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Prediction of the Islamic Stock Price Index and Risk of Loss Using the LSTM (Long Short-Term Memory) and VaR (Value at Risk) Methods

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Abstract: Investment aims to increase the value of capital or earn additional Income through asset growth, dividends or profits. One investment instrument that is in demand, especially among the Muslim community, is Islamic stocks, which are in accordance with Islamic principles that focus on a healthy economy. This research is focused on predicting Islamic stock prices using the Long Short-Term Memory (LSTM) method and measuring risk with Value at Risk (VaR) using the Cornish-Fisher Expansion (ECF) method. Stock price data from the food sector (PT Indofood), technology sector (Telkom Indonesia), and construction sector (Indocement) for the period 2018-2023 were analyzed. The results show that the ADAM model provides the best performance with the lowest prediction error rates for INTP and TLKM stocks (around 1.22%, 1.98%, and 1.41%). In addition, the SGD model shows limitations in accurate predictions with an error rate above 12%. VaR analysis reveals a slightly higher level of risk in INTP stocks, with a VaR value of around 2.85% at the 95% confidence level. Meanwhile, TLKM stock shows a lower level of risk, with a VaR of around 2.25% at the same confidence level. An in-depth understanding of the risk and growth characteristics of each stock, as well as the selection of the optimization model, are key in making wise investment decisions.

Keywords: Prediction;Deep Learning; LSTM (Long Short-Term Memory); Investment Risk;Value at Risk (VaR);Islamic Stock Price Index.

1. Introduction

Investment serves the purpose of increasing capital value or generating additional income through asset value growth or earnings such as interest, dividends, and capital gains [1]. Investment characteristics include the need for relatively small capital, enabling individuals with various income levels to participate. There is a swift turnover of money, with investment instruments being bought and sold in the stock market daily, providing investors with quick access and flexibility to adjust portfolios as needed. In the digital era, online platforms and financial intermediary apps make various investment instruments easily accessible, allowing for swift and straightforward investment without complex processes [2].

One impactful investment instrument is stocks, issued by companies to raise additional capital for operational and performance growth [3]. This includes Sharia stocks in Indonesia, adhering to Islamic principles and gaining popularity among the Muslim community for contributing to a healthy and Islamic-values-aligned economy.

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Sharia stocks not only serve as investment tools but also play a role in inclusive and sustainable economic development, positively impacting corporate governance and business transparency [4]. However, stock prices are dynamic, leading to fluctuations, necessitating modeling to aid investors in predicting price changes.

In addition to predicting stock prices, this study focuses on predicting Value at Risk (VaR) using the Cornish-Fisher Expansion (ECF) method. VaR measures and manages potential investment risks, calculating potential losses within a specific time frame and confidence level [5]. While investment holds strong financial appeal, it is crucial to acknowledge the inherent risks (Maruddani & Astuti, 2021). The research also delves into predicting VaR risk, crucial in aiding investors to make informed decisions by integrating risk factors into their investment strategies.

Previous studies on LSTM and VaR have been conducted, emphasizing the importance of selecting the right model for risk estimation, such as the Cornish-Fisher Expansion (ECF), which considers skewness and kurtosis [6]. The research aims to deepen understanding and provide insights into the integration of risk in investment decision-making, facilitating wiser strategies and more informed choices for investors. The Sharia stock price index data for this study comes from three sectors: food (PT Indofood), technology (Telkom Indonesia), and construction (Indocement), spanning from 2018 to 2023.

2. Related Works

There some methods and approaches to create a forecast model. Such as linear and non-linear The first study titled "Analysis of Banking Sector Stock Price Prediction Using Long-Short Term Memory (LSTM) Algorithm" by Prismahardi Aji Riyantoko, presented in the Proceedings of the 2020 National Informatics Seminar(SEMNASIF 2020), focuses on utilizing LSTM for predicting stock prices in the banking sector. The author collected stock data from BRI, BNI, BTN, and Mandiri, employing LSTM as the prediction model after preprocessing the dataset, consisting of 1257 rows and 7 columns. The findings emphasized the impact of epoch variations on computational time, with larger epochs requiring more computation time. Additionally, the optimization model significantly influenced the outcomes in terms of loss and accuracy at various epoch values [7].

