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Prediction of Crime Rate in Banjarmasin City Using RNN-GRU Model

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Abstract: Crime is a crime that violates the law and social norms so that it can harm society. Every year there is an increase in criminal cases. The rise of various criminal acts caused disturbances to the community's comfort and the surrounding environment, especially in Banjarmasin City, the capital of South Kalimantan Province in Indonesia. The economic status of a region, such as the inflation rate and the local population's lack of purchasing power, can contribute to crime. This study proposes a model to predict the crime rate in Banjarmasin using the Recurrent Neural Network (RNN) with the Gated Recurrent Unit (GRU) architecture, taking inflation rate and discretionary income into consideration. This study utilizes data on criminal offences handled by the Banjarmasin District Court and data on inflation and the cost of staple foods in the Banjarmasin City markets. We evaluate the model by using RMSE and R-Squared. The results showed that the GRU-RNN model showed promising results with an R-Squared value of 0.84 and an RMSE value of 2.21.

Keywords: *Banjarmasin; crime; inflation; prediction; RNN-GRU.*

1. Introduction

Crime is a common social problem affecting a country's quality of life, economy, growth, and reputation. Crime is a crime that violates the law and social norms so that it can harm society. Criminal acts also become a threat to the broader community [1]. The emergence of crime can occur due to 2 things, namely internal and external factors. Internal factors are factors that come from themselves. External factors are factors that come from outside of themselves [2]**.** Crimes rate has increased every year. Based on data from 2018 to 2019 from the Central Bureau of Statistics of Indonesia, there was a significant crime rate increase in the city of Banjarmasin. There are several factors for the occurrence of criminal acts. In this case, from the economic sector, there is the inflation rate and the purchasing power of the people [3], [4].

Prediction of an event that will occur is generally due to an event that will repeat itself. In this case, the study uses a time series approach because this approach focuses on any information recorded periodically with the time used to predict events related to the information. [5]. Time series data occurs naturally in countless domains, including financial analysis, medical analysis, weather condition prediction, and renewable energy production. This pattern also applies to crime where it is predictable because criminals are active and operate in areas considered safe for them to operate [1]. In real applications, it is natural for the time-series statistic to change over time, i.e., TS is non-stationary. Recently, better performance was achieved by RNN work. RNN makes no assumptions on the temporal structure and can find highly non-linear and complex dependency relationships across time series [5]. Many fields have used this method in predicting time series, including economics, health, and tourism [6]–[10]. Several studies have shown that the neural network performs better than statistical predictions. In a study by Prakash Singh, who used the Recurrent Neural Network using the GRU architecture and produced predictions with the lowest error values compared to other model architectures, even though they were included in the Recurrent Neural Network or other methods [11]. A study by Tsion Eshetu used a Recurrent Neural Network using the LSTM architecture and produced predictions with an accuracy value of 95% [12]. The research by Xin Wei uses Recurrent Neural Network using GRU, LSTM, and Artificial Neural Network and produces a 90% accuracy value by GRU & LSTM architecture [13]. In the research of Sean et al., who used ARIMA and RNN with the LSTM and GRU algorithms, the results showed much better accuracy values shown by RNN than ARIMA due to the many variations and the data used [14]. Based on the related research above, this study will examine the prediction of crime events based on events that have occurred before with the RNN algorithm with the GRU architecture because, in some studies, GRU has better results than LSTM [11], [13], [15]–[18]. The difference between this study and related research is that there will be additional variables in the form of monthly inflation parameters and the price of food needs on the market.

