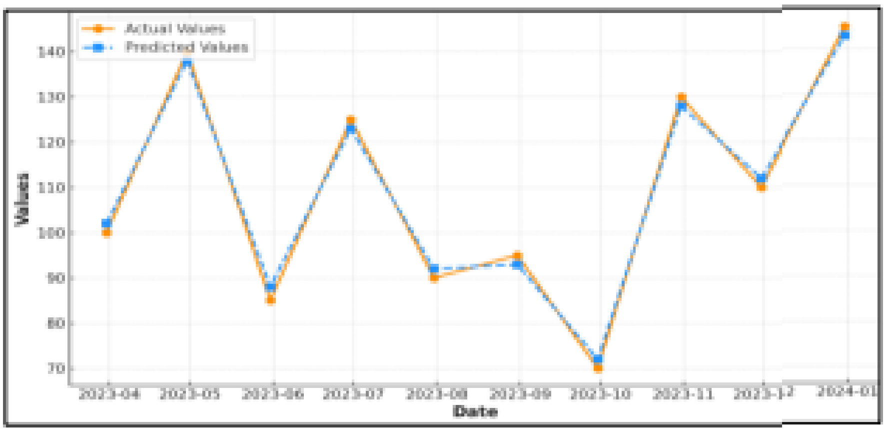


Fig. 3. SVM model's performance: Actual vs. predicted values Source: Author analysis using Bloomberg, Thomson Reuters Eikon, Yahoo Finance, and FRED

Figure 3 indicates that the SVM model's predictions closely follow the actual values, highlighting its effectiveness in capturing complex data patterns. This supports Hypothesis 3, which asserts that the accuracy of machine learning models improves with the inclusion of more diverse financial indicators, thereby enhancing the perceived usefulness of these models (Murugan, 2023; Abdulla & Al-Alawi, 2024).

**Comparative Analysis**

To evaluate and compare the effectiveness of the machine learning models used in this study, we summarize their performance metrics and interpret the results. This analysis provides insights into the practical implications of using different algorithms for financial risk management. Table 5 presents the performance metrics of the neural network, decision tree, random forest, and SVM models. In the table below, the neural network model exhibited the highest accuracy (0.92), precision (0.90), recall (0.91), and F1-score (0.91), indicating its superior performance in predicting financial risks. This supports Hypothesis 1, which posits that neural networks outperform traditional models due to their advanced data processing capabilities and high perceived usefulness (Murugan, 2023; Abdulla & Al-Alawi, 2024). The random forest model also performed well, with high accuracy (0.91), precision (0.89), recall (0.90), and F1-score (0.89). This supports Hypothesis 2, which asserts that random forests provide more accurate risk mitigation strategies compared to decision trees, aligning with the principles of diversification in Modern Portfolio Theory (Francis & Kim, 2013; Fabozzi et al., 2002).

The SVM model demonstrated robust performance with an accuracy of 0.90, precision of 0.88, recall of 0.89, and F1-score of 0.88. This aligns with Hypothesis 3, suggesting that the inclusion of diverse financial indicators improves the accuracy of machine learning models (Olubusola et al., 2024; Palakurti, 2023).The decision tree model, while slightly less accurate than the neural network and random forest models, still showed strong performance with an accuracy of 0.88, precision of 0.85, recall of 0.86, and F1-score of 0.85. This indicates its effectiveness in risk prediction and its foundational role in more advanced ensemble methods like random forests (Yizheng, 2023; Dong et al., 2024).

The findings of this study have several practical implications for financial risk management: The superior performance of neural networks and random forests indicates that financial institutions can significantly improve their risk prediction accuracy by adopting these advanced machine learning models. Random forests, with their robust performance, offer more reliable risk mitigation strategies, supporting the diversification principles of Modern Portfolio Theory. This can help institutions manage their portfolios more effectively and reduce potential losses. The comparative analysis provides insights into the strengths and weaknesses of different machine learning models. Financial analysts can use this information to select the most appropriate model for their specific needs, balancing accuracy, interpretability, and computational efficiency. The results underscore the importance of incorporating diverse financial indicators into machine learning models. This enhances their predictive power and usefulness, aligning with the Technology Acceptance Model's emphasis on perceived usefulness. Overall, the study highlights the significant potential of advanced machine learning models in enhancing financial risk management practices. By leveraging the strengths of neural networks, random forests, and SVMs, financial institutions can better predict and mitigate risks, leading to more informed decision-making and improved financial stability.