The second study, "Prediction of Sharia Stock Prices Using Long Short-Term Memory (LSTM)" by Gunawan Budiprasetyo, Mamluatul Hani'ah, Darin Zahira Aflah, published in the National Journal of Technology and Information System, explores the application of LSTM in predicting daily closing stock prices of five Sharia emitters. The research involved normalization, LSTM model creation, denormalization, and model evaluation. The findings revealed accurate predictive performance for all five emitters, as indicated by the obtained MAPE values [8].

Feby Seru's study, "Analysis of VAR and CVAR Risk on the Prediction of Astra International Tbk Stock Prices," published in the Journal of Silogisme - Mathematical Sciences and Learning Studies, investigates the use of Geometric Brownian Motion for predicting PT. Astra International Tbk stock prices. The study incorporates Value at Risk (VaR) and Conditional Value at Risk (CVaR) for risk prediction. The findings highlighted the VaR and CVaR values at different confidence levels, indicating a proportional relationship between risk and confidence level .

Nikanor Goreglyad's work, "The LSTM Approach for Value at Risk Prediction," conducted at Charles University, presents an approach to forecasting Value at Risk (VaR) using LSTM and compares it with traditional models such as FIGARCH and EVT-POT. The study showcased the competitive forecasting capabilities of the LSTM approach during normal volatility periods, despite the need for certain assumptions during VaR estimation.

Lastly, "Optimization of Stock Portfolio with Monte Carlo Simulation for Value at Risk (VaR) Measurement" by Sarah Hardiana, Muhammad Subhan, Dewi Murni, published in UNPjoMath, delves into portfolio optimization using Monte Carlo simulation. The study used return data from LQ-45 stocks and the Composite Stock Price Index, involving various steps such as data normalization, model creation, and risk measurement. The findings revealed the optimal portfolio composition and associated risks, providing insights for investors seeking to balance risk and return in their portfolios [9].

3. Experiment and Analysis

The experiments conducted were to compare the optimiser in the LSTM model and perform risk prediction. Experiments included pre-processing the data, splitting the data, modelling and determining the parameters in building the LSTM model. Also, calculating the return value and calculating risk predictions for a certain period. Each treatment is carried out using stock data from three sectors, namely, ICBP, INTP and TLKM. Furthermore, the evaluation results of the computational validation of the LSTM model are shown and the risk prediction results are also displayed. Additional information that will be obtained is the best optimiser to build the LSTM model and the risk of stock losses.

3.1. Dataset

In this study, stock price data from three sectors are used. The data used are the daily time series data of the stock price index from 2018 to 2023. This study uses stock price data from three sectors. The data used are daily time series data of the stock price index from 2018 to 2023. Figure 1 shows the time series of the closing variable. It also shows the graph pattern of the dataset.

