Technical Analysis of the Indonesian Stock Market with Gated Recurrent Unit and Temporal Convolutional Network

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Abstract - Big data is essential in the age of 4.0 industry as it becomes the basis of decision making. Deep learning research in the last few years has been proven effective in understanding complex big data patterns, especially in the finance sector. The rapid growth of the Indonesian stock market in the last 20 years, which was driven by globalization, prompted fluctuation in the Bursa Efek Jakarta (JKSE) which was influenced by stock prices, commodity prices, and exchange rate. This study identifies the main indicators of Indonesian stock market crisis, applies and compares deep learning models, particularly Gated Recurrent Unit (GRU) and Temporal Convolutional Network (TCN), in predicting stock prices. This study identified 20 JKSE crisis points between the 2002-2023 period with average return value at around -6%. All variables correlated positively with JKSE, with SET.BK as the highest correlated variable in lag 0. The American and European stock market, commodity price, and exchange rate tend to show a pattern opposite to the JKSE crisis. Predictor variables such as STI, HIS, KLSE, KS11, SET.BK, PSEI.PS, RUT, and USDIDR are chosen based on significant cross correlation and average return plot. Hyperparameter tuning and cross validation within a 3 years window concluded that the GRU model is accurate and efficient, with RMSE value at 43.35568 and MAE value at 33.66909 in the validation data.

Keywords: GRU, JKSE, stock market crisis, TCN

I. INTRODUCTION

The growth of technology and internet access in the age of 4.0 industry eases information access, which leads to the big data concept. Big data plays as the base of crucial decision making, particularly if it is continuously updated and originated from various sources. Deep learning approaches can extract complex data patterns at a fast rate which then allows it to process big data with certain characteristics, such as periodicity and fluctuation [1], without depending on linearity data assumption [2]. Machine learning algorithms in the last few years are used in the development of efficient prediction models. The study of [3] shows that machine learning approach, particularly in the context of big data, is more efficient compared to classic approach with significant growth in accuracy. Demands from industry and government for smart prediction models increase, hoping that deep learning, which is a part of machine learning, will be able to detect crisis, especially in the finance industry [4].

Globalisation era pushes the integration of international relations in the liberalisation of the finance industry [4]. This positive advantage is crucial for Indonesia as a developing country who is in urgent need of capital to support the economic growth. The integrated international stock market subsequently impacts the rapid growth of the Indonesian stock market. As per Indonesian Stock Exchange [5], 903 issuers are recorded with stock trade volume as the most popular investment instrument in Indonesia, peaking at 54.14 billion rupiahs at the end of 2023. Jakarta Stock Exchange (JKSE), as the main index of combined stock price performance in Indonesia, experiences fluctuations in the last 20 years which was influenced by internal factors and external factors [2]. External factors which influence JKSE are global stock price, commodity price, and exchange rate. Global stock exchange tends to move in the same direction [6], as appears in the global financial crisis of October 2008. The decrease of index in the United States causes a domino effect to the other index markets, including Indonesia. JKSE also experiences another sudden decrease from Fed Taper Tantrum in 2013 to Covid-19 Pandemic in 2020.

An analysis in stock movement is needed to anticipate future market crash. The analysis in this research focuses on the technical aspect, which is observing stock movements from time to time. The methods used in this research are deep learning algorithms, Gated Recurrent Unit (GRU) and Temporal Convolutional Network (TCN). A study by [7] about closing stock price JKLQ45 shows that deep learning with GRU is superior compared to Recurrent Neural Network (RNN) and Long Short-

Term Memory (LSTM). Meanwhile, TCN is a combined Convolutional Neural Network (CNN) architecture and RNN, adopting a convolutional process to process sequential data adjacent to possessing a simple and clear architecture [8]. TCN is proven more accurate and more efficient in predicting stock price movement trends compared to LSTM [2]. Based on the stated background, the objective of this research is to identify variable or leading indicators that influence JKSE market crash. Furthermore, this research is aimed to apply and compare the model performance of GRU and TCN deep learning algorithms in detecting Indonesian market crashes. Therefore, this deep learning model is expected to be able to detect crises with such accuracy that it can help the prevention or risk minimization in Indonesian stock exchange in the future.

