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Convolutional Long Short-Term Memory (C-LSTM) For Multi Product Prediction

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Abstract

The retail company PT Terang Abadi Raya has a solid commitment to supporting distributors of LED lights and electrical equipment who have joined them, helping to spread their products widely in various regions. To face increasingly intense market competition, it is essential to produce high-quality products to win the competition and meet consumer demands. To achieve this, efficient production planning is necessary. The Convolutional Long Short-Term Memory (C-LSTM) method is used in this study to forecast product sales at PT Terang Abadi Raya. The research results show that C-LSTM has the potential to predict sales effectively. Evaluation is conducted using Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The calculations reveal that the smallest values are obtained at epoch 10, with an MAE of 0.1051 and a MAPE of 22% in the testing data. For the cable data, the smallest values are found at epoch 100, with an MAE of 0.0602 and a MAPE of 44% in the testing data. The Long Short-Term Memory (LSTM) method with ten neurons produces the most minor errors during training. The contribution of this research is speed optimization in neural network training, especially in multi-product data prediction. C-LSTM can increase accuracy by 11% higher than the LSTM algorithm.

Keywords—*Prediction, Retail Business, Convolutional Long Short-Term Memory (C-LSTM)*

Abstract

Perusahaan retail PT Terang Abadi Raya mempunyai komitmen yang kuat dalam mendukung distributor lampu LED dan peralatan listrik yang telah bergabung dengan mereka, membantu menyebarkan produknya secara luas di berbagai daerah. Untuk menghadapi persaingan pasar yang semakin ketat, maka penting untuk menghasilkan produk yang berkualitas agar dapat memenangkan persaingan dan memenuhi permintaan konsumen. Untuk mencapai hal tersebut, diperlukan perencanaan produksi yang efisien. Metode Convolutional Long Short-Term Memory (C-LSTM) digunakan dalam penelitian ini untuk meramalkan penjualan produk pada PT Terang Abadi Raya. Hasil penelitian menunjukkan bahwa C-LSTM berpotensi memprediksi penjualan secara efektif. Evaluasi dilakukan dengan menggunakan Mean Absolute Error (MAE) dan Mean Absolute Percentage Error (MAPE). Perhitungan menunjukkan bahwa nilai terkecil diperoleh pada epoch 10, dengan MAE 0,1051 dan MAPE 22% pada data pengujian. Untuk data kabel, nilai terkecil terdapat pada epoch 100, dengan MAE sebesar 0,0602 dan MAPE sebesar 44% pada data pengujian. Metode Long Short-Term Memory (LSTM) dengan sepuluh neuron menghasilkan kesalahan paling kecil selama pelatihan. Kontribusi penelitian ini adalah optimasi kecepatan dalam pelatihan jaringan saraf, khususnya dalam prediksi data multiproduk. C-LSTM dapat meningkatkan akurasi sebesar 11% lebih tinggi dibandingkan algoritma LSTM.

Keywords— *Prediksi Bisnis Ritel, Convolutional Long Short-Term Memory (C-LSTM)*

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1. INTRODUCTION

C-LSTM is a combination of the Convolutional Neural Network (CNN) algorithm and the Long Short-Term Memory (LSTM) algorithm. By the name, the construction of the C-LSTM model places the LSTM algorithm in the last layer in the CNN network model so that before entering the LSTM network, the input vector must go through the CNN algorithm process, after which the LSTM network. The LSTM method has several regressions, and one of them is LSTM for Regression with Timer Series Data, which is a collection of data from time to time to provide an overview of the development of activities from time to time. Hence, this method is very suitable for forecasting [1].

Prediction or forecasting is an activity to predict what will happen in the future. This activity is carried out by paying attention to past or current data or information either mathematically or statistically [2]–[4]. Estimation or forecasting is an activity that aims to predict or predict everything related to production, supply, demand, and the use of technology in an industry or business. Companies and operational management will ultimately use estimates for planning related to business activities in specific periods [5], [6]. In business, forecasting can also be a reference for designing the running of the business in the future.