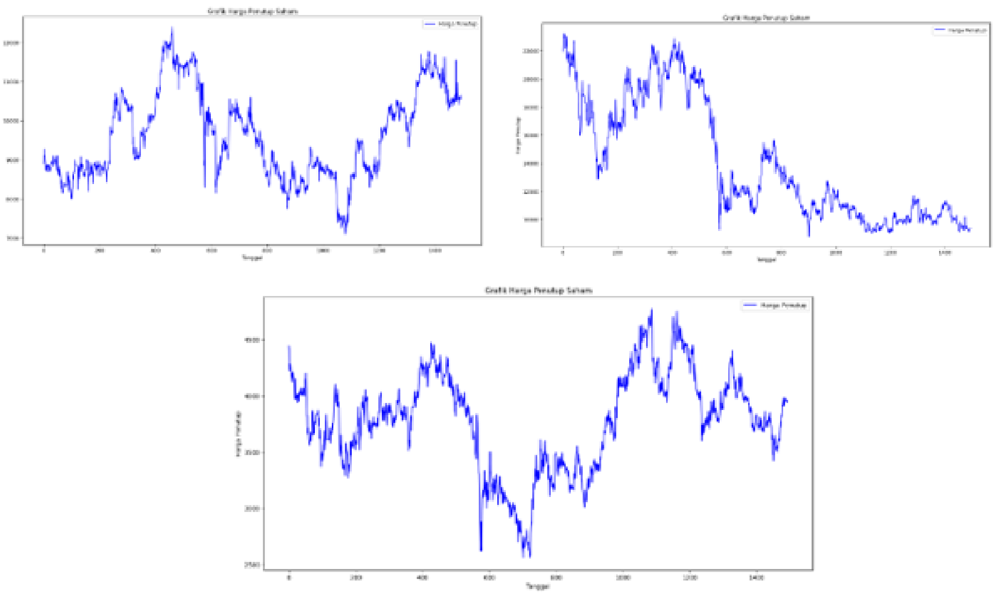

Figure 1. ICBP, INTP, TLKM Stocks Dataset Graph

The dataset graphs show fluctuating chart patterns for the three stocks - ICBP, INTP and TLKM - within their respective sectors. Each stock index has its own unique characteristics and potential for gains or losses, and this common occurrence in stock prices reflects dynamic changes and fluctuations over time. The ICBP, INTP and TLKM stocks exhibit fluctuating data, commonly referred to as price volatility, which affects the values calculated in the model and results in different outcomes. These graphs provide valuable insight into the dynamic nature of stock prices by illustrating patterns of data that show increases, decreases or consistency over a period of time.

The horizontal line represents the date and the vertical line represents the closing price when interpreting the data graph. The date does not follow the day/month/year format. Instead, it indicates the number of changes in the closing price or the sequential occurrence of closing prices over time. The closing prices of each stock index are shown on the vertical lines. In particular, the ICBP reaches a high above 12000 and a low below 7000; the INTP reaches a high above 22000 and a low below 10000; and the TLKM reaches a high above 4500 and a low below 2500.

3.2. Methodology

The research methodology that has been determined will then be implemented in stages and done using the python programming language. The results and discussion of the coding work will be discussed in the section below. Starting with the stages of doing the stock price prediction process until the visual results of the prediction using LSTM, then continued with the stages of predicting risk using VaR ECF method.

In the LSTM process, the initial stage involves separating information from Ct-1 using a forget gate. The task of this gate is to check the values of st-1 and xt, producing a value between 0 and 1 for each element in Ct-1. In formulation, it is as described [7], as follows:

$$f_t = \sigma(W_f . [s_{t-1}, x_t] + b_f) \quad (1)$$

For elements in Ct-1, temporary subject information can be stored, allowing the use of appropriate pronouns. When facing a new subject, the old elements in Ct-1 can be removed. The next stage involves an input gate that determines the values to be updated. Next, the hyperbolic tangent layer (tanh) generates a new context candidate vector, namely $\tilde{C}t$ (C tilde). Next, these two pieces of information are combined to update the context, and in this context, the process can be explained as follows:

$$i_t = \sigma(W_i . [s_{t-1}, x_t] + b_i) \quad (2)$$

$$C_t = tanh(W_c . [s_{t-1}, x_t] + b_c) \quad (3)$$

At this time, the step to be taken is to update the old context Ct-1 into the new context, Ct. To remove information that is no longer needed, the forget gate (ft) in equation (1) is used to multiply with the old context as in equation (2) and equation (3). This results in a new equation as follows:

$$C_t = f_t * C_{t-1} + i_c * \tilde{C}_t \quad (4)$$

In the output gate stage, updates will be applied to the cells and sigmoid layers to determine which parts of the context to generate. This results in the following equation:

$$o_t = \sigma(W_o . [s_{t-1}, x_t] + b_o) \quad (5)$$

$$s_t = o_t * \ tanh(C_t) \quad (6)$$

With:
f_t: *Forget gate*

i_t: *Input gate*

o_t: *Output gate*

c_t: *Cell state*

s_t: *Hidden state*

s_{t-1}: *hidden state*

C_t: new candidate *cell state*

σ: *Sigmoid*

b_f, b_i, b_c, b_o: bias vector

s_{t-1}, x_t: Combined value of previous hidden state and current input data

W_i, W_f, W_c, W_o: Weight matrix

$tanh$: Target activation function with value range (-1, 1))

In conducting research on the LSTM program carried out in the python programming language, the first step is to import the required library, then retrieve or input the data that has been obtained, then perform pre-processing on the input data, then correct missing data, filtering to select appropriate features, the selected feature is the closing price on the stock price index dataset, the next process is to normalize the data with the aim of helping the features to run well when modeling and avoiding inappropriate scales.