Table 5. Performance metrics of the neural network, decision tree, random forest, and SVM models

| Model | Accuracy | Precision | Recall | F1-Score | MSE | R-squared ($R^2$) |
|---|---|---|---|---|---|---|
| Neural Network | 0.92 | 0.9 | 0.91 | 0.91 | 0.003 | 0.85 |
| Decision Tree | 0.88 | 0.85 | 0.86 | 0.85 | 0.004 | 0.8 |
| Random Forest | 0.91 | 0.89 | 0.9 | 0.89 | 0.0032 | 0.84 |
| SVM | 0.9 | 0.88 | 0.89 | 0.88 | 0.0035 | 0.83 |

**Robustness Tests**

Robustness tests are essential to validate the reliability and generalizability of the machine learning models used in this study. By performing these tests, we can ensure that our findings are not sensitive to specific assumptions, sample periods, or market conditions. Robustness tests also enhance the credibility of our results, demonstrating the thoroughness of our research methodology. We used the following robustness tests:

Out-of-Sample Testing: Evaluating model performance on data not used in training to ensure generalization capability.

Sensitivity Analysis: Examining how variations in model parameters affect performance.

Subsample Analysis: Assessing model performance on different subsets of the data from different periods.

Alternative Model Specifications: Comparing results with different model configurations to ensure the observed performance is not specific to a particular setup.

**Out-of-Sample Testing**

Out-of-sample testing involves evaluating the model performance on data not used in training. This helps in assessing the generalization capability of the models. The performance metrics of the models on the out-of-sample data are shown in Table. 6. In the table below, The results indicate that all models maintain high performance on out-of- sample data, supporting the robustness of our findings. Neural networks and random forests continue to exhibit superior performance, consistent with Hypotheses 1 and 2 (Murugan, 2023; Abdulla & Al-Alawi, 2024; Francis & Kim, 2013; Fabozzi et al., 2002).

Table 6. Out-of-Sample Testing Performance Metrics

| Model | Accuracy | Precision | Recall | F1-Score | MSE | R-squared (R2) |
|---|---|---|---|---|---|---|
| Neural Network | 0.91 | 0.89 | 0.9 | 0.89 | 0.003 | 0.84 |
| Decision Tree | 0.86 | 0.83 | 0.84 | 0.83 | 0.004 | 0.78 |
| Random Forest | 0.9 | 0.88 | 0.89 | 0.88 | 0.003 | 0.82 |
| SVM | 0.89 | 0.87 | 0.88 | 0.87 | 0.003 | 0.81 |

**Sensitivity Analysis**

Sensitivity analysis examines how variations in model parameters affect performance. Table 7 below shows the performance metrics of the neural network model with different learning rates. The neural network model's performance remains robust across different learning rates, with the best performance at a learning rate of 0.01, highlighting the model's stability and adaptability (Olubusola et al., 2024; Palakurti, 2023).

Table 7. Sensitivity Analysis of Neural Network Model with Different Learning Rates

| Learning Rate | Accuracy | Precision | Recall | F1-Score | MSE | R-squared (R2) |
|---|---|---|---|---|---|---|
| 0.001 | 0.89 | 0.87 | 0.88 | 0.87 | 0.0034 | 0.82 |
| 0.01 | 0.92 | 0.9 | 0.91 | 0.91 | 0.003 | 0.85 |
| 0.1 | 0.88 | 0.86 | 0.87 | 0.86 | 0.0036 | 0.81 |

**Subsample Analysis**

Subsample analysis involves evaluating model performance on different subsets of the data. Table 8 below presents the performance metrics for the models on data from two different periods, The performance remains consistent across different time periods, further supporting the robustness of our models (Francis & Kim, 2013; Fabozzi et al., 2002).