2. Literature Review

Crime comes from the word *"Crimen"*, which means crime or unlawful action. According to the Big Indonesian

Dictionary, crime is a form of "deviant behaviour" which can be punished according to the applicable law[13]. Prediction is systematically estimating something that might happen in the future based on past and present information so that errors can be minimized. Prediction does not have to give a definite answer to an event but tries to find an answer as close as possible to what will happen [19]. There are two methods to make predictions, namely qualitative and quantitative methods. Qualitative methods are based on subjective factors, while quantitative are based on historically available data. The quantitative technique is divided into 2, namely the time series data model and the regression model [20]–[22]. A time series is a sequential collection of data points, usually measured at successive times, collected over a long period, and ordered chronologically [23]. Deep Learning is a sub-section of Artificial Intelligence that focuses on modelling large/giant neural networks capable of making data-driven choices. Deep Learning is suitable for carrying out processes using large datasets and high complexity [12]. The concept of Deep Learning is to use the concept of Machine Learning which has several layers, namely the input layer, hidden layer, and output layer. One of the main features of time series data is the sequential pattern of the dataset. Time series data points carry information from a series of past data points. Therefore if we train a Neural Network, it should not learn every information from scratch but should have a memory to store the sequential information passed through the model. The limitation of NN is due to the fixed size of the input and output vectors. This approach does not allow the model to store the evolving context by reading the input over time. A recurrent Neural Network is an advancement from conventional neural networks that store information from the previous step [13], [24]–[27].

Several studies discuss the crime rate prediction system in time series or the application of the GRU architecture in making a prediction system using time series. Tsion Eshetu et al. research in 2019 aims to predict crime in their area. Data was collected from 2014 to 2018 with criminal cases of fraud, violence, drugs, and theft, accompanied by information on the place and date of the incident so that 6033 data were obtained. Using RNN and applying LSTM, the accuracy of the model is obtained with an accuracy rate of 87% for monthly predictions, 92% for daily predictions, and 95% for hourly predictions [12]. Research conducted by Prakash Singh et al. in 2018 to predict crime. Data collected from 2001 to 2007 consisted of descriptions of crimes, types of crimes, and severity. The types of crimes included in the data collected are theft, pickpocketing, and bicycle theft. Using RNN and applying the GRU architecture obtained a low error value compared to other methods. Other methods used in this study are CNN and LSTM. The error value obtained is 36.39% with GRU, while using CNN, the error value is 37.6% and using LSTM, it is 36.47% [11]. The research that applies the use of GRU in other fields, such as the research conducted by Xin Wei et al. in 2021 regarding the prediction of Pore Water Pressure in which the methods used are GRU, LSTM, and MLP, and the results are that GRU and LSTM have an accuracy of 90% [13]. Research conducted by M.Pavithra et al. in 2019 aims to predict disease progression using the GRU method and comparisons with other methods such as LSTM. The GRU accuracy value reaches 70%, while the accuracy of the LSTM is only 60%. Research conducted by Zhang Xu et al. in 2019 aimed to predict Wind Speed on two pieces of land using the GRU, LSTM and ARIMA methods tested with MAPE and RMSE. For GRU, the MAPE and RMSE values on land 1 were 9% and 0.36, and on land 2 were 16% and 0.42. For LSTM, the MAPE and RMSE values on land 1 are 10% and 0.33 and on land 2 are 17% and 0.42. For ARIMA, the MAPE and RMSE values on land 1 are 11% and 0,39, while on land two, it was 19% and 0.42[16], [18].

3. Methodology

The procedure in the system design is as shown in Fig 1:

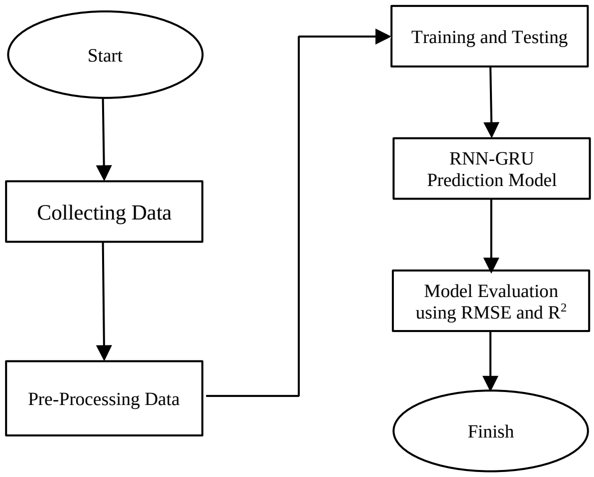

Fig1 Research Flow

3.1. Collection Data

The data was gathered from several sources. The website of the Banjarmasin Court District was scraped for data on crimes. The National Strategic Market Price Information Center's official website was scoured for data on the price of staple foods. Finally, inflation rate data were acquired from the official website of the Banjarmasin Central Bureau of Statistics. The acquired data is then consolidated to produce the monthly periodic dataset.