II. METHOD

A. Data

This research uses daily data (five working days per week) from January 1, 2002, to December 29, 2023, covering 5739 days. The total number of observations is 155054 filled and 5739 blank. The blank observations will be imputed, resulting in a total of 160692 complete observations. The data sources are Yahoo Finance and Investing Indonesia, which provide credible financial data on stock markets, exchange rates, and commodity prices. The study includes 1 response variable (JKSE) and 27 predictor variables. Details of the variables used can be seen as in Table 1.

B. Data Analysis Methods

Gated Recurrent Unit (GRU): Gated Recurrent Unit (GRU) is a modified RNN algorithm and relatively simpler than LSTM. GRU can produce an accurate prediction comparable to LSTM with faster training rate

TABLE I
THE VARIABLES USED

Variable	Code	Description	Source	Reference
Stock Market	JKSE	All stock exchanges on the IDX	Yahoo Finance	[9]
	KLSE	Malaysia stock exchanges		
	STI	Singapore 30-stock exchanges		
	SET.BK	Thailand stock exchanges		
	KS11	South Korea stock exchanges		
	SSEC	China stock exchanges		
	N225	Japan 225-stock exchanges		
	HIS	Hong Kong 50-stock exchanges		
	PSEI.PS	Philippines stock exchanges		
	GDAXI	Germany 30-stock exchanges		
	FCHI	France 40-stock exchanges		
	DJIA	United States 30-stock exchanges		
	GSPC	United States 500-stock exchanges		
	RUT	United States 2000-stock exchanges		
	IXIC	United States all-stock exchanges		
	FTSE	London 100-stock exchanges		
	LSEG.L	London all-stock exchanges		
	AXJO	Australian stock exchanges		
Commodity Prices	GC. F	Gold futures contract	Yahoo Finance	[10]
	CL.F	Crude oil futures contract		
Exchange to Indonesian Rupiah	USDIDR	United State Dollar exchange rate	Investing Indonesia	[10]
	SGDIDR	Singapore Dollar exchange rate		
	MYRIDR	Malaysian Ringgit exchange rate		
	THBIDR	Thai Baht exchange rate		
	EURIDR	Euro exchange rate		
	GBPIDR	British Poundsterling exchange rate		
	JPYIDR	Japanese Yen exchange rate		
	AUDIDR	Australian Dollar exchange rate		

since it is able to control the forget factor and perform an update to the unit in hidden state at the same time. Moreover, GRU can pick up dependencies which affect prediction results with adaptive change [11].

According to [7], GRU uses two gates to control information flow, which are update gate and reset gate. Update gate determines the amount of input from past period to be forwarded into the future period using sigmoid activation function $\sigma(\cdot)$, which limits the input value between 0 and 1. An input will be ignored in the update gate when it approaches 0 and will be kept if the value approaches 1. Input is also processed by reset gate, which determines the amount of information from past period to be forgotten using sigmoid activation function $\sigma(\cdot)$. The result from reset gate then will be used to calculate candidate state with hyperbolic tangent activation function ($\tanh(\cdot)$), which limits the input value between -1 and 1 to help regulate the value that flows inside the network. After the calculation, GRU calculates the hidden state to save the output which is then forwarded to the next unit [12]. GRU architecture can be seen as in Fig. 1.

As for the formulas in GRU model are as shown in (1)–(4).

$$\boldsymbol{u}_t = \sigma(\boldsymbol{W}_{hu} \cdot \boldsymbol{h}_{t-1} + \boldsymbol{W}_{xu} \cdot \boldsymbol{x}_t + \boldsymbol{b}_u) \quad (1)$$

$$\boldsymbol{u}_t = \sigma(\boldsymbol{W}_{hu} \cdot \boldsymbol{h}_{t-1} + \boldsymbol{W}_{xu} \cdot \boldsymbol{x}_t + \boldsymbol{b}_u) \quad (2)$$

$$\widetilde{\boldsymbol{h}}_t = \tanh(\boldsymbol{W}_{hh} \cdot (\boldsymbol{r}_t \odot \boldsymbol{h}_{t-1}) + \boldsymbol{W}_{xh} \cdot \boldsymbol{x}_t + \boldsymbol{b}_h) \quad (3)$$

$$\boldsymbol{h}_t = (1 - \boldsymbol{u}_t) \odot \boldsymbol{h}_{t-1} + \boldsymbol{u}_t \odot \widetilde{\boldsymbol{h}}_t \quad (4)$$

with $\boldsymbol{u}_t$ is update gate, $\boldsymbol{r}_t$ is reset gate, $\widetilde{\boldsymbol{h}}_t$ is candidate state, $\boldsymbol{h}_t$ is hidden state, $\boldsymbol{W}_h$ and $\boldsymbol{W}_x$ is weight matrices, $\boldsymbol{h}_{t-1}$ is past information vector, $\boldsymbol{x}_t$ is new input vector, $\boldsymbol{b}$ is bias vector, and $\odot$ is Hadamard product multiplication operation.

