BAREKENG: Journal of Mathematics and Its Applications
June 2026 Volume 20 Issue 2 Page 1693–1708
P-ISSN: 1978-7227 E-ISSN: 2615-3017
https://doi.org/10.30598/barekengvol20iss2pp1693-1708

APPLICATION OF THE RANDOM FOREST ALGORITHM FOR ESTIMATING CONDITIONAL VALUE AT RISK (CVAR) ON THE STOCK PORTFOLIO OF INSURANCE COMPANIES IN INDONESIA

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Article Info

Article History:

Received: 12th August 2025
Revised: 1st September 2025
Accepted: 21st October 2025
Available Online: 26th January 2026

Keywords:

Conditional Value at Risk;
Insurance companies;
Random Forest;
Stock.

ABSTRACT

This study aims to estimate Conditional Value at Risk (CVaR) for insurance company stock portfolios using a machine learning approach to improve the accuracy of financial risk measurement under extreme market conditions. The application of machine learning, particularly the Random Forest algorithm, is crucial for the Indonesian insurance sector, which faces increasing exposure to market volatility and uncertainty. The model predicts stock returns based on technical indicators such as moving averages, volatility, and lagged returns. The analysis uses historical data from ten insurance companies listed on the Indonesia Stock Exchange (IDX) for the period 2022–2025. To assess model performance, Mean Absolute Error (MAE), Mean Squared Error (MSE), and Kupiec backtesting are employed. The model produces CVaR estimates of 1.65% and 1.94% at the 95% and 99% confidence levels, respectively. It also achieves a low MAE of 0.006701 and MSE of 0.000091, indicating high estimation accuracy. The Kupiec test results further confirm the statistical reliability of the CVaR estimates. This study contributes methodologically by highlighting the effectiveness of non-parametric ensemble learning in financial risk modeling. The findings offer practical implications for insurance firms and portfolio managers in adopting adaptive, data-driven risk mitigation strategies, especially in volatile market environments.

How to cite this article:

Purwanto and A. Olivia., "APPLICATION OF THE RANDOM FOREST ALGORITHM FOR ESTIMATING CONDITIONAL VALUE AT RISK (CVAR) ON THE STOCK PORTFOLIO OF INSURANCE COMPANIES IN INDONESIA", *BAREKENG: J. Math. & App.*, vol. 20, no. 2, pp. 1693-1708, Jun, 2026.

Journal homepage: *https://ojs3.unpatti.ac.id/index.php/barekeng/*
Journal e-mail: *barekeng.math@yahoo.com; barekeng.journal@mail.unpatti.ac.id*

Research Article · Open Access

1. INTRODUCTION

In the current rapid development of global financial markets, companies and financial institutions face major challenges in managing financial risks arising from market fluctuations [1][2]. These risks can have a significant impact on a company’s financial stability and performance, including asset value, cost of capital, and long-term profitability [3]. For companies, failure to manage financial risk can lead to liquidity pressures, decrease company value, and bankruptcy [4][5]. For investors, the inability to measure risk can lead to adverse investment decisions and portfolio losses.

Ineffective financial risk management not only impacts individual companies or investors but can also destabilize the economy as a whole [6]. Poorly managed financial risks can create a chain effect that triggers instability in various sectors. Financial institutions that lend to such companies may experience liquidity problems, reducing their ability to extend credit to other businesses and consumers. This contraction in credit can lead to a decline in business investment, reduced purchasing power, and a slowdown in economic growth. In addition, investors who own stocks or bonds of such companies may also suffer heavy losses, potentially lowering stock market indices and weakening overall market confidence [7].

One industry that relies on financial markets is the insurance industry [8][9]. Insurance companies not only collect premiums from customers, but also invest these funds to generate profits and ensure operational sustainability. Therefore, stock market fluctuations have a significant impact on their financial performance. The movement in an insurance company's share price reflects investors' expectations of its profitability and financial stability. Market risks, such as stock price volatility, can affect the value of insurance companies' assets. For instance, as of early 2025, PT MSIG Life Insurance Indonesia (LIFE) recorded an annualized stock volatility of over 53%, which is significantly higher than the industry average of 20% to 25%, making it one of the most volatile insurance stocks on the market.

For insurance companies, accurately measuring and managing market risk is a critical task. One of the widely adopted metrics for this purpose is Value at Risk (VaR) [10], which quantifies the maximum potential loss—expressed either as a percentage or a monetary value—that an investment may incur over a specified time horizon at a given confidence level. Despite its usefulness, VaR has a notable limitation: it only identifies the loss threshold without accounting for the possibility of more severe losses that exceed this limit. To overcome this shortcoming, Conditional Value at Risk (CVaR), or Expected Shortfall, is employed. CVaR estimates the average loss beyond the VaR cutoff, thereby capturing tail risk in the loss distribution [11][12][13]. By focusing on extreme adverse outcomes, CVaR provides a more comprehensive and reliable risk metric, especially for insurance companies.

Traditional methods of calculating VaR and CVaR have limitations in capturing nonlinear patterns in financial data and in predicting risk under volatile market conditions. Along with the development of technology and the increasing availability of data, Machine Learning is being applied in financial risk analysis to improve prediction accuracy [14][15]. In addition, many researchers have applied ML methods to predict stock market returns [16]. Machine learning techniques, such as Random Forests, can recognize complex patterns in data and improve the effectiveness of CVaR estimation.