Before entering into the computational process, the inputted dataset is divided into 2 parts, the first part for training data, and the second for test data. The training data is divided into 80% and the test data is 20%. After the data is divided into 2 parts, the next step is to make LSTM modelling. Here the model is formed and adjusted its parameters so that it can perform good computation and produce validation of training data and test data and their predictions.

To find out how well the model runs or during computing data, loss is used which is calculated using MSE. The results of loss validation are shown to see how good the model is during computation. Models that have successfully performed computations produce predicted values, to measure how well the model is in making predictions using MAPE calculations.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right| \times 100 \quad (7)$$

Where:

- n is the number of observations,

- Y_i is the actual value, and

- $\hat{Y}_i$ is the predicted value.

Table 1. MAPE Evaluation

MAPE	**Kategori**
< 10	Accurate prediction model performance
10 – 20	Good prediction model performance
20 – 50	The performance of the prediction model is decent
21 > 50	Inaccurate prediction model performance

This table provides a general guide for evaluating model performance. The lower the MAPE value, the better the model is at predicting the data. This categorisation aids the interpretation of the evaluation results by giving an idea of how accurate the model is in terms of the percentage error relative to the actual values [8].

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \quad (8)$$

n = Number of data samples

y_i = True value of the i-th observation

$\hat{y}_i$ = Predicted value for the i-th observation given by the model.

MSE measures the average of the squared difference between the true value and the predicted value. The smaller the value of MSE, the better a model is in performing the computational process to produce predicted values [10].

Value at Risk (VaR) is a method used to measure and manage risk in investment and portfolio management. VaR describes the extent to which the value of an investment or portfolio can fluctuate in a given period of time with a certain level of confidence [11]. The basis of VaR is the recognition that all investments involve risk, and it is important for investors and risk managers to have an understanding of the extent to which potential losses can occur [6]. VaR with a confidence level of 100(1 - α)% is calculated using the ECF formula :

$$S = \frac{M^3}{s^3} = \frac{\frac{1}{n}\sum_{i=1}^{n}\left(X_i - \bar{X}\right)^3}{s^3} \quad (9)$$

$$K = \frac{M^4}{s^4} = \frac{\frac{1}{n}\sum_{i=1}^{n}\left(X_i - \bar{X}\right)^4}{s^4} \quad (10)$$

Where:
S: A measure of the degree of skewness
K: A measure of the degree of skewness
n: Number of data
X_i: The i-th data
s: Standard deviation