1) Temporal Convolutional Network (TCN): Convolutional approaches are superior compared to RNN algorithm in domain sequence processing and recurrent network [8], particularly in overcoming vanishing gradient problems [2]. TCN employs one dimensional dilated convolution adjacent to residual connections to achieve wide and flexible receptive field. TCN has causal convolution characteristics, ability to see far into the future, easy to parallelize, and has the ability to adjust parameters [8] [13].

Fig. 2 shows the TCN architecture. TCN has two main principles:(1) maintain the length of the same output and input, and (2) prevent information leaks from the future to the past. TCN employs 1D Fully-Convolutional Network architecture and zero padding to maintain the length of output and input. Padding value can be calculated as $k-1$, with k is the kernel size [8]. Convolutional 1D (Conv1D) is used to conform with the second principle with regard to the causal convolution principle, which only elements from t time and earlier are taken into account for the output at t time [2]. Dilated convolution expands the receptive field without increasing the value of parameters, enabling a wider scope of information from further past period and mitigates the event of information loss in the merging process [13].

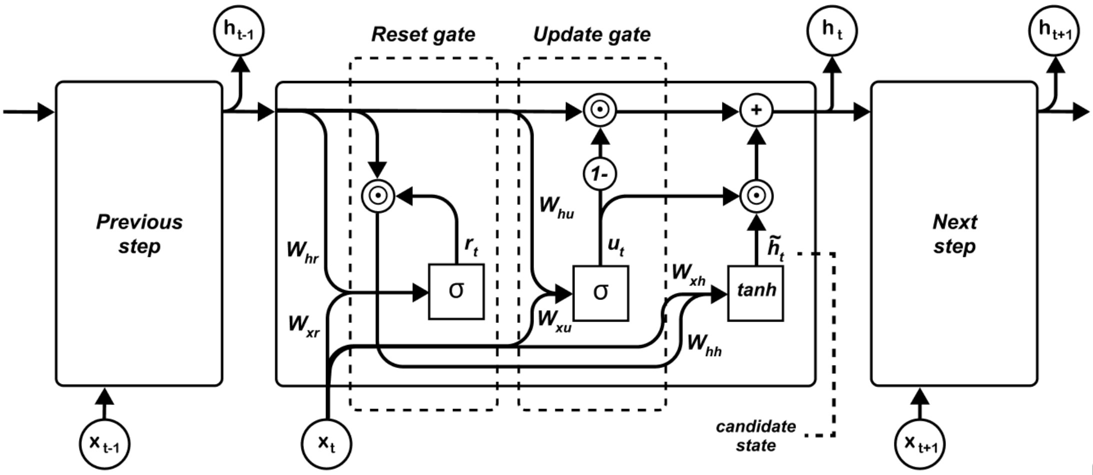


Fig. 1 Gated Recurrent Unit (GRU) architecture

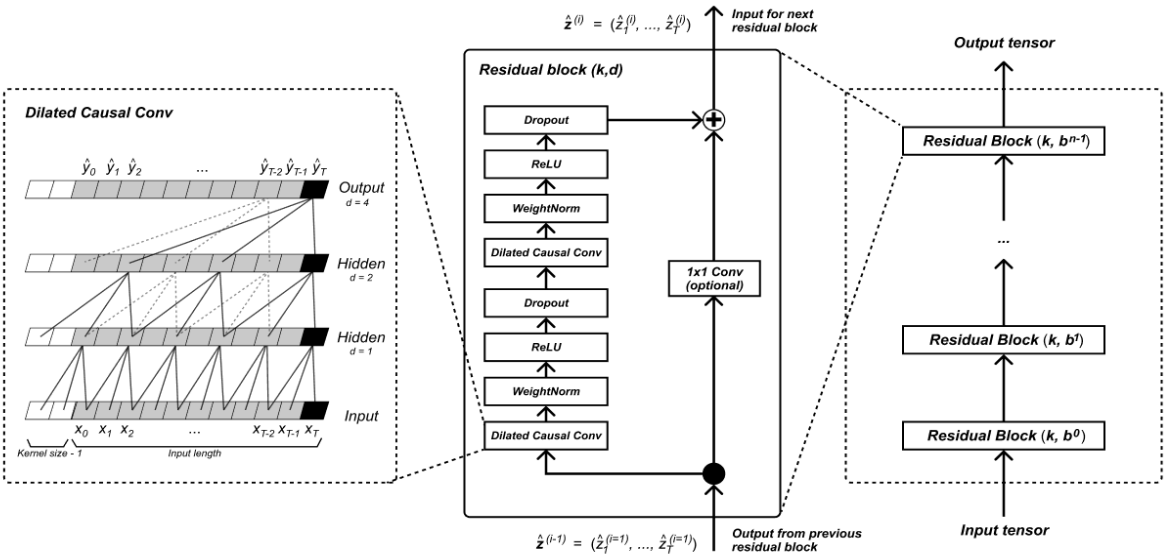


Fig. 2 Temporal Convolutional Network (TCN) architecture

C. Data Analysis Procedure

Data analysis is performed with aid from Microsoft Excel, R software, and Google Colaboratory. The steps of data analysis in this research involve:

1) *Perform data preprocessing which includes:*
   - Adjust date and time format between variables.
   - Fill in empty data with linear data interpolation method.
   - Calculate one-day return at t period for each variable with the (5).

$$r_t = \frac{x_t - x_{t-1}}{x_{t-1}} \times 100\% \qquad (5)$$

   with r_t is daily return value at t period, x_t is x value of t period, dan x_{t-1} is x value at $t-1$ period.
   - Identify JKSE crisis variables.
2) Perform data exploration to determine data characteristics, including the creation of average return plot near crisis (identified from 1d) until normal.
3) Select variables that influence JKSE crises based on data exploration (point 2).