PT Terang Abadi Raya is a company operating in the retail industry. PT Terang Abadi Raya fully supports the distributors of LED lights and electrical equipment that have joined so that the distributors have succeeded in spreading the products widely in their respective areas. To win competition in the market, retail companies must produce quality products. To produce quality products, excellent and efficient production planning is needed. One of the basics of production planning is sales prediction. PT Terang Abadi Raya still carries out production planning manually, namely by guessing production quantities by increasing or decreasing quantities based on demand reports. However, the predictions produced need to be more accurate, causing it to be not optimal in meeting market demand.

Sales forecasting (forecasting) plays a vital role in planning and decision-making at PT Terang Abadi Raya. Production and operations management activities use demand forecasting in planning related to production planning. Bad sales forecasting will automatically lead to poor production planning. As a result, inventory becomes very high or vice versa; sales are lost due to the unavailability of goods to be sold. Inventory that is too high results in increased costs because existing resources become inefficient. In the opposite condition, it will cause a product vacancy on the market. This condition creates opportunities for competitors to enter, resulting in the loss of existing market opportunities (loss opportunity).

Forecasting using the C-LSTM method has often been used in previous research. As in research conducted in [7], the results of this research are in the form of average error evaluation values from modeling training data and testing data. Later, his research has also been applied to weather forecasting [8], experiments show that the C-LSTM network captures spatiotemporal correlation better and consistently outperforms FC-LSTM and the state-of-the art operational ROVER algorithm for nowcasting spatiotemporal precipitation. It is a model that represents natural phenomena observed in spatial and temporal dimensions. Based on this research, product sales predictions at PT Terang Abadi Raya can use the C-LSTM method, where this method shows better accuracy than other methods. Sales prediction is a crucial aspect of business operations, as it allows companies to make informed decisions regarding inventory management, resource allocation, and revenue forecasting. Various neural network models have been employed for sales prediction, and the Convolutional Long Short-Term Memory (ConvLSTM) algorithm has gained attention for its ability to capture both spatial and temporal dependencies in sales data. ConvLSTM combines the capabilities of convolutional neural networks (CNN) and Long Short-Term Memory (LSTM) networks. This hybrid architecture is particularly effective in capturing spatiotemporal patterns in sales data. For instance, it can account for both seasonal variations and regional differences in sales, which can be challenging for traditional feedforward neural networks

Based on the problems described above, the author proposes to conduct research with the title "Application of Convolutional Long Short-Term Memory (C-LSTM) to Predict Product Sales at PT Terang Abadi Raya."

2. METHODS

The flow of the research stages of the sales prediction model using the Convolutional Long Short - Term Memory (C-LSTM) method can be seen in Figure 1. Convolutional Long Short-Term Memory, is a specialized neural network architecture that combines the spatial learning capabilities of Convolutional Neural Networks (CNNs) with the sequential modeling power of Long Short-Term Memory (LSTM) networks. This architecture is particularly effective for spatiotemporal data, making it valuable in various prediction tasks, including sales prediction. Here's a more in-depth explanation of ConvLSTM for prediction. ConvLSTM integrates convolutional layers and LSTM layers in a single architecture. Convolutional layers are primarily used for spatial feature extraction, while LSTM layers handle sequential modeling. This combination allows the model to capture both spatial and temporal dependencies within the data. Convolutional layers in the ConvLSTM are responsible for extracting spatial features from the input data. These layers apply convolutional operations, which help the model identify patterns and relationships in the data that are spread across different spatial dimensions. This is especially useful in tasks where the data has a grid-like or image-like structure, such as sales data across multiple store locations.