Previous studies have widely used statistical methods such as VaR and CVaR to measure financial risk using the Monte Carlo simulation approach [17]. While Monte Carlo simulation is effective in estimating potential losses under different market conditions, it relies heavily on traditional methods and assumes a specific probability distribution, which may not always capture the dynamic and nonlinear nature of financial risks in the insurance sector. Meanwhile, research on Machine Learning in the insurance industry has mostly concentrated on premium prediction and decision support [18][19]. This research demonstrates that ML can enhance the accuracy of underwriting processes and claim assessments. However, it does not address how ML can be applied specifically to CVaR estimation, which is crucial for assessing extreme losses in insurance portfolios. Next, ML models have been implemented for VaR calculations, but their focus was on general financial markets rather than the unique risk characteristics of the insurance industry [20].

Despite this potential, research on the application of ML-based CVaR estimation in the insurance sector remains limited. Most existing studies focus on the banking or broader investment sectors, while the insurance industry, particularly in Indonesia, has received less attention in this context [21]. To fill this research gap, this research applies the Random Forest algorithm to estimate CVaR for a portfolio of stocks from ten publicly listed Indonesian insurance companies. These firms represent both general and life insurance sectors, providing a comprehensive analysis across the industry. The goal is to assess the effectiveness of Machine

Learning, specifically Random Forest, in improving CVaR estimation accuracy and enhancing market risk management practices in the Indonesian insurance industry.

2. RESEARCH METHODS

2.1 Data Collection Methods

This research utilizes secondary data obtained from publicly available financial sources. The data used are daily closing stock prices of insurance companies for the period January 2022 to March 2025, selected using a purposive sampling method. The selected companies include:

Table 1. List of Insurance Companies Used in the Study

No.	Stock Code	Company Name
1	AMAG	PT Asuransi Multi Artha Guna Tbk
2	ASBI	PT Asuransi Bintang Tbk
3	ASDM	PT Asuransi Dayin Mitra Tbk
4	BHAT	PT Bhakti Multi Artha Tbk
5	LIFE	PT MSIG Life Insurance Indonesia Tbk
6	LPGI	PT Lippo General Insurance Tbk
7	MTWI	PT Malacca Trust Wuwungan Insurance Tbk
8	PNIN	PT Paninvest Tbk
9	TUGU	PT Asuransi Tugu Pratama Indonesia Tbk
10	VINS	PT Victoria Insurance Tbk

The purposive sampling approach ensures that the selected companies meet the criteria of being publicly listed on the Indonesia Stock Exchange (IDX) and having sufficient historical stock price data for risk analysis, using daily stock price data over a period of 3 years to ensure sufficient historical observations for accurate risk estimation. The confidence levels used in this research are 95% and 99%, which are standard risk assessment thresholds in financial analysis.

2.2 Return Portfolio

The primary objective of investing is to generate profit. Within the framework of investment management, this profit level is referred to as the return [22]. In securities analysis, the natural logarithm ratio method is frequently used, as it yields expected returns that are not substantially different from those obtained with the conventional approach. The advantage of using the natural logarithm method lies in its ability to deliver unbiased and more consistent return calculations across various time horizons [23]. The computation of stock returns can be expressed using the following formula:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right), \tag{1}$$

where R_t is the stock return at time t, P_t is the closing stock price in period t, and P_{t-1} is the closing stock price in period t-1. The function of the natural logarithm (ln) in the return formula is to convert price change into a form that is more suitable for financial analysis. Specifically, ln helps avoid unrealistic negative values that can occur with simple percentage returns, especially when prices drop significantly.

When considering a portfolio composed of multiple assets, the portfolio return is calculated as the weighted average of the individual asset returns. The portfolio return can be defined as [24]:

$$R_p = \sum_{i=1}^{n} w_i R_i, \tag{2}$$

where R_p is the portfolio return, w_i is the weight or proportion of asset i, and R_i is the return of asset i.

2.3 Mean-Variance Efficient Portfolio (MVEP)

The Mean-Variance Efficient Portfolio (MVEP) method, first introduced by Markowitz (1952), is a cornerstone of Modern Portfolio Theory, which emphasizes the balance between expected return and risk in selecting a portfolio [25]. Under this framework, investors can construct an optimal portfolio by diversifying assets to either maximize the expected return for a specified level of risk or minimize risk for a given expected return. The outcome of this optimization yields the efficient frontier—a collection of portfolios that offer the best possible trade-off between risk and return [26]. The optimization of MVEP can be expressed as follows:

$$\min_{w} \quad w^T \sum w, \tag{3}$$
$$\text{subject to} \quad w^T \mu = R_p, \qquad w^T 1 = 1,$$

where w is a vector of portfolio weights, Σ is the covariance matrix of asset returns, μ is a vector of expected returns, R_p is the target portfolio return, and 1 is a vector of ones to ensure the weights sum to 1. Mathematically, the elements of the covariance matrix are defined as [27]:

$$\sigma_{ij} = Cov\left(R_i, R_j\right) = \frac{1}{T-1}\sum_{t=1}^{T}\left(R_{i,t} - \bar{R}_i\right)\left(R_{j,t} - \bar{R}_j\right), \tag{4}$$

where $R_{i,t}$ is the return asset i at time t, $\bar{R}_i$ is the mean return of asset i, T is the total number of time periods, and σ_{ij} is the covariance between assets i and j. The covariance matrix takes the following general form [28]:

$$\sum = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1n} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{n1} & \sigma_{n2} & \cdots & \sigma_{nn} \end{bmatrix}, \tag{5}$$

where the diagonal element σ_{ii} represent the variances of individual assets, and the off-diagonal elements σ_{ij} represent the covariances between different asset pairs.

2.4 Risk

In capital market investment activities, risk is always associated with the activity. Risk is commonly interpreted as a deviation between expectation and reality [29][30]. When an investor invests, they have certain expectations about the return they will get. However, in practice, reality often differs from these expectations, either due to internal factors, such as company performance, or external factors, such as changes in economic conditions or political turmoil. Risk refers to the potential loss that occurs when expected investment returns do not materialize. In other words, risk is the effect of uncertainty on goals.