4) Perform GRU and TCN deep learning modelling on real data which include:
   - Perform normalisation with Min-Max Scaler method with the (6).

$$x_{norm} = \frac{x_t - x_{min}}{x_{max} - x_{min}} \qquad (6)$$

   with x_{norm} is normalisation result, x_t is x value at t period to be normalised, and x_{min} and x_{max} minimum value and maximum value of x variable.
   - Divide data into training data (5475 days or around 95% of the data) and validation data (264 days or around 5% of the data).
   - Transform data into arrays in accordance with the Multiple-Input Multiple-Output (MIMO) Strategy, which produces prediction value from the past d for H vectors of future values with the (7) [14].

$$\hat{x}_{i+1},, \dots, \hat{x}_{i+H} = \hat{f}(x_i, \dots, x_{i-d+1}) \qquad (7)$$

   - Conduct Hyperparameter tuning and cross-validation on the training data using the expanding window method. This method trains and tests the model on several folds of training data that are continuously expanded, with validation data shifted, and the final error scores calculated from the average of each fold [15].
   - Select the best parameters based on the smallest Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) [16] values with (8) and (9).

$$RMSE = \sqrt{\sum_{t=1}^{n} \frac{(x_t - \hat{x}_t)^2}{n}} \qquad (8)$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n} |\hat{x}_t - x_t| \qquad (9)$$

   with x_t is actual value of x in period t, $\hat{x}_t$ is prediction value of x in period t, and n is the number of prediction period.

- Test the model on the validation data using the best models from GRU and TCN by creating comparison plots between actual and predicted values and calculating RMSE and MAE value.

5) *Select the best model based on the smallest RMSE and MAE as well as appropriate plots.*
6) *Draw conclusions from the best model.*

III. RESULT AND DISCUSSION

A. Data Preprocessing

Data preprocessing involves four steps. First, adjust the intervariable date and time format to account for significant time zone differences, as these can impact stock market activity. For example, the U.S. and Indonesia have an 11-hour time difference. When the Indonesian stock market opens, the American stock market has just closed. To address this, variables from the American stock market (GSPC, IXIC, DJIA, and RUT) are moved forward by one day.