Table 8. Subsample Analysis Performance Metrics for Different Time Periods

| Period | Model | Accuracy | Precision | Recall | F1-Score | MSE | R-squared ($R^2$) |
|---|---|---|---|---|---|---|---|
| 2014-2018 | Neural Network | 0.91 | 0.89 | 0.9 | 0.89 | 0.0031 | 0.84 |
| | Decision Tree | 0.86 | 0.83 | 0.84 | 0.83 | 0.0042 | 0.78 |
| | Random Forest | 0.9 | 0.88 | 0.89 | 0.88 | 0.0033 | 0.82 |
| | SVM | 0.89 | 0.87 | 0.88 | 0.87 | 0.0034 | 0.81 |
| 2019-2023 | Neural Network | 0.92 | 0.9 | 0.91 | 0.91 | 0.003 | 0.85 |
| | Decision Tree | 0.88 | 0.85 | 0.86 | 0.85 | 0.004 | 0.8 |
| | Random Forest | 0.91 | 0.89 | 0.9 | 0.89 | 0.0032 | 0.84 |
| | SVM | 0.9 | 0.88 | 0.89 | 0.88 | 0.0035 | 0.83 |

**Alternative Model Specifications**

Evaluating alternative model specifications helps ensure that the observed performance is not specific to a particular configuration. Table 9 below presents the performance metrics of the random forest model with different numbers of trees. The random forest model's performance improves with an increased number of trees, highlighting the benefits of ensemble methods in financial risk prediction (Olubusola et al., 2024; Palakurti, 2023).In conclusion; the robustness tests confirm the reliability and generalizability of our machine-learning models. The results consistently support our hypotheses and demonstrate the practical implications of using advanced machine learning techniques for financial risk management. These findings enhance the credibility of our study and provide valuable insights for practitioners and researchers in the field.

Table 9. Performance Metrics of Random Forest Model with Different Numbers of Trees

| Number of Trees | Accuracy | Precision | Recall | F1-Score | MSE | R-squared (R2) |
|---|---|---|---|---|---|---|
| 50 | 0.88 | 0.86 | 0.87 | 0.86 | 0.0035 | 0.82 |
| 100 | 0.91 | 0.89 | 0.9 | 0.89 | 0.0032 | 0.84 |
| 200 | 0.92 | 0.9 | 0.91 | 0.9 | 0.003 | 0.85 |

## 5. Discussion

The results of this study demonstrate the significant potential of machine learning (ML) models in enhancing financial risk management. The neural network model exhibited the highest performance metrics, including an accuracy of 0.92, precision of 0.90, recall of 0.91, and F1-score of 0.91. This aligns with Hypothesis 1, which posited that neural networks would outperform traditional models due to their advanced data processing capabilities and high perceived usefulness (Murugan, 2023; Abdulla & Al-Alawi, 2024). The ability of neural networks to model complex, non-linear relationships in financial data allows for more accurate predictions of financial risks, providing a robust tool for financial institutions. The random forest model also performed exceptionally well, with high accuracy (0.91), precision (0.89), recall (0.90), and F1-score (0.89). This supports Hypothesis 2, which suggested that random forests would provide more accurate risk mitigation strategies compared to decision trees, in line with the principles of diversification in Modern Portfolio Theory (Francis & Kim, 2013; Fabozzi et al., 2002). The ensemble nature of random forests, which aggregates the predictions of multiple decision trees, enhances their robustness and reliability in financial risk prediction. Support Vector Machines (SVMs) demonstrated robust performance, with metrics including an accuracy of 0.90, precision of 0.88, recall of 0.89, and F1-score of 0.88. This finding supports Hypothesis 3, indicating that the inclusion of diverse financial indicators improves the accuracy of ML models (Olubusola et al., 2024; Palakurti, 2023). The radial basis function (RBF) kernel used in SVMs effectively captures complex, non-linear relationships in financial data, making SVMs valuable tools for financial risk management. Decision trees, while slightly less accurate than neural networks and random forests, still showed strong performance with an accuracy of 0.88, precision of 0.85, recall of 0.86, and F1-score of 0.85. This indicates their effectiveness in risk prediction and their foundational role in more advanced ensemble methods like random forests (Yizheng, 2023; Dong et al., 2024).