3.2. Pre-Processing Data

We modelled the data using a multivariate time series technique after constructing the dataset with a monthly period. Initially, it is essential to use the ADF test to determine whether or not the data is stationary. The p-value must be less than 0.05 to satisfy the data stationery criterion [28], [29]. For data that does not match the criteria for data stationarity, the differencing technique will be applied such that the data becomes stationary. For the time-series data to become stationary, the value of the difference between d forecasting periods is calculated. After the data is stationary, we will continue with data normalization using Min-Max Normalization or min-max scaler with a value range of 0 to 1.

3.3. Training and Testing

Before entering the training and testing stage, the dataset will be split into two groups: training data and data testing. The distribution of the dataset is divided by taking data as much as a specified percentage of the dataset to be used as training data, and the rest will be used as testing data. the percentage comparison between training data and testing data is as follows:

1. 60% training data and 40% testing data
2. 70% training data and 30% testing data
3. 80% training data and 20% testing data
4. 90% training data and 10% testing data

3.4. RNN-GRU Prediction Model

Gated Recurrent Unit (GRU) is one of the modified RNN algorithms. [30]. GRU is proposed to make each unit repeatable to adaptively capture dependencies from different timescales [31]. In contrast to the Long-Short Term Memory Neural Network (LSTM), another variation of RNN that can also withstand remote dependence, the architecture of the GRU Neural Network unit is much simpler [32]. GRU has the advantage that its computation is more straightforward than LSTM but still has the same accuracy and is effective in dealing with Vanishing Gradient problems [33]–[35]. The computational simplicity of the GRU can be seen from only two gates owned by the GRU, namely the reset gate and the update gate. The existence of an input gate and forget gate that initially existed in the LSTM was combined into an update gate in the GRU [36]. Another advantage of GRU is its compatibility with data that is not as much as LSTM, where generally, the data applied to LSTM is in the thousands. At the same time, GRU can achieve optimal results even though only with not that much data[31]. There are two gate structures in the GRU: Update gate (zt) and Reset gate (rt). Update Gate decides how many neural units are updated, and Reset Gate decides how many states were previously forgotten by neural units. It can be calculated as the following formula:

$$z_t = \sigma(\mathrm{Wz}\,\mathrm{xt} + \mathrm{Uz}\,h(t-1) + \mathrm{bz}) \quad (1)$$

$$r_t = \sigma(\mathrm{Wr}\,\mathrm{xt} + \mathrm{Ur}\,h(t-1) + \mathrm{br}) \quad (2)$$

Description:
z_t = update gate
σ = activation of sigmoid function
Wz = weight of update gate
Uz = weight of hidden state
xt = value input(vector input x in timestep t)
h(t-1) = previous cell state vector value
bz = bias update gate
r_t = reset gate
Wr = reset gate weight
Ur = hidden state weight
br = bias reset gate

The application of the RNN – GRU prediction model is used with the suitability of research between the use of the GRU as the architecture of the RNN to predict the crime rate whose data is multivariate time-series, besides that the data in this study is also more suitable to be applied to the GRU because it is less when compared to studies that get optimal value using LSTM [31].

3.5. Model Evaluation using RMSE and R^2

The evaluation of the RNN-GRU prediction model uses the RMSE and R2 metrics because, in several studies, these two test methods are better than other test methods. RMSE is more suitable for measuring the error value between the predicted results and the original data, and this is because the RMSE is more sensitive to the differences that occur between the predicted data and the original data. R2 is used to measure the correlation between the predicted results and the original data.