The second step is to fill in unrecorded data with a linear interpolation method. Unrecorded data from weekends (Saturday and Sunday) are ignored as it has been ignored from the beginning. Meanwhile, unrecorded data from workdays which was caused by national holiday or significant index decrease which then led to temporary suspension, are found in 5638 observations or around 3.50858% from total observations. Variable with the most unrecorded data is AXJO, with 687 observations. These unrecorded data will be filled with the average of data prior to unrecorded and the data after [17]. The third step is to calculate a one day return for each variable. The last step is to identify the JKSE crisis variable, which is marked by a return value decrease more than or equal to 5% [18]. Twenty JKSE are identified with a return average around -6%.

B. Data Exploration

Data exploration was conducted to understand the characteristics of the data. Based on Fig. 3, the movement pattern of the JKSE fluctuates significantly. The highest peak occurred on September 13, 2022, reaching 7318.01611 points. This was driven by several positive sentiments, including the government's push for the development of the electric vehicle industry. Meanwhile, the lowest level was recorded on October 14, 2002, reaching 337.47501 points, as a result of the Bali Bombing I event on October 12, 2002. The average and standard deviation of JKSE values over 22 years are approximately 3829.43733 and 2157.15625 points, respectively.

The movement patterns of stock market indices on the same continent tend to be similar and aligned. For instance, STI (Singapore) with HIS (Hong Kong), FCHI (France) with FTSE (London), and others. This is consistent with the research by [6], which found that the stock market movements of neighbouring countries tend to be relatively aligned. The economic conditions of a country or other macro factor can explain why these movements are relatively aligned. Similarly, with exchange rate patterns, such as SGDIDR (Singapore), MYRIDR (Malaysia), and THBIDR (Thailand).

Cross-correlation can help identify which variables and how many lags are suspected to affect the JKSE. From the cross-correlation calculation, the highest correlation value is possessed by the variable SET.BK at 0.96173 at lag 0. The maximum lag is held by the variables USDIDR and JPYIDR, each at -10 and 10 with correlation values of 0.84730 and 0.80290, respectively. Many variables have their maximum lag value at lag 0. Meanwhile, all variables have a positive correlation with JKSE. This means that an increase in the points of the exchange rate variables is suspected to influence the increase in the points of the JKSE variable. Details of the cross-correlation of each predictor variable with JKSE can be seen in Table II.

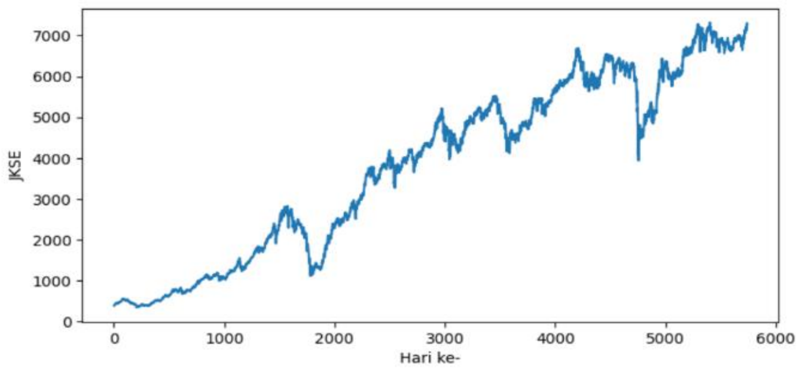


Fig. 3 JKSE Movement from 01 January 2002–29 December 2023 period

TABLE II
CROSS-CORRELATION OF PREDICTOR VARIABLES WITH RESPONSE VARIABLES

Variable	Cross-Correlation Value	Maximum Lag	Variable	Cross-Correlation Value	Maximum Lag
SET.BK	0.96173	0	GSPC	0.84580	0
SGIDIR	0.94870	0	EURIDR	0.82984	0
PSEI.PS	0.94684	0	AXJO	0.82823	0
GDAXI	0.93436	0	IXIC	0.81806	0
THBIDR	0.92837	0	JPYIDR	0.80290	10
KS11	0.91833	0	LSEG.L	0.79636	1
AUDIDR	0.91489	1	N225	0.77996	1
RUT	0.90031	0	STI	0.77929	0
FTSE	0.88787	0	HSI	0.75848	0
GC.F	0.88083	0	FCHI	0.64896	0
DJIA	0.87333	0	SSEC	0.58817	0
MYRIDR	0.87222	0	GBPIDR	0.53930	0
KLSE	0.85865	0	CL.F	0.30671	0
USDIDR	0.84730	-10			