Risks can be divided into two categories: systematic and unsystematic. Systematic risk is the risk that fluctuations in total investment returns are directly related to changes in the market or the general economic situation. On the other hand, unsystematic risks are specific to a particular company or industry, such as business or financial risk.

2.5 Conditional Value at Risk

Conditional Value at Risk, or CVaR, is a risk measure used to evaluate the potential extreme losses in a portfolio or investment over a certain period. CVaR measures the average loss that exceeds the VaR. CVaR is considered a more consistent and comprehensive measure of risk than VaR [31]. With this, CVaR is often used as an alternative to VaR for risk measurement, helping reduce the problems that arise in VaR calculations. As with VaR, CVaR has two parameters: Time Horizon and Confidence Level. Both of these parameters have the same function as the VaR parameter.

The advantage of CVaR is that it is a coherent, convex, and subadditive measure of risk. The convexity condition states that CVaR is a convex function of the loss distribution. This means that if two loss distributions are combined (for example, by combining two portfolios), the combined CVaR is greater than or at least equal to the linear combination of the CVaR value of the respective distributions. Meanwhile, the sub-additive nature refers to the concept that the combined CVaR does not exceed the sum of the CVaR of its individual components. In this context, sub-additive means that when two-loss distributions are combined, the combined CVaR is less than or equal to the sum of the CVaR of each individual distribution. By combining these two properties, it allows for more accurate and consistent estimates of CVaR in risk measures. These properties make CVaR an effective tool for aggregating and evaluating investment portfolios with comprehensive risk assessment [32]. Mathematically, CVaR can be expressed by the formula [33]:

$$CVaR_\alpha = \mathbb{E}[L|L \geq VaR_\alpha], \tag{6}$$

where L represents the portfolio loss, VaR_α is the VaR at confidence level α is the confidence level (typically 90%, 95%, or 99%). CVaR is considered more robust than VaR because it accounts for the entire tail of the loss distribution, rather than a single threshold point. This leads to the practical, sample-based formula [34]:

$$CVaR_\alpha = \frac{1}{k}\sum_{i=1}^{k} L_i \, , where \ L_i \geq VaR_\alpha. \tag{7}$$

2.6 Random Forest

In recent years, the use of statistical or machine learning algorithms has increased in financial management. Among these, Random Forest has emerged as a robust and reliable ensemble learning technique widely applied for predictive modeling, including financial distress prediction and portfolio risk estimation. Random Forest can effectively enhance companies' early warning capabilities for financial distress, thereby supporting sustainable corporate operations [35]. Random Forest was introduced by Breiman (2001). Random Forest is an ensemble learning technique that builds on the concept of decision trees and additionally combines multiple decision trees to create a more accurate and stable model, reducing the risk of overfitting that often occurs with a single decision tree.

More specifically, ensemble learning algorithms such as random forests are well-suited for medium- to large-scale datasets [36]. When the number of independent variables exceeds the number of observations, linear and logistic regression algorithms will not run, because the number of parameters to be estimated exceeds the number of observations. Random forest works because not all predictor variables are used at once. Another advantage of Random Forest is its ability to measure feature importance, which helps identify the most influential variables in the model.

In Random Forest, overfitting can occur if the trees grow too deep without constraints, or if the number of features considered at each split is too high. An overfitted model exhibits low bias but high variance, performing exceptionally well on the training data while generalizing poorly to new, unseen data. Proper hyperparameter tuning, such as setting a reasonable maximum tree depth and limiting the number of features at each split, is critical to mitigate these risks and achieve an optimal trade-off between bias and variance [37].

The Random Forest algorithm is built upon two key principles: bootstrap aggregating (bagging) and feature randomness. Bagging is a statistical approach that reduces variance by training each decision tree in the forest on a randomly selected subset of the training data, sampled with replacement. This sampling strategy introduces variation among the trees, thereby enhancing the model's ability to generalize. Furthermore, during each split in a decision tree, only a randomly chosen subset of features is evaluated. This feature randomness decreases the correlation between trees and increases the model's robustness against noise in the data [38].

Formally, the Random Forest prediction for a given input x is obtained by averaging the predictions from all individual decision trees in the ensemble. The general form of the Random Forest model is given by [39]:

$$\hat{y} = \frac{1}{B}\sum_{b=1}^{B} h_b(x), \tag{8}$$

where B is the total number of trees in the forest, and $h_b(x)$ represents the prediction result of the b-th decision tree. This ensemble approach can enhance predictive accuracy while reducing the risk of overfitting [40].

2.7 Error Measurement

Mean Absolute Error (MAE) is a performance evaluation metric that quantifies the average magnitude of the absolute differences between predicted and actual values. In this study, MAE measures the deviation between the predicted and observed CVaRs. The MAE is computed using the following formula [41]:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \widehat{y_i}|, \tag{9}$$

where n is the number of observations, y_i is the actual value, and $\widehat{y_i}$ is the predicted value. A lower MAE value indicates a more accurate model, while a higher MAE suggests greater prediction error. In other words, the smaller the MAE, the more accurate the model.

Another error metric is Mean Squared Error (MSE). MSE is a measurement of the accuracy of a model by calculating the average squared differences between predicted and actual values. The MSE can be written as:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \widehat{y_i})^2. \tag{10}$$

2.8 Backtesting

Backtesting is a validation technique used to assess the accuracy of predictive models by comparing their forecasts with actual observed results. One widely used approach is the Kupiec Test, which examines whether a CVaR model accurately predicts the expected frequency of extreme loss events. This test applies a Likelihood Ratio (LR) statistic to determine whether the number of occurrences in which actual losses exceed the predicted CVaR—referred to as exceptions—aligns with the model's expectations. The Kupiec Test can be expressed as follows [42]:

$$LR_{uc} = -2ln[(1-p)^{T-N}p^N] + 2ln\left\{\left[1-\left(\frac{N}{T}\right)\right]^{T-N}\left(\frac{N}{T}\right)^N\right\}, \tag{11}$$

where LR_{uc} is the loglikelihood ratio approach, T represents the total number of observations in the dataset, while N denotes the total number of failures or violations, which occur when actual losses exceed the predicted CVaR, and the expected violation probability is denoted by p.