4. Model Evaluation

At this stage, the model will be evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), R-Squared (R^2), and Mean Absolute Percentage Error (MAPE).

4.1. RMSE

RMSE is one way to test the accuracy of prediction results. The calculation system is to calculate the value of the difference between the predicted value and the original value. The result of this value is then the square root. With the assessment principle that the lower the value obtained, the better the model [24], [37]–[40]. Testing this method will get more optimal results if the assessment is normally distributed [71]. The following is the equation:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2 \quad (3)$$

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}} \quad (4)$$

Information:
n=lots of data
i= total data
y_i= actual value
$\tilde{y}_i$= predicted value of

4.2. MAE

MAE is one way of testing by measuring the absolute error between the original and predicted data. The MAE value is in the range of 0 to ∞, with the smaller the value obtained, the better the model [41]–[43]. Testing this method will get more optimal results if the error assessment is not normally distributed. For example, data error is distributed not normally when data has a significant presence compared to other data [71]. The following is the equation:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \widetilde{y_i}| \quad (5)$$

Information:
n=lots of data
i= overall data
y_i= actual value
$\widetilde{y_i}$= predicted value of

4.3. R-Square

R-Square or determinant coefficient measures statistics to study the correlation between actual and expected output. The value R2, the lower the value of R2, the less good, which means the model is getting better [38], [44], [45]. Here is the equation:

$$R^2 = \frac{n(\sum xy)-(\sum x)(\sum y)}{\sqrt{\left[n^*(\sum x^2-(\sum x)^2)\right]*\left[n^*(\sum y^2-(\sum x)^2)\right]}} \quad (6)$$

Description:
r = correlation coefficient
n= lots of data
x= variable first
y= second variable

4.4. MAPE

MAPE is the calculation of absolute error in each period divided by the observed value for that period. Then the percentage value is averaged. This approach is practical when the predictive measure is significant in evaluating prediction accuracy [46], [47]. MAPE shows how much error in predicting compared to the actual value. MAPE is better if used only pays attention to positive values and data that is not continuous. The following is the equation:

$$MAPE = \sum_{t=1}^{N}|PE_t|/n \quad (7)$$

Description:
MAPE = absolute average percentage of error
$|PE_t|$ = absolute value of the percentage of forecasting errors
n = number of data

5. Analysis and Results

5.1. Dataset

This study uses a dataset comprised of previously obtained data, notably statistics on criminal cases each month compiled from the official website of the Banjarmasin District Court. Then, the prices of staple items in Banjarmasin are acquired from the National Strategic Food Price Information Center's official website. On the website, weekly prices for rice, shallots, garlic, chicken eggs, cooking oil, beef, chicken meat, and sugar were obtained. The information is then compiled into monthly data. Finally, monthly inflation data is taken from the Banjarmasin Central Statistics Agency's official website. This website has compiled fifty inflation values from July 2017 to August 2021. After analyzing the acquired data, it is determined that the dataset for this study has 207 data consisting of 13 input data variables and one variable that predicts the number of crimes in the following month. The 13 variables are Weeks 4,3,2 and 1 as past data on crime events, Rice Prices (HB), Chicken Meat Prices (HDA), Beef Prices (HDS), Chicken Egg Prices (HTA), Shallot Prices (HBM), Garlic Prices (HBP), Cooking Oil Prices (HMG), Sugar Prices (HGP) and Inflation.