Plots of the average returns from pre-crisis and post-crisis periods between JKSE and other variables is then viewed. The average return pattern of JKSE is fluctuating, but there is a consistent decline over four periods, dropping significantly one period before the crisis. Nevertheless, the average return value of JKSE returned to normal within one period after the crisis. The average return plot also shows that the movement patterns of stock market return between countries on the same continent tend to be similar and aligned. Unlike the stock markets in Asian countries, stock markets in America and Europe have movement directions different from JKSE. Almost all stock markets in American and European countries experienced an increase in points one period before the crisis, although the decline patterns in these countries are like JKSE from four to two periods before the crisis.

Like the movement patterns of stock markets in American and European countries, commodity prices and exchange rates tend to move oppositely to JKSE. During the crisis, commodity prices and exchange rates experienced an increase in returns and tended to have positive values. This is due to the rise in foreign currency prices encouraging investors to invest in the money market, causing trading on the stock exchange to become sluggish [19].

Based on the data exploration results, predictor variables were selected to optimise the deep learning model results that will be analysed. Predictor variables were chosen based on a cross-correlation value > 0.90, indicating a near-perfect correlation [20]. Additionally, the average return plot of variables significantly affecting the JKSE crisis was considered in the selection of variables. It is noteworthy that there are several variables from the same country, so variables will be selected based on the highest cross-correlation value. The predictor variables selected for this study include SET.BK, SGDIDR, JPYIDR, HSI, GDAXI, KS11, RUT, and PSEI.PS.

C. Modelling with Deep Learning

Modelling using actual data allows investors and the government to view and compare predicted values with actual values. Hyperparameter tuning was conducted to find the best combination of parameters for each deep learning algorithm. The parameters are taken from several existing references [21], where research [22] concluded that the greater the number of units in the hidden layer, the closer the prediction results will be to the actual value. Thus, the parameters used include units (filters) in layer 1 (input layer) of 32 and 64, and units in layer 2 (hidden layer) of 128 and 256. This research also utilized dropout rates of 10^{-3} and 10^{-4}, and batch sizes of 16 and 32. Additionally, the best combinations of timesteps in and timesteps out were sought, with values ranging from 1 to 10.

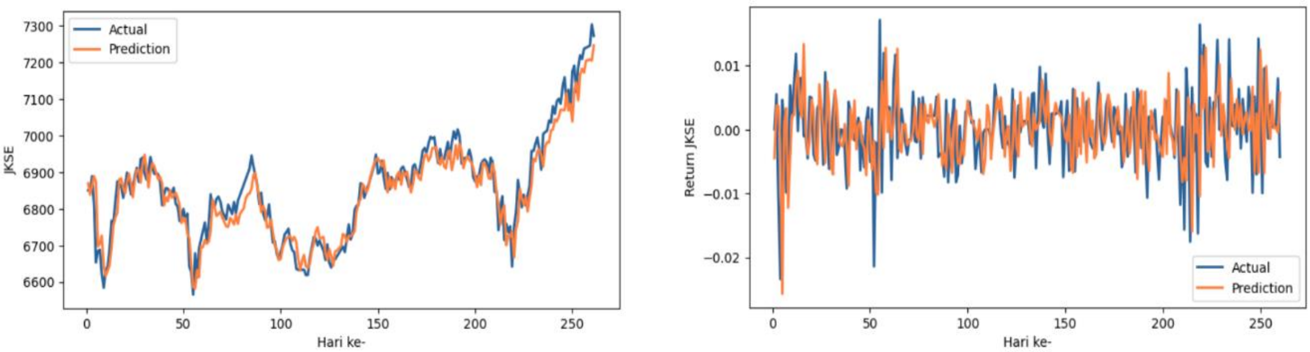
Hyperparameter tuning was performed on the training data, which consists of 21 years. Cross-validation was also carried out on the training data, alongside hyperparameter tuning, to prevent overfitting. Cross-validation used the expanding window method with a window size of 3 years. This means the data for the first window is 3 years, then it is expanded by 3 years for the next window. Meanwhile, the data used for validation is 3 years for each window. The 21 years of training data form 6 windows. The final year was used as validation data. This validation data is separate from the training process to evaluate the model's performance on new data not used in previous training.