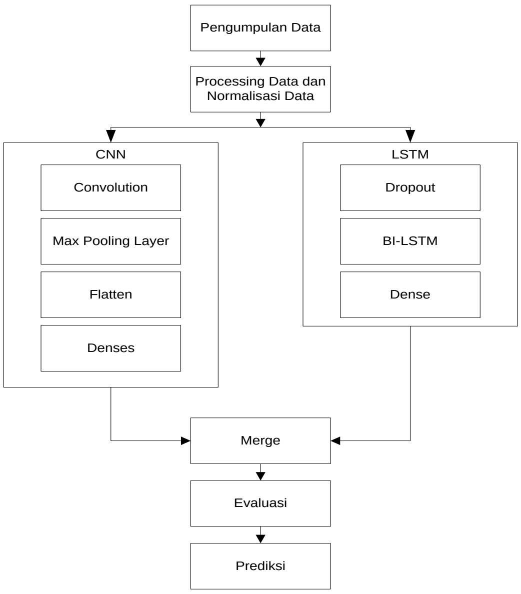

Figure 1 Research Methods

2.1 Data Collection

The dataset was obtained from the product sales data of PT. Terang Abadi Raya Cab. Bali, with a total of 19,290 data collected. This data is daily product sales data for one year, namely 2012. Each data instance contains two attributes, namely date and value, where date is the date of daily sales and value is the total rupiah value of product sales per day. The aim of using the rupiah value is to provide information to two sections, namely the production section and the marketing section. If only the qty value is used for prediction, then only production purposes can be known. However, the marketing department will not get information such as how much it is worth in rupiah.

2. 2 Preprocessing Data

Data preprocessing in this study includes data normalization. The existing data is normalized by dividing the data value by the data range value (maximum data value-minimum data value). The data is normalized into two intervals, namely [-1,1] and [0,1], to ensure which interval produces the best value [1]. The objectives of Normalization are:

1. To remove duplicate data.
2. To reduce complexity.
3. To make it easier to modify data.

$$x_n = \frac{x_0 - x_{min}}{x_{max} - x_{min}} \quad (1)$$

2. 3 Convolution Neural Network

Convolution Neural Network is a type of Deep Learning that is widely applied to image data because the network depth is relatively high. In this Convolution Neural Network method, each neuron will be represented in 2 dimensions. Convolution Neural Network has four layers, which can be seen in the image below, namely:

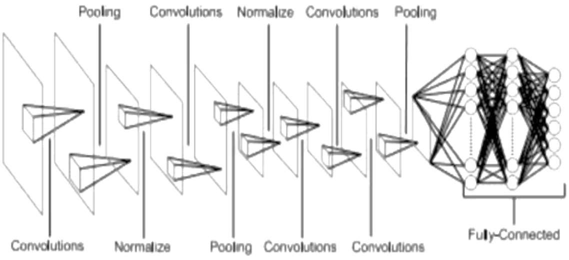

Figure 2 Convolution Neural Network

2. 4 Convolution Layer

At the Convolution Layer stage, a convolution operation will be carried out between the incoming image matrix and the filter matrix. The filter is shifted across the surface of the image and will produce a feature map. The following layer also carries out convolution on the input and output of other functions repeatedly, the aim of which is to extract features from the input image. The matrix shift equation 2 used:

$$h_{ij} = (A * P_1) + (B * P_2) + \cdots + (1 * P9) \quad (2)$$

2. 5 Pooling Layer

At this Pooling Layer stage, it will reduce the size from before, and the type used is the max pooling layer, which selects the maximum value in a particular grid. This process will produce an output value in the form of a matrix with the total value that will be chosen. The purpose of the pooling layer is to help reduce the number of parameters and the calculation time when training the network.

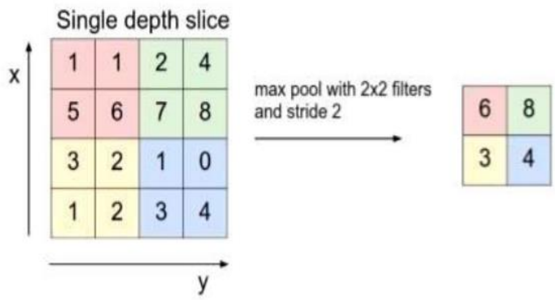

Figure 3 Pooling Layer

2. 6 Fully Connected Layer

At the Fully Connected Layer stage, the previous layer convolution and pooling process will be carried out, where neurons will be taken and connected to existing single neurons. Fully Connected has neurons that are entirely secured.