3.3 Prediction Using LSTM

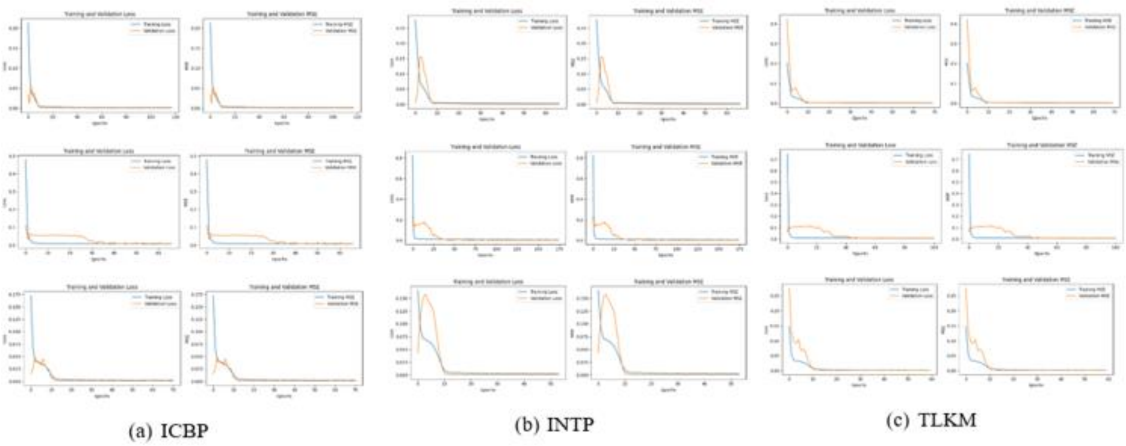

Figure 2. Model validation results on the training data

From figure 2. the top result is the ADAM optimiser, the middle is SGD, and the bottom is RMSprop, these are the validation results on the training data. Optimisations such as ADAM, SGD, and RMSprop were evaluated for three stocks: ICBP, INTP, and TLKM. RMSprop showed the best performance on ICBP stock with a MAPE of 1.27% and MSE of 0.0019, while ADAM had the smallest MAPE of 1.22%. On INTP stock, ADAM has the lowest MAPE of 1.98%, although the MSE is quite high at 0.0023. For TLKM stock, ADAM came back with the smallest MAPE of 1.41% and MSE of 0.0017. However, SGD showed the poorest performance across all stocks with a MAPE above 12%, showing limitations in better prediction.

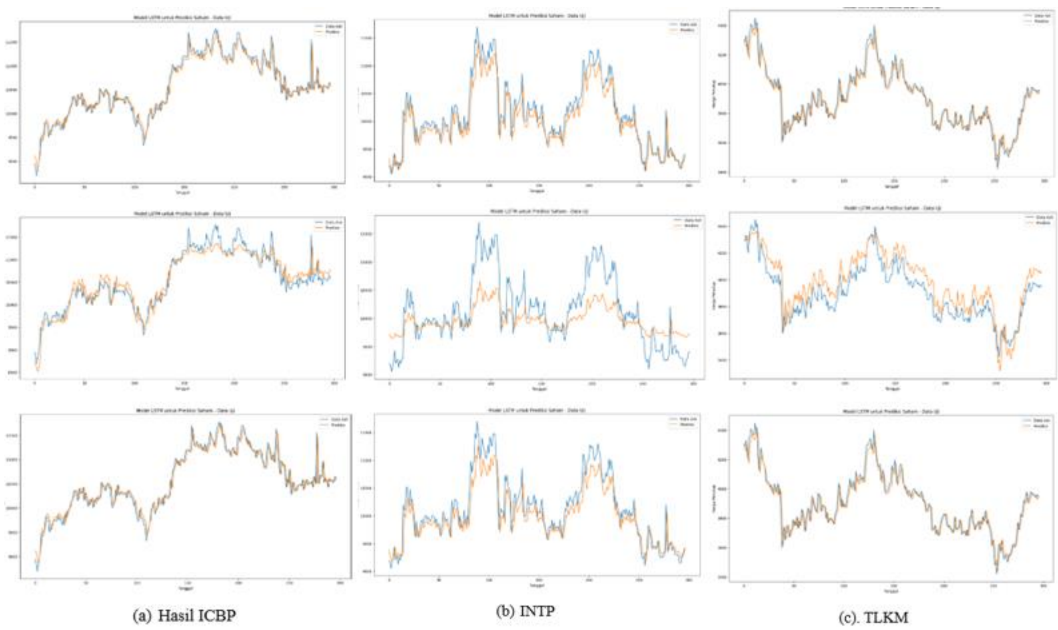

Figure 3. Prediction Results

From the prediction results of the test data, various optimisation models such as ADAM, SGD, and RMSprop were evaluated for ICBP, INTP, and TLKM stocks. For ICBP stock, RMSprop has a slightly lower MAPE than ADAM, which is 2.03%, and MSE 0.00091. For INTP stocks, ADAM has the lowest MAPE of 2.63%, with a lower MSE than SGD and RMSprop, which is 0.0024. For TLKM stock, ADAM returns as the optimiser with the smallest MAPE, 1.30%, and MSE of 0.0006. It should be noted that SGD showed the lowest performance with a significant MAPE, the lowest in the test data validation results of 30.25%, indicating the limitations of the model in predicting the test data, although it has not reached the desired level of accuracy.