3. RESULTS AND DISCUSSION

3.1 Descriptive Analysis

3.1.1 Historical Return Trends of Selected Insurance Companies

This research used historical return data from ten insurance companies listed on the IDX. The return data spans from 2022 to 2025 and is calculated using log returns based on the adjusted closing prices. These return data form the foundation for portfolio construction and subsequent risk modeling using the Random Forest algorithm.

To provide a clearer illustration, Fig. 1 presents time-series plots of the stock returns for a selection of representative companies in the dataset. These plots highlight the fluctuations and volatility patterns observed during the study period, which reflect the market dynamics affecting the Indonesian insurance sector.

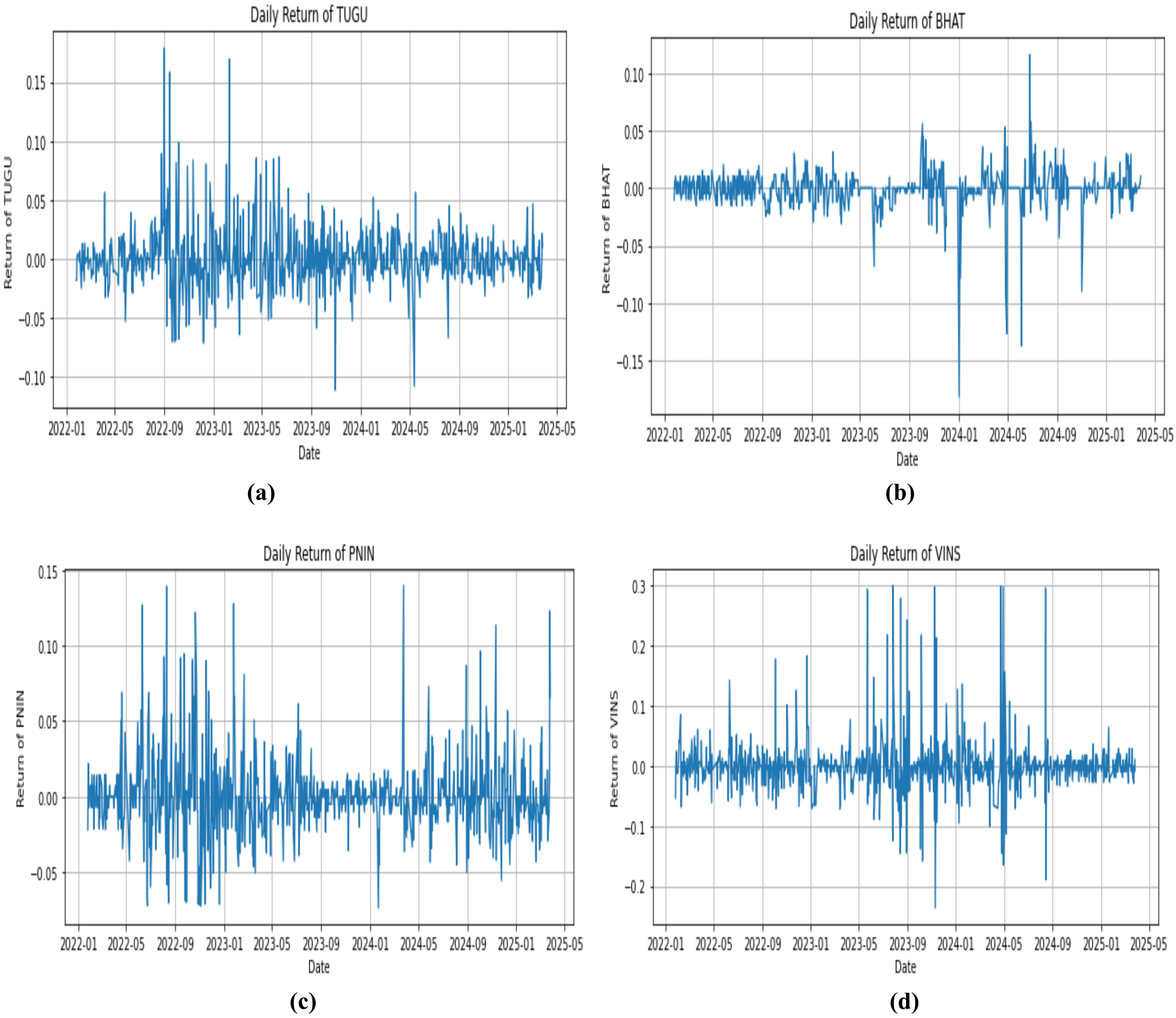


Figure 1. **Time-Series Plots of Representative Insurance Stock Returns (2022–2025)**

As seen in the plots, each stock shows different levels of return volatility; some are more stable, while others fluctuate more. These differences reflect the unique risk profiles of the stock, which together form a diversified portfolio. Although individual volatilities differ, the combined portfolio allows for overall risk analysis through aggregation.