2. 7 Long Short Term Memory

According to [1], LSTM is a variant of the Recurrent Neural Network (RNN) unit. LSTM generally consists of a cell, input gate, output gate, and forget gate. LSTM neural networks are very suitable for classifying processing time series data because there may be unknown durations between events in a time series. LSTM adds a selection process in the control contact (cell) so that it can select which information is suitable to be forwarded, as well as being a solution to the vanishing gradient problem [2]. In LSTM, the recurrent or looping process is carried out at the node and layer levels. Input gates control LSTM cells to remember or forget the information they have based on the output of the LSTM.

2. 8 Convolution LSTM (C-LSTM)

CNN and LSTM are the two methods most commonly used to solve classification-related problems. However, CNNs that are used to carry out processing often ignore the relationships between contexts in documents. A study [3] combined two deep learning architectures, namely CNN and LSTM, to classify news texts. The combination of these two architectures is called Convolutional Long Short-Term Memory (C-LSTM).

A convolutional layer is a sparse matrix whose dimensions are smaller than the dimensions of the data being processed [3], [4]. The convolution technique is a technique for multiplying the input matrix with a matrix called the kernel to produce output. The convolution technique performs matrix multiplication differently from matrix multiplication in general. In mathematical formulas, the convolution operation is generally symbolized by an asterisk (*). Equation (3) shows the basic formula for the convolution process.

$$s(x) = (I * K)(x) = \sum_{n} 1(n - x)K(n) \tag{3}$$

In the LSTM analysis for regression in this research, the problem can be formulated as a regression problem. Write a simple function to convert one column of data into a two-column data set: the first column contains (t) the number of products this month, and the second column contains (t+1) the number of products next month, which will be predicted.

In this research, the LSTM analysis for regression used is time step regression, where data preparation for the LSTM network includes time steps. Some sequencing problems may have varying numbers of time steps per sample. For example, Physical machine measurements lead to a failure point or surge point. Such an event would be a sample of observations leading up to that event, would be a time step, and the observed variables would be a feature.

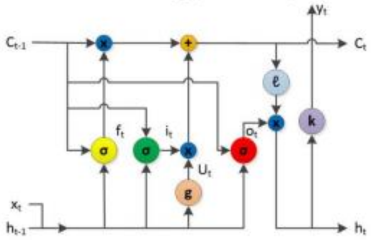

Figure 4 Design LSTM

In this research, the LSTM analysis for regression used is time step regression, where data preparation for the LSTM network includes time steps. Some sequencing problems may have varying numbers of time steps per sample. For example, Physical machine measurements lead to a failure point or surge point. Such an event would be a sample of observations leading up to that event, would be a time step, and the observed variables would be a feature.

The method used in this research is C-LSTM, where this method is a method that combines CNN and LSTM. C-LSTM determines the future state of a particular cell in the grid by its input and the past state of its local neighbors. This can be easily achieved using convolution operators in state-to-state and input-to-state transitions. The central equation of C-LSTM is shown in the equation below, where '*' denotes the convolution operator and 'o', as before, will represent the product, namely:

$$W = -\frac{1}{\sqrt{d}}, \frac{1}{\sqrt{d}}$$

$$W = -\frac{1}{\sqrt{12}}, \frac{1}{\sqrt{12}}$$

$$i_t = \sigma(\mathrm{Wi} \times [\mathrm{ht} - 1 \times \mathrm{xt}] + \mathrm{bi})$$

$$f_t = \sigma(Wf \times [ht - 1 \times xt] + bf)$$

$$C'_t = tanh\,(\mathrm{Wc}.[\mathrm{ht} - 1, \mathrm{xt}] + \mathrm{bc})$$

$$o_t = \sigma(\mathrm{Wo} \times [\mathrm{ht} - 1 \times \mathrm{xt}] + \mathrm{bo})$$