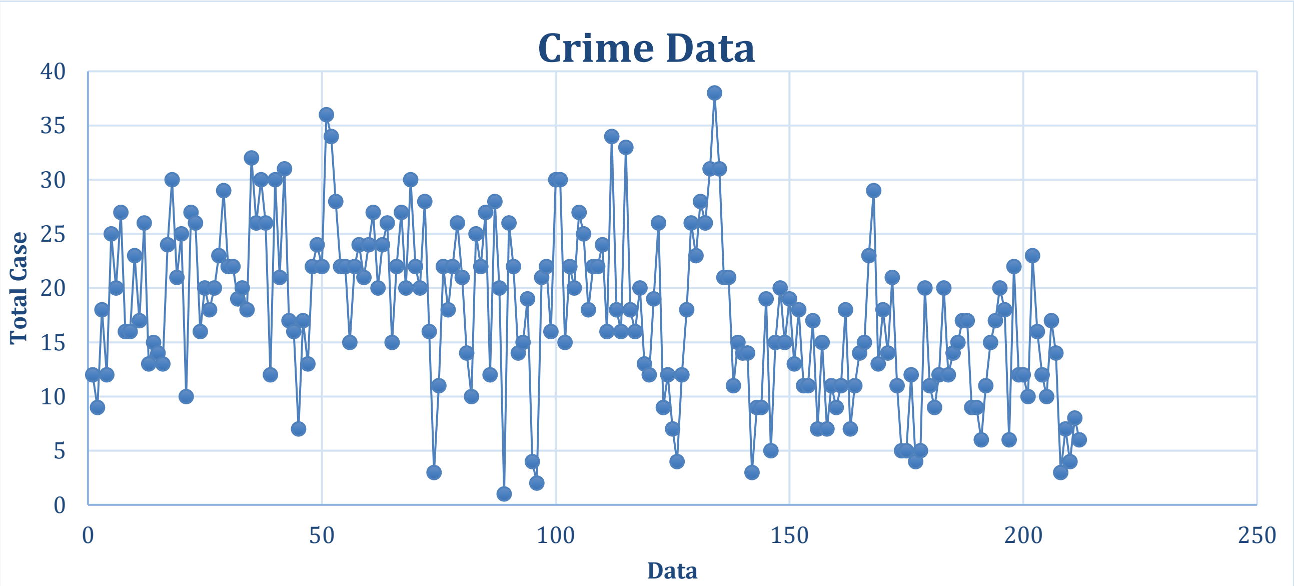

Figure 1. Crime Data

The following forms of the dataset are used in this study:

Table 1. The Dataset

Week 1	**Week 2**	**Week 3**	**Week 4**	**HB**	**HDA**	**HDS**	**HTA**	**HBM**	**HBP**	**HMG**	**HGP**	**Inflation**	**Target**
12	9	18	12	13.6	33.35	129.4	21.35	23	24.25	12.95	13.8	0.03	25
9	18	12	25	13.6	35.25	129.4	21.6	23.5	24.25	12.95	13.7	0.03	20
18	12	25	20	13.6	33.9	129.4	22.25	23	23.6	12.95	13.7	0.03	27
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17	14	3	7	13.6	35.5	130.65	24.5	37.5	30	14.85	13.15	0.19	4
14	3	7	4	13.6	36.65	130.65	23.5	33.65	28.5	14.95	13.1	0.19	8
3	7	4	8	13.6	130.65	36.95	23.5	29.4	28.4	15.05	13	0.19	6

5.2. Data Pre-Processing

The pre-processing data was first tested using the ADF Test and obtained several stationery variables: Inflation, HBP, HBM, HDA, and HTA. Meanwhile, other variables include data that is not stationary and must go through the differencing process before proceeding to the data normalization stage. The data that has been through the differencing process with a significant amount of 0 or NaN value will not be used, and only data with a small value of 0 will continue to be used in this study. Finally, the stationery variable will go into the scaling using Min-Max Scaler. Data that has gone through this stage will have a value in the range of 0 to 1.

5.3. Dataset Splitting

The separation of training and testing data is accomplished by selecting as many training data points as the % of training data, beginning with the first training data point and ending with the last training data point. The residual data that was not used during training is then utilized for data testing. This method applies the time-series concept, which considers historical data to anticipate future events and forecast future events to predict things that will happen in the future.

5.4. The RNN-GRU Models

The model uses the Gated Recurrent Unit by applying it to the function sequential. In the training process, 125 input neurons, three hidden layers each have 100, 75, 50, and 25 neurons and end with one output layer. The loss is an error calculation from the mean absolute error while the optimizer uses adam. The use of MAE to calculate loss during training the prediction model to obtain the error value from the training with the actual number results because the nature of using MAE is the absolute value of the error obtained. The model training was carried out several times according to the previously mentioned data sharing size experiment. The results form several models that aim to determine the quality of the predictive model and can compare the results of these various conditions. The quality of the prediction model is obtained by calculating the percentage value of the prediction error against the original value. The value that will be compared is the error's value from the model's predicted value to the actual value.