3.1.2 Portfolio Weights with the Mean-Variance Efficient Portfolio (MVEP)

Based on calculations using the MVEP approach, optimal weights were determined for each of the 10 insurance company stocks included in this research. These weights were calculated to minimize overall portfolio risk while accounting for each stock's expected return. The average return is calculated from historical daily returns over the observation period. The optimization process yields portfolio weights for each stock that are strictly positive and sum to 100%. The following are the results of the portfolio weights obtained:

Table 2. **The Portfolio Weights of Each Stock**

No.	Stock	Weights
1	AMAG	27.85%
2	ASDM	9.66%
3	ASBI	0.80%
4	BHAT	26.34%
5	LPGI	0.27%

No.	Stock	Weights
6	LIFE	11.32%
7	MTWI	6.24%
8	PNIN	6.90%
9	TUGU	7.85%
10	VINS	2.76%

Table 2 shows that AMAG and BHAT have the largest weights in the portfolio, at 27.85% and 26.34%, respectively. This indicates that these two stocks have a more favorable risk-return profile than the other stocks in the portfolio. Conversely, LPGI and ASBI stocks have very small weights, 0.27% and 0.80% respectively, which means that their contribution to the efficient portfolio is relatively low, possibly due to higher risk or less competitive returns.

Meanwhile, stocks such as ASDM (9.66%), LIFE (11.32%), and TUGU (7.85%) fall into a moderate-weight category. These stocks likely strike a balance between risk and return, contributing to portfolio diversification without introducing excessive volatility. Similarly, MTWI (6.24%) and PNIN (6.90%) are assigned modest weights, suggesting that although they are not among the most efficient individually, they still add value to the overall portfolio when combined with other assets. Lastly, VINS, which received a weight of 2.76%, may represent a stock with higher risk or relatively unstable returns. These portfolio weights reflect the optimization process that balances expected return and risk. Stocks with higher weights are considered more efficient in contributing to the overall portfolio objective. These weights are then used to calculate the daily portfolio return by multiplying each weight by the daily return for each stock.

3.1.3 Portfolio Return Analysis

After analyzing the individual return patterns of each stock and calculating the portfolio weights, the next step is to combine all the returns into a portfolio to reflect their overall performance. The portfolio return is calculated using Eq. (2).

The daily return is the percentage change in a stock's price from one day to the next, and it is a key indicator in risk measurement. After calculating each stock's return, the data is combined and organized into a diversified portfolio. Figure 2 shows the portfolio return over time, with fluctuations reflecting both upward and downward movements during the observation period. Compared to individual stock returns, the portfolio return appears relatively more stable, although certain spikes and drops are still noticeable.