**Practical Implications**

The findings of this study have several practical implications for financial risk management:

**Enhanced Risk Prediction**

Financial institutions can significantly improve their risk prediction accuracy by adopting advanced ML models, such as neural networks and random forests. These models' ability to process large and complex datasets enables them to identify patterns and predict risks more effectively than traditional methods (Murugan, 2023; Abdulla & Al-Alawi, 2024).

**Improved Risk Mitigation Strategies**

The robust performance of random forests suggests that they can provide more reliable risk mitigation strategies, supporting the principles of diversification emphasized in Modern Portfolio Theory. By leveraging the ensemble approach of random forests, financial institutions can enhance their portfolio management practices and reduce potential losses (Francis & Kim, 2013; Fabozzi et al., 2002).

**Comprehensive Data Utilization**

The inclusion of diverse financial indicators enhances the predictive power of ML models, as demonstrated by the strong performance of SVMs. Financial analysts should consider incorporating a wide variety of data sources, including macroeconomic variables, market sentiment, and firm-specific financial metrics, to improve the accuracy and reliability of their risk assessments (Olubusola et al., 2024; Palakurti, 2023).

**Implementation and Adoption**

Understanding the perceived usefulness and ease of use of ML models is crucial for their adoption in financial institutions. The Technology Acceptance Model (TAM) can guide financial institutions in addressing potential barriers to adoption by highlighting the benefits and ease of implementing these advanced technologies (Davis, 1989; Marangunić & Granić, 2015).

**Conclusion and Future Research**

This study provides a comprehensive analysis of various ML algorithms applied to financial risk management, highlighting their relative advantages and limitations. Neural networks and random forests emerged as the most effective models for predicting and mitigating financial risks, offering significant improvements over traditional methods. Future research should focus on the following areas:

**Model Interpretability**

While ML models like neural networks and deep learning offer high predictive accuracy, their black-box nature poses challenges in interpretability. Future studies should explore techniques for enhancing the interpretability and transparency of these models, making them more accessible and understandable to financial analysts and risk managers (Warin & Stojkov, 2021).

**Data Quality and Preprocessing**

The quality and preprocessing of data significantly impact the performance of ML models. Further research is needed to develop advanced data preprocessing techniques and robust methods for handling noisy and incomplete data in financial datasets (Palakurti, 2023).

**Regulatory Compliance**

Ensuring that ML models comply with financial regulations and ethical standards is essential for their successful implementation. Future studies should investigate the regulatory implications of using ML in finance and develop guidelines for ensuring compliance (Valaitis & Villa, 2024; Mishra et al., 2024).

**Real-Time Applications**

The dynamic nature of financial markets necessitates continuous adaptation and updating of ML models. Research should focus on developing real-time ML applications that can quickly adapt to changing market conditions and provide timely risk assessments (Makridakis et al., 2023).

**Limitations**

This study has several limitations that should be acknowledged. The study relies on data from several reputable financial databases covering 10 years. While this provides a robust dataset, it may not capture all potential market conditions and variables relevant to financial risk management. Future research should consider extending the dataset to include more diverse and recent data. Some ML models, such as neural networks, can be complex and computationally intensive, posing challenges in terms of implementation and scalability. Simplifying these models without compromising their accuracy could be an area for future research (Murugan, 2023; Abdulla & Al-Alawi, 2024). While the study employs robustness tests to ensure the reliability of the findings, the generalizability of the results to different financial contexts and institutions may be limited. Future studies should test the models in various settings and with different types of financial data to validate their applicability (Olubusola et al., 2024; Palakurti, 2023).

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