5.5. Model Evaluation

Several models obtained from the training will be tested in the testing phase. The model tested is Model 1, which only uses past crime data from week -4 to week -1. Model 2 uses past crime data from week -4 to week -1 complemented with a monthly inflation rate variable. Model 3 uses past crime data from week -4 to week -1 added with the price of staple food variable. While Model 4 uses all variables from past crime data, inflation rate and staple food prices. Before testing, it is necessary to return the normalized dataset value scale to measure the actual error value when the data is in its original scale. The following are the results of the MAE, RMSE, R-Squared, and MAPE values from each model that has been made.

Table 2 Value of Root Mean Squared Error

Model	**RMSE Value Data Comparison**			
	90%:10%	80%:20%	70%:30%	60%:40%
Model 1	3.0779	2.5642	2.8255	3.0484
Model 2	2.2124	3	3.5111	3.3019
Model 3	2.4921	2.9496	3.2743	3.0364
Model 4	3.1288	3.0863	3.4212	3.6726

The RMSE values for each model are compared in Table 2. Model 2, with a train-test split ratio of 90:10, performs better than other models, as seen by its RMSE value of 2.214, which is the lowest among all models.

Table 3 Value Mean Absolute Error

Model	MAE Value Data Comparison			
	90%:10%	80%:20%	70%:30%	60%:40%
Model 1	2.4211	2.6098	1.975	2.4098
Model 2	1.7368	2.45	2.6557	2.6585
Model 3	2.1053	2.4	2.6885	2.439
Model 4	2.4211	2.425	2.7869	2.9512

Table 3 compares the MAE of all models. Once again, Model 2 with a train-test split ratio of 90:10 yields the best results with an MAE of 1.7368,

Table 4 Mean Absolute Percentage Error

Model	MAPE Value Data Comparison			
	90%:10%	80%:20%	70%:30%	60%:40%
Model 1	26.6119 %	20.9945 %	20.7427 %	25.2321 %
Model 2	20.4986 %	29.7138 %	25.0259 %	23.5534 %
Model 3	18.2572 %	22.6902 %	25.084 %	20.7808 %
Model 4	26.3436 %	24.9014 %	27.5787 %	26.9718 %

Table 4, which compares the MAPE values, showed that Model 3 and Model 2 with a train-test split ratio of 90:10 obtained better results than other models with MAPE values of 18.2572% and 20.4986%, respectively.

Table 5 Value of R-Squared

Model	R-Squared Value Data Comparison			
	90%:10%	80%:20%	70%:30%	60%:40%
Model 1	0.7063	0.7764	0.7289	0.8044
Model 2	0.8483	0.6939	0.5814	0.7705
Model 3	0.8075	0.7041	0.6359	0.806
Model 4	0.6965	0.676	0.6025	0.7161

Lastly, in Table 5, The R-Squared values for each model are compared. Model 2, with a 90:10 train-test split ratio, again yielded the best results compared with other models.

5.6. Discussion

Several results are obtained from the tests that have been carried out, namely, what variables are used to get the best results and the distribution of the best data ratios to get the best prediction results. The following is a comparison of the models that have the best performance based on each method which will be shown in the table and graph below

TABLE 6 Comparison of Model With Best Results

Model	Test Results				Percentage
	RMSE	MAE	MAPE	R-Squared	
Model 1	2.5642	2.6098	20.9945 %	0.7764	80%; 20%
Model 2	2.2124	1.7368	20.4986 %	0.8483	90%; 10%
Model 3	2.4921	2.1053	18.2572 %	0.8075	90%; 10%