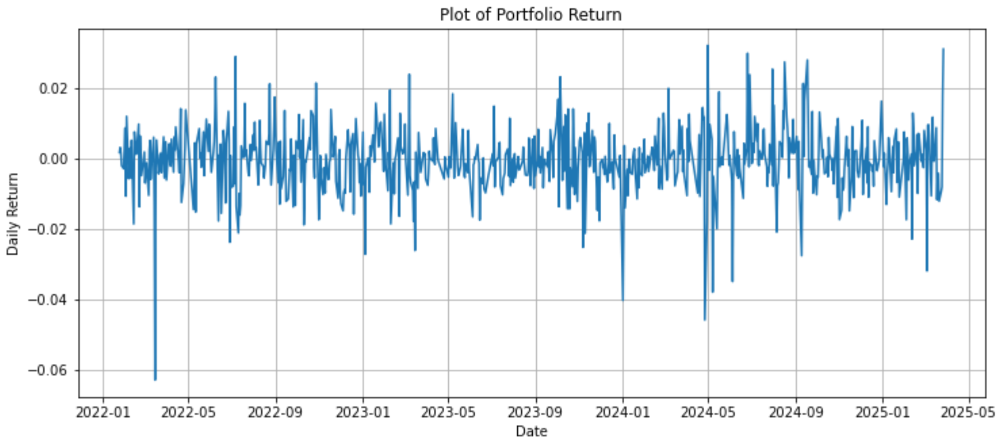


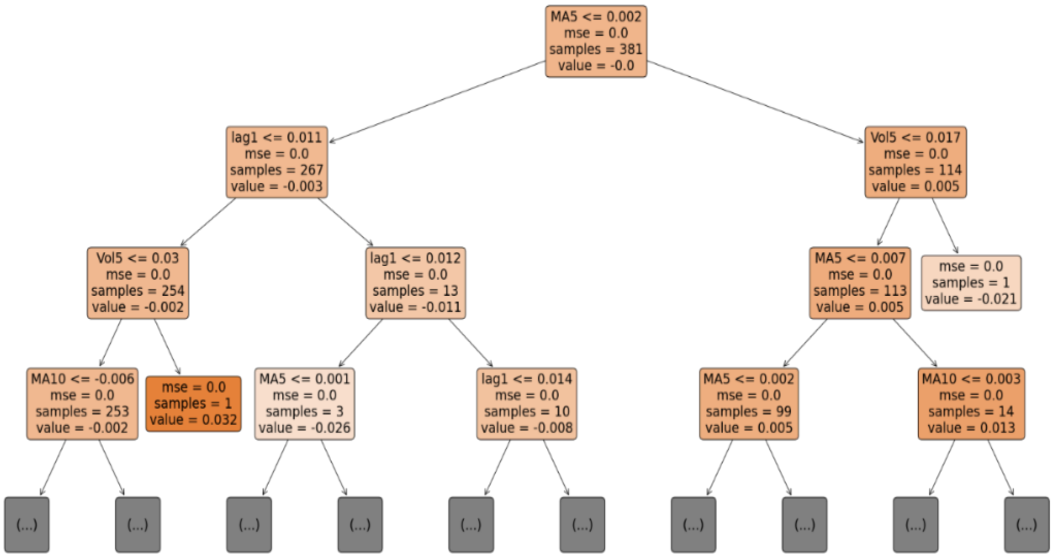
Figure 2. Plots of Portfolio's Returns

3.2 Data Analysis and Discussion

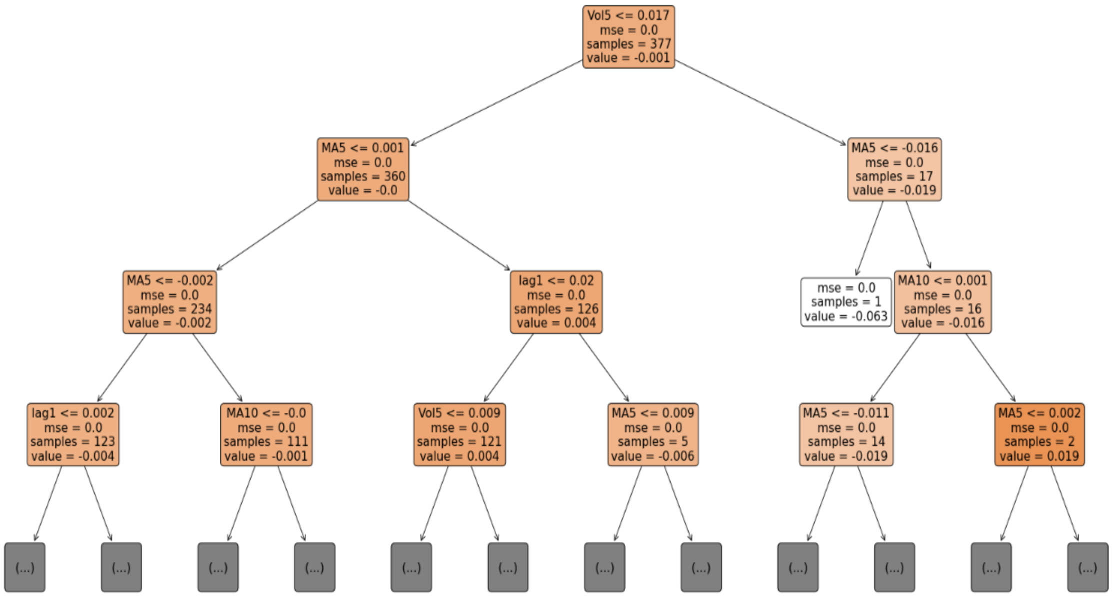
3.2.1 Random Forest Modelling

After constructing the portfolio return data, the next step was to build a predictive model using the Random Forest algorithm. This model was trained on 80% of the data, with the remaining 20% used for testing to assess its ability to generalize to unseen data. Random Forest, as an ensemble learning method, creates multiple decision trees and combines their outputs to improve prediction accuracy and reduce overfitting.

Fig. 3 presents the sample decision trees from the Random Forest model used in this research. Although the model consists of many trees, only a few are visualized for interpretability. Each tree is built on a random subset of the training data and includes different features and splitting thresholds at various levels. From the visualizations, it can be observed how certain features appear more frequently at the upper levels of the trees. Features that consistently appear in these early splits are typically considered more important by the model, as they contribute significantly to reducing prediction error early in the decision process.



(a)



(b)

Figure 3. Visualization of the Decision Trees in Random Forest

3.2.2 Feature Importance Analysis

Feature importance analysis identifies which input variables contribute most to predicting CVaR. Fig. 4 below shows the feature importance rankings calculated by the Random Forest model. From the chart, it is evident that feature MA5 (5-day moving average) has the highest importance score, indicating that it is the most influential feature.

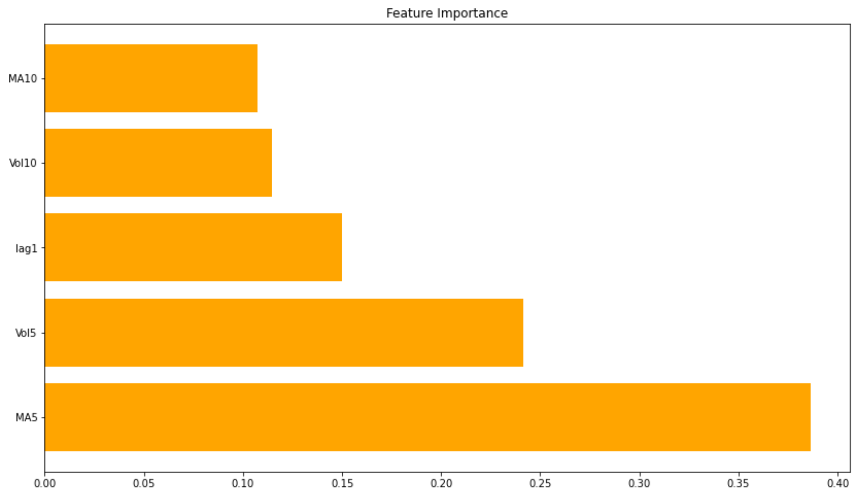


Figure 4. Feature Importance from the Random Forest Model

The 5-day moving average gives more timely signals on price trends than other technical indicators in this research. By focusing on the most recent five trading days, MA5 quickly reflects short-term market sentiment and price changes. In Indonesia's insurance sector, stock prices often react rapidly to short-term fluctuations due to lower liquidity and market depth.

MA10 has a lower importance score, suggesting that a longer moving average window smooths recent price movements and reduces its ability to reflect immediate market dynamics. Likewise, the volatility measures (VOL5 and VOL10), though commonly used for risk estimation, do not capture the directional trend of price movements. LAG1, representing the previous day's return, also has lower importance, likely because single-lagged returns have limited predictive power for daily stock return forecasting. This research's use of Random Forest aligns with earlier studies: machine learning, especially Random Forest, is a powerful tool for estimating financial risk. For instance, [35] demonstrated the model's ability to identify extreme risk conditions.