The following are the results of the training and test data presented in table form to see the overall evaluation more easily, as follows:

Tabel 2. Training Data Evaluation Results on 3 Stocks

Model Optimizer	**ICBP**			**INTP**			**TLKM**		
	Loss	MAPE	MSE	*Loss*	MAPE	MSE	*Loss*	MAPE	MSE
ADAM	0.0018	1.22 %	0.0018	0.0023	1.98%	0.0023	0.0017	1.41 %	0.0017
SGD	0.0070	12.69%	0.0070	0.0066	14.51%	0.0066	0.0048	13.18%	0.0048
RMSprop	0.0019	1.27%	0.0019	0.0027	2.39%	0.0027	0.0019	1.54%	0.0019

Tabel 3. Test Data Evaluation Results on 3 Stocks

Model Optimasi	**ICBP**			**INTP**			**TLKM**		
	Loss	MAPE	MSE	*Loss*	MAPE	MSE	*Loss*	MAPE	MSE
ADAM	0.00092	2.04%	0.00092	0,0024	2.63%	0,0024	0.0006	1.30%	0.0006
SGD	0.0013	11.47%	0.0013	0,0088	30,25%	0,0088	0.0025	20.44%	0.0025
RMSprop	0,00091	2.03%	0,00091	0,00029	3.78%	0,00029	0.0007	1.41%	0.0007

From the training data validation table, the evaluation of various optimisation models such as ADAM, SGD, and RMSprop for ICBP, INTP, and TLKM stocks revealed that RMSprop showed the best performance on ICBP with a MAPE of 1.27% and MSE of 0.0019, while ADAM had the smallest MAPE of 1.22%. On INTP, ADAM has the lowest MAPE of 1.98%, albeit with a fairly high MSE of 0.0023. For TLKM, ADAM returns as the optimiser with the smallest MAPE of 1.41% and MSE of 0.0017. Nonetheless, SGD showed the poorest performance across all stocks with a MAPE above 12%, indicating limitations in better prediction. Reviewing the test data validation results, RMSprop was slightly lower than ADAM on ICBP, with a MAPE of 2.03% and MSE of 0.00091. On INTP, ADAM has the lowest MAPE of 2.63%, with a lower MSE than SGD and RMSprop, at 0.0024. For TLKM, ADAM returns as the optimiser with the smallest MAPE of 1.30% and MSE of 0.0006. It should be noted that SGD showed the lowest performance with a significant MAPE, the lowest in the test data validation result of 30.25%, indicating the model's limitation in predicting the test data, although it has not reached the desired level of accuracy.

3.3 Risk Prediction Using VaR

The second programme is to measure the level of risk present in the stock data. However, before getting the results of risk prediction or Value at Risk value, there are several processes and programming that must be carried out. These processes are, importing the library needed to run the programme, retrieving the return value of the close variable in the database, the dataset to be used is determined in the 2022-2023 period only, this is done because the desired result is the result of risk prediction with new data information so as to produce the latest value and the latest risk information. Calculate the VaR function, using Cornish-Fisher Expansion. Then, calculate VaR with a certain level of confidence, namely, 95% and 99%. Next, display the visualisation results and the VaR area results.