1) GRU Model: The hyperparameter tuning process for GRU used timesteps in of 1, timesteps out of 1, and 50 epochs. Table III shows the results of hyperparameter tuning for the GRU model, which are the averages from cross-validation results for each window. The best parameter combination is selected based on the smallest RMSE and MAE values, as well as prediction and actual plots on training and validation data. According to these criteria, the best parameter combination is 64 units for layer 1, 128 units for layer 2, a dropout rate of 10^{-4}, and a batch size of 16.

2) The best parameters for timesteps in and timesteps out are 3 and 1, respectively, resulting in a RMSE of 0.01493 and a MAE of 0.01140. The best-performing GRU model shows predicted values that closely approximate the actual JKSE stock prices on the validation data. This can be seen in Fig. 4(a), which is the result of the inverse transformation of the previous normalization. The RMSE and MAE values of the prediction results are 43.35548 and 33.66909. Meanwhile, Fig. 4(b) compares the predicted stock price returns with the actual returns. The predicted JKSE return has an RMSE of 0.00773 and an MAE of 0.00582. Based on Figure 4b, no crisis occurred throughout 2023. Overall, the GRU model can capture the patterns of JKSE prices and returns quite accurate.

TABLE III
RESULTS OF HYPERPARAMETER TUNING FOR GRU MODEL

Parameter				Result	
Units layer 1	**Units layer 2**	**Dropout**	**Batch size**	**RMSE**	**MAE**
32	128	10^{-3}	16	0.03594	0.02735
		10^{-3}	32	0.04409	0.03138
		10^{-4}	16	0.03256	0.02412
		10^{-4}	32	0.03362	0.02446
	256	10^{-3}	16	0.04592	0.03357
		10^{-3}	32	0.03769	0.02698
		10^{-4}	16	0.03250	0.02365
		10^{-4}	32	0.03614	0.02581
64	**128**	10^{-3}	16	0.03634	0.02716
		10^{-3}	32	0.03301	0.02432
		$\mathbf{10^{-4}}$	**16**	**0.02543**	**0.01865**
		10^{-4}	32	0.02898	0.02185
	256	10^{-3}	16	0.03492	0.02473
		10^{-3}	32	0.03476	0.02520
		10^{-4}	16	0.03230	0.02316
		10^{-4}	32	0.03442	0.02491



(a) (b)

Fig 4. Prediction results of GRU model on validation data: (a) price and (b) return from price

3) TCN Model: TCN has additional parameters compared to GRU. The kernel size in TCN refers to the input area at each step of the convolution process, typically ranging from 2 to 8. The smaller the kernel size, the faster the training and the more accurate the predictions. The optimal kernel size used in this study is 3 [8]. Additionally, there is dilation, which extends the distance between the input and the convolution filter by inserting gaps between the filter elements. The dilatation value used is 2^{i}, where i ranging from 0 to n layers. This study also uses one stack or vertical convolution layer and a skip connection that directly connects the input to the output.

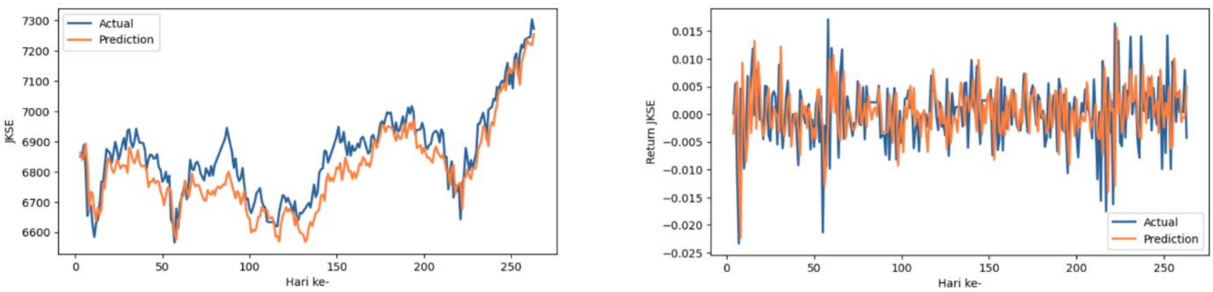
Table IV shows the results of hyperparameter tuning for the TCN model, which are the averages from cross-validation results for each window. The tuning used timesteps in and timesteps out of 1, and 50 epochs. The best parameter combination is 64 filters for layer 1, 256 filters for layer 2, a dropout rate of 10^{-4}, and a batch size of 32, resulting in an RMSE of 0.03142 and an MAE of 0.02399. The best-performing TCN model shows predicted values that closely approximate the actual JKSE stock prices on the validation data. This can be seen in Fig. 5(a), with RMSE and MAE values of the predictions being 68.53000 and 58.13354. Meanwhile, Fig. 5(b) compares the predicted stock price returns with the actual returns, resulting in an RMSE of 0.00739 and an MAE of 0.00556. Overall, the TCN model can capture the patterns of JKSE prices and returns quite well and accurately.