3.2.3 Estimation of CVaR

The next stage of this research is to estimate CVaR using the Random Forest model. CVaR is a risk measure that provides an estimate of the average loss exceeding the VaR at a given confidence level. The initial capital investment used in this research is assumed to be IDR 1,000,000,000. After training and evaluating the Random Forest model, the estimated VaR and CVaR at the 95% and 99% confidence levels have been calculated. VaR represents the maximum expected loss that will not be exceeded with 95% and 99% confidence, while CVaR estimates the average loss in the worst 5% and 1% of cases beyond the VaR threshold. The result is presented in Table 3 below.

Table 3. Optimized Portfolio Weights for Insurance Company Stocks

Confidence Level	VaR (%)	VaR (IDR)	CVaR (%)	CVaR (IDR)
95%	1.33%	IDR 13,250,789	1.65%	IDR 16,489,122
99%	1.85%	IDR 18,524,438	1.94%	IDR 19,430,917

Based on the estimation, the VaR at the 95% confidence level is 1.33%, meaning that under normal market conditions, the maximum expected loss is approximately IDR 13,250,789 from the initial investment. Meanwhile, the CVaR of 1.65% indicates that if losses exceed the VaR threshold, the average loss in the worst-case scenarios is about IDR16,489,122.

At the 99% confidence level, the estimated VaR is 1.85%, indicating that there is only a 1% probability that the portfolio will experience a loss exceeding IDR 18,524,438 under extreme market conditions. This higher confidence level captures more severe but less frequent adverse events compared to the 95% level. The CVaR at 99% is calculated at 1.94%, implying that in the worst 1% of cases, the portfolio is expected to incur an average loss of approximately IDR 19,430,917. As expected, both VaR and CVaR values at the 99% confidence level are higher than those at the 95% confidence level, reflecting higher potential risk exposure when accounting for more extreme tail events. This indicates that if rare and severe market downturns were to occur, the portfolio's financial impact would be significantly higher than under normal or moderate stress conditions.

These results are further supported by Fig. 5, which compares actual portfolio returns with the estimated risk thresholds (VaR and CVaR). The blue line represents actual returns, while the red dashed line indicates the VaR threshold. The shaded red area below the VaR line highlights the CVaR zone, which represents average losses for the most extreme 5% of cases.

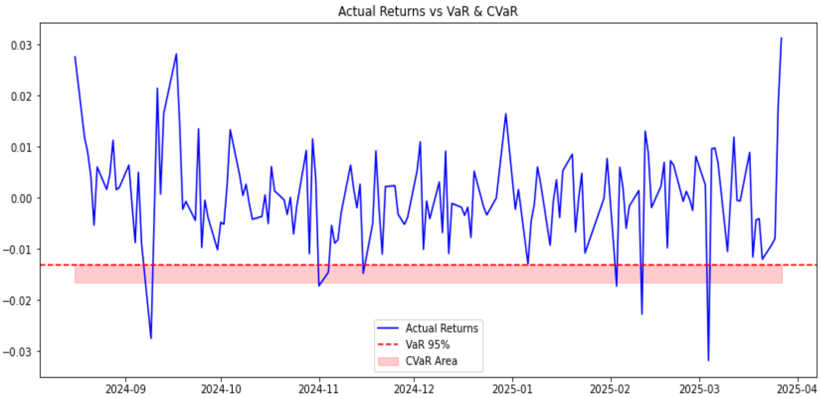


Figure 5. Comparison of Actual Returns and CVaR Estimation (95%)

From Fig. 5, several return points fall below the VaR line, confirming the presence of extreme losses. The CVaR area quantifies the expected shortfall during these events, providing a more comprehensive risk measure than VaR alone. The relatively limited number of breaches aligns with the 5% confidence level, indicating that the Random Forest model successfully captures tail risks without excessive false alarms.

In addition to the 95% confidence level analysis, Fig. 6 presents the risk estimation result at the 99% confidence level. At this higher confidence threshold, the VaR line is positioned further in the lower tail of the return distribution, reflecting a stricter criterion for extreme loss events. The red dashed line represents the 99% VaR threshold, while the shaded area below this line indicates the CVaR zone, capturing the average loss in the most extreme 1% of cases.

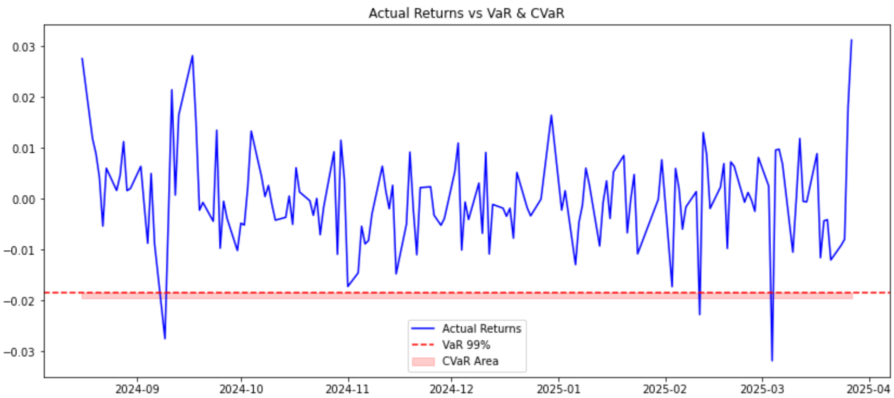


Figure 6. Comparison of Actual Returns and CVaR Estimation (99%)

As shown in Fig. 6, the actual return points (blue line) rarely breach the 99% VaR threshold compared to the 95% level. This outcome is consistent with the nature of the 99% confidence level, where extreme losses are expected to occur with only 1% probability. The CVaR region under this setting quantifies the potential magnitude of these rare but severe losses, providing valuable insight into the portfolio's exposure to tail risk under extreme market conditions.

The results of this research align with previous research that emphasizes the strength of machine learning, particularly Random Forest, in modeling financial risk. Earlier studies, such as [39], have shown that Random Forests perform well at estimating complex financial outcomes, especially under volatile market conditions.