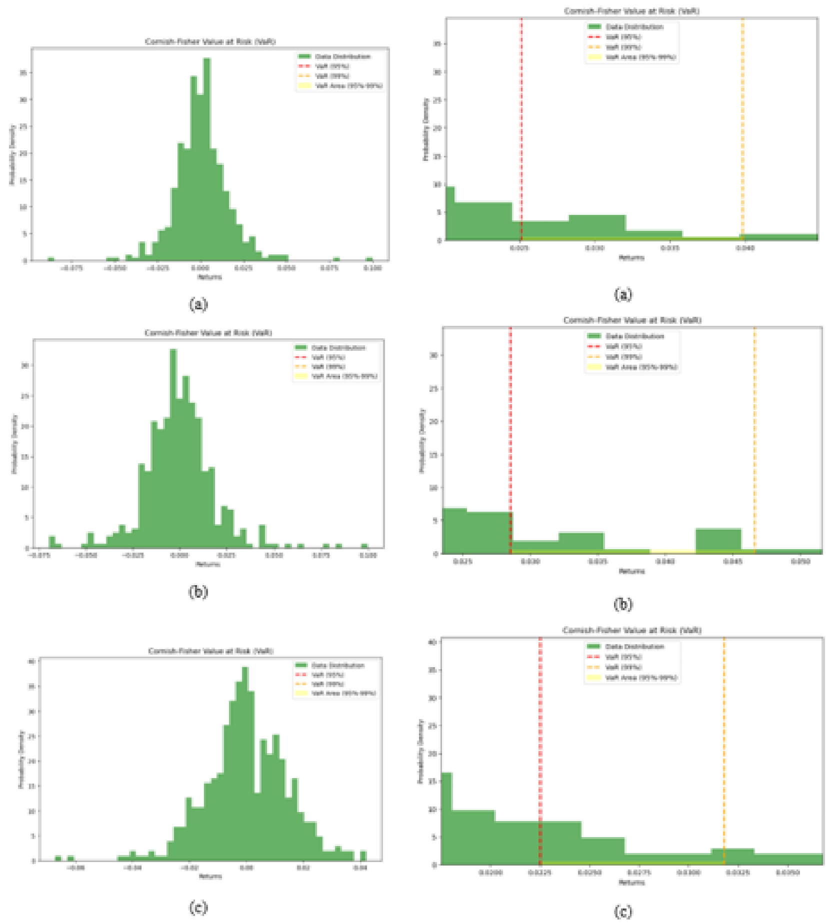

Figure 4. (a) ICBP VaR Result, (b) INTP VaR Result, (c) TLKM VaR Result

In the Value at Risk (VaR) prediction analysis for ICBP, INTP, and TLKM stocks at the 95% and 99% confidence levels, it can be seen that ICBP stocks show a well-controlled level of risk. The VaR at the 95% confidence level is 0.0251 and 99% is 0.0398, indicating that the daily loss at the 95% confidence level is not expected to exceed 2.51% of the portfolio value, while at the 99% confidence level, the daily loss limit is not expected to exceed 3.98%. The histogram analysis of returns is also supportive, showing the majority distribution is on the positive side, reflecting positive growth with reasonable fluctuations. In contrast, INTP stock has a slightly higher level of risk, with a VaR at the 95% confidence level of 0.0285 and 99% of 0.0466. Nonetheless, the return histogram shows significant positive growth, providing a balanced picture between risk and potential gain.

When VaR is applied to TLKM shares, a lower level of risk can be seen with VaR at 95% confidence level of 0.0225 and 99% of 0.0318. This indicates that at the 95% confidence level, the daily loss of TLKM stock is not expected to exceed 2.25% of the portfolio value, and at the 99% confidence level, the daily loss limit is not expected to exceed 3.18%. The return histogram also shows a distribution of values that are mostly on the positive side. Overall, VaR analysis and return histograms provide useful information for investors to make wiser investment decisions, considering the level of risk and potential profit in accordance with their respective preferences.

4. Conclusion

Based on the research of stock price prediction using deep learning LSTM architecture model on ICBP, INTP, and TLKM stocks, as well as risk analysis using Value at Risk Cornish-Fisher Expansion method, some important findings can be concluded. First, the performance of the LSTM model is strongly influenced by the choice of optimiser, where ADAM generally gives the best results and is better than RMSprop and SGD which need further improvement. Secondly, VaR analysis at 95% and 99% confidence level shows that ICBP and TLKM stocks have a controlled risk level, while INTP stocks have a slightly higher risk level.

For further development, research can focus efforts on improving the LSTM model by exploring various hyperparameter settings and model structures. More diverse hyperparameter tuning processes, including learning rate tuning, can be applied to improve model performance. In addition, other strategies in the use of VaR can be explored, or alternative VaR methods can be used to compare the risk analysis results of various approaches. These steps can further contribute to the understanding and development of stock price prediction and risk management in financial markets.

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Data Availability Statement: This data is collected by expert investment managers. Access to this data can be checked at https://finance.yahoo.com

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Conflict of Interest: The authors declare no conflict of interest.

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