D. Comparison and selection of the best model

The best model is selected based on the smallest RMSE and MAE values. Based on Table V, the GRU model has these two criteria on the original data. Meanwhile, TCN can capture the pattern of return better. However, the overall prediction pattern of GRU model is quite close to the actual value, coupled with the lower computation time and cost compared to TCN. Thus, GRU is chosen as the best model compared to TCN, in accordance with the research of [23].

TABLE IV
RESULTS OF HYPERPARAMETER TUNING FOR TCN MODEL

Parameter				**Result**	
Filter layer 1	**Filter layer 2**	**Dropout**	**Batch size**	**RMSE**	**MAE**
32	128	10^{-3}	16	0.04208	0.03235
		10^{-3}	32	0.04016	0.03028
		10^{-4}	16	0.03659	0.02925
		10^{-4}	32	0.03835	0.02879
	256	10^{-3}	16	0.03909	0.03061
		10^{-3}	32	0.04118	0.03076
		10^{-4}	16	0.03815	0.02991
		10^{-4}	32	0.04385	0.03309
64	128	10^{-3}	16	0.03673	0.02798
		10^{-3}	32	0.03869	0.03062
		10^{-4}	16	0.03643	0.02830
		10^{-4}	32	0.03714	0.02881
	256	10^{-3}	16	0.03657	0.02870
		10^{-3}	32	0.03718	0.2838
		10^{-4}	16	0.03897	0.03120
		10^{-4}	**32**	**0.03142**	**0.02399**



(a) (b)

Fig 5. Prediction results of TCN model on validation data: (a) price and (b) return from price

TABEL V
COMPARISON BETWEEN GRU AND TCN MODELS ON VALIDATION DATA

Model	Result of Price		Result of Return	
	RMSE	**MAE**	**RMSE**	**MAE**
GRU	**43.35568**	**33.66909**	0.00773	0.00582
TCN	68.53000	58.13354	**0.00739**	**0.00556**

IV. CONCLUSION

The research results identified 20 JKSE crisis points during the 2002–2023 period with an average return of around -6%. Cross-correlation shows that all variables have a positive correlation with JKSE, with SET.BK having the highest correlation value of 0.96173 at lag 0. Almost all variables have their maximum lag at lag 0. The price and return movement patterns of stock markets in countries on the same continent tend to be similar and aligned. In contrast, stock markets in America and Europe, commodity prices, and exchange rates tend to show patterns that oppose the JKSE crisis pattern. Predictor variables were selected based on cross-correlation values > 0.90 and average return plots that significantly impact the JKSE crisis. The chosen predictor variables include SET.BK, SGDIDR, JPYIDR, HSI, GDAXI, KS11, RUT, and PSEI.PS. Both the GRU and TCN models can predict JKSE crises with relatively low error rates. The GRU model has the smallest RMSE and MAE values on the original data of 43.35568 and 33.66909, while TCN has the smallest RMSE and MAE values on returns of 0.00739 and 0.00556. Overall, GRU is more accurate and efficient than TCN so it is chosen as the best model. Suggestions or further development of this research method include extending the data to a more recent timeframe for more accurate results. Variable selection should consider geographical distance and the economic conditions of the countries, and other selection methods besides correlation and average return plots, such as stepwise, should be used. Additionally, modelling could use other approaches such as LSTM, hybrid models, or more complex models to better predict JKSE crises.

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