3.3 Error Measurement

The predictive performance of the Random Forest model was assessed using two standard error metrics, MAE and MSE. These metrics evaluate the model's predictive accuracy by comparing forecasted values to actual values in the test set. The results are summarized in Table 4 below.

Table 4. Model Performance Results

Performance Model	Metric	Value
Error Measurement	MAE	0.006701127
	MSE	0.000091119

The MAE and MSE values presented in Table 4 show that the Random Forest model demonstrates strong predictive performance. The MAE value of 0.006701 indicates that the model's predicted portfolio returns differ only slightly, on average, from actual returns. Meanwhile, the MSE of 0.000091 shows that the squared differences between predictions and actual values are also minimal, suggesting that large deviations are rare. These two metrics together confirm that the model achieves both high accuracy and stability, which are essential for reliable CVaR estimation.

The evaluation of CVaR estimation accuracy in this research, as measured by MSE and MAE, indicates that the Random Forest model can achieve high accuracy and stability. Although previous research by [NO_PRINTED_FORM] [39] reported that Neural Networks slightly outperformed Random Forests in overall accuracy metrics, Random Forests still demonstrated strong predictive performance, highlighting their effectiveness in modeling financial risk. Its ensemble structure, which combines multiple decision trees, yields stable, reliable results, especially when working with noisy or nonlinear financial data. These findings align with prior studies by [NO_PRINTED_FORM] [43], which emphasized Random Forest's robustness and practical utility in financial forecasting. Therefore, despite not being the most accurate among all ML models, Random Forest provides a balanced trade-off between interpretability, computational efficiency, and predictive reliability in estimating CVaR.

3.4 Backtesting

To evaluate the reliability of the VaR and CVaR estimates generated by the Random Forest model, a backtesting procedure was conducted using the Kupiec Proportion of Failures test at both the 95% and 99% confidence levels. The Kupiec test assesses whether the actual number of VaR and CVaR breaches aligns with the expected frequency of violations under the assumed confidence levels. The results of the backtesting are summarized in Table 5 below.

Table 5. Model Validation Results

Evaluation Model	Confidence Level	P-Value
Backtesting (Kupiec Test)	95%	0.835382
	99%	0.282731

The Kupiec backtest at the 95% confidence level yielded a p-value of 0.835382, further supporting the model's validity. Since the value is well above the 0.05 significance level, it indicates that the number of times actual losses exceed the VaR threshold is consistent with the expected 5% exceedance rate. Similarly, at the 99% confidence level, the p-value of 0.282731 also exceeds the threshold, suggesting that the observed frequency of extreme losses aligns with the expected 1% tail risk.

These findings are consistent with previous research by [NO_PRINTED_FORM] **[44]**, who emphasized the importance of backtesting in validating VaR estimation methods. In other words, the Random Forest model does not underestimate potential losses, as the actual number of exceedances observed in backtesting closely aligns with the theoretical expectations set by the CVaR confidence levels. This consistency indicates that the model provides a realistic estimation of extreme risk events. Consequently, the Random Forest model successfully passes the Kupiec backtest, demonstrating its validity as a tool for modeling tail risks. It is important in insurance portfolio management, where accurate risk assessment of rare but severe events is critical for maintaining financial stability and capital adequacy.

4. CONCLUSION

1. This research demonstrates the effectiveness of applying Machine Learning, particularly the Random Forests algorithm, in estimating Conditional Value at Risk (CVaR) for insurance company stock portfolios. By incorporating historical stock returns, engineered features such as moving averages, and ensemble-based predictive modelling, the Random Forest approach successfully captured complex and nonlinear patterns in financial data.
2. The model, trained using portfolio returns optimized through the MVEP method, provided adaptive, data-driven CVaR estimates that reflect the dynamic behavior of insurance stock portfolios. The results show that the Random Forest model achieved high predictive accuracy, indicated by low error metrics (MAE = 0.0067; MSE = 0.000091) and reliable CVaR estimates at both 95% (1.65%) and 99% (1.94%) confidence levels.
3. Backtesting through the Kupiec Proportion of Failures test further validated the model's reliability, with p-values of 0.8353 and 0.2827 exceeding the standard significance threshold. This confirms that the frequency of losses beyond the CVaR limits aligns with theoretical expectations, reinforcing the model's robustness in capturing extreme tail risks.
4. In practical terms, these findings highlight the potential of machine learning-based approaches to enhance the precision and robustness of financial risk assessment in the insurance sector. The Random Forest model provides a reliable framework for anticipating extreme losses, improving portfolio resilience, and supporting data-driven decision-making. Overall, this research confirms that Random Forest can serve as an effective and practical tool for CVaR estimation and risk management in volatile market environments, offering valuable insights for both academics and practitioners in financial risk analysis.

Author Contributions

Purwanto: Supervision, Validation, Writing–Review and Editing. Agna Olivia: Conceptualization, Methodology, Data Curation, Formal Analysis, Software, Visualization, and Writing–Original Draft. All authors discussed the results and contributed to the final manuscript.

Funding Statement

This work was supported by the Government of Indonesia through the Research and Community Service Program in 2025.

Acknowledgment

The authors would like to express their sincere gratitude to the Government of Indonesia for providing financial support through the Research and Community Service Program in 2025. The authors also wish to thank President University and the Faculty of Business for their guidance, facilities, and academic support throughout this research.

Declarations

The authors declare no competing interests.

Declaration of Generative AI and AI-assisted technologies

Generative AI (ChatGPT) was used exclusively for language editing and stylistic improvement. The authors take full responsibility for the content and confirm that all analyses, results, and interpretations are their own. The final manuscript was reviewed for linguistic accuracy by an English-language expert.

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