RMSE and MAE got the lowest results in Model 2. The MAPE test results found the lowest percentage in Model 3, while Model 2 came second. For R-Squared, the highest value was obtained in Model 2. The week variable represents the historical data input variable for criminal events recorded in the dataset, for inflation contains the value inflation recorded in the dataset, while Basic Materials represents several prices of staple foods, which are used as input variables recorded in the dataset. Based on the results obtained, the model containing the historical data variable for events from 4 weeks to 1 week before the predicted target along with the inflation value gets the best prediction model results compared to prediction models using only historical data on criminal events or models using historical criminal data along with material price data. This conclusion is based on the results in Table 6, where RMSE and MAE have the lowest values , and R-Squared has the highest values, although MAPE has a higher average percentage than the results in other models. In addition, it is also shown from the results that the inflation rate variable has a better effect on the model.

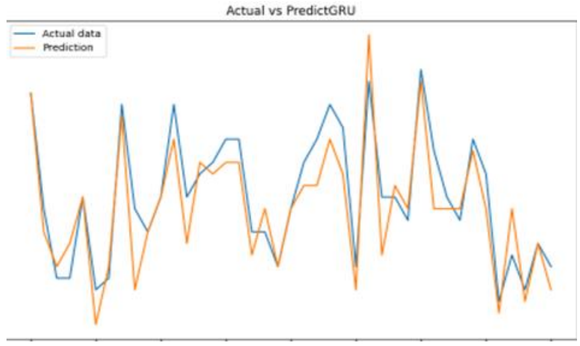

Fig 3. Graph of Prediction Results Model 1

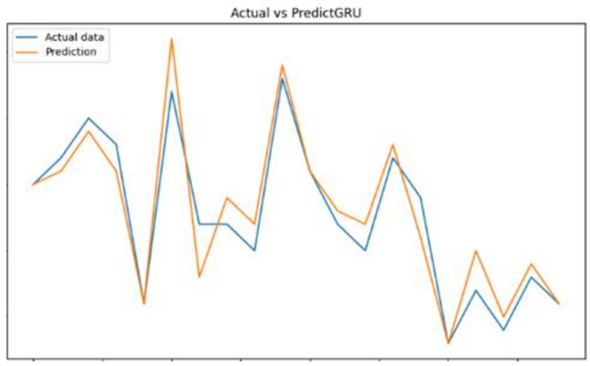

Fig 4. Graph of Prediction Results Model 2

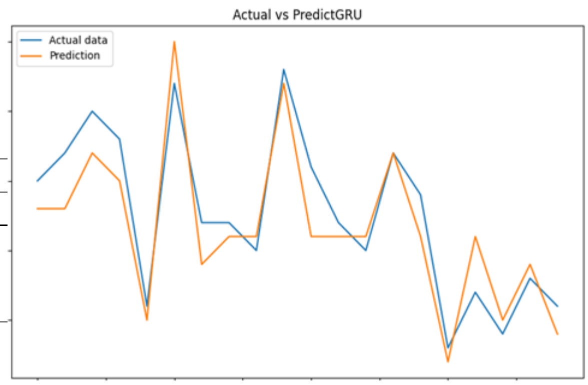

Fig 5. Graph of Prediction Results Model 3

The predictive value of crime is obtained based on the prediction model results. Based on the previous explanation, Model 2 produces a predictive value that is close to the original value. As in Figure 4, it is known that the predicted value obtained is indeed close to the original value. In contrast to Figures 3 and 5, the predicted value is not too close to the original value compared to Figure 3.

6. Conclusion

Based on the results of the analysis that has been carried out, it is concluded that the application of the RNN-GRU model in this study by preparing data in advance by collecting from various sources. Source and arranged according to the input data format so that the total data collected is 207 data. Furthermore, the data is normalized either by differencing the data so that the data becomes stationary. Then normalization of the scale is carried out before being applied in making the model. After making the model, the best three results were obtained. This GRU model is the best compared to other experiments because it has the lowest MAE & RMSE values, which are 1.7368 & 2.21, respectively, and the R-Squared value is 0.84, which shows that the prediction results have a good model performance.

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