$$C_t = \sigma(\mathrm{ft} \times \mathrm{Ct} - 1 + \mathrm{it} \times \mathrm{C't})$$

$$H_t = \mathrm{ot} \times tanh(\mathrm{Ct})$$

3. RESULTS AND DISCUSSION

3. 1 Sales Data and Charts

Data processing is carried out at this stage, which will later be used. The data processed to carry out this prediction or forecasting process is lamp and cable sales data totaling 3,904 for lamp sales and 1,164 for cable sales. Below in Figures 2 and 3 below are the data that will be processed in this research.

	Tanggal	Kode Barang	Nama Barang	Qty
0	2012-01-02	1BACEC75.005B	LAMPU C7,5 ACE BIRU	0.000490
1	2012-01-02	1BACEC75.005D	LAMPU C7,5 ACE CLEAR	0.000990
2	2012-01-02	1BACEC75.005D	LAMPU C7,5 ACE CLEAR	0.019990
3	2012-01-02	1BACEC75.005H	LAMPU C7,5 ACE HIJAU	0.000490
4	2012-01-02	1BBESC75.005M	LAMPU C7,5 BESS MERAH	0.000490
...	...	...	...	...
3899	2012-12-29	1BVSC3-U.028D	LAMPU VE 28W-3U VISICOM/72	0.071991
3900	2012-12-29	1BVSC4-U.036D	LAMPU VE 36W-4U VISICOM/48	0.023990
3901	2012-12-29	1BVSC2-U.005D	LAMPU VE 5W-2U VISICOM/72	0.000050
3902	2012-12-29	1BVSC2-U.008D	LAMPU VE 8W-2U VISICOM/72	0.000050
3903	2012-12-29	1BVSCV-N.011W	LAMPU VN 11W-3U VISICOM WW	0.002990

[3904 rows x 4 columns]

Figure 5 Lamp Sales Data

	Tanggal	Kode Barang	Nama Barang	Qty
0	2012-01-04	1EVSCKLD.001K	KALENDER GANT.KABEL VISICOM 2014	0.037697
1	2012-01-04	1EVSCKLD.001K	KALENDER GANT.KABEL VISICOM 2014	0.037697
2	2012-01-04	1EVSCKLD.001K	KALENDER GANT.KABEL VISICOM 2014	0.037697
3	2012-01-04	1EVSCKLD.001K	KALENDER GANT.KABEL VISICOM 2014	0.037697
4	2012-01-04	1EVSCKLD.001K	KALENDER GANT.KABEL VISICOM 2014	0.001705
...	...	...	...	...
1159	2012-12-29	1AVSCT-V.RG6D	KABEL TV RG-6U 305M VISICOM GRADE	0.011934
1160	2012-12-29	1EVSCKLD.001K	KALENDER GANT.KABEL VISICOM 2014	0.003599
1161	2012-12-29	1EVSCKLD.001K	KALENDER GANT.KABEL VISICOM 2014	0.003599
1162	2012-12-29	1EVSCKLD.001K	KALENDER GANT.KABEL VISICOM 2014	0.005493
1163	2012-12-29	1EVSCKLD.001K	KALENDER GANT.KABEL VISICOM 2014	0.003599

[1164 rows x 4 columns]

Figure 6 Cable Sales Data

3. 2 Results using the Cross Validation Method

At this stage, the researcher used the k-fold cross-validation method, a variant of the cross-validation method. This model aims to eliminate bias in the data by dividing the data into k subsets/folds into five folds. Below in Tables 4.13 and 4.14 are the results of the cross-validation method, which are calculated using MAE and RMSE calculations.

Table 1 Lamp Sales cross validation results

Fold Ke-	Epoch 50		
	MAE	RMSE	Time Taken
1	0.0423	0.0583	00:00:07
2	0.0565	0.1125	00:00:08
3	0.0372	0.0600	00:00:15
4	0.0364	0.0638	00:00:07
5	0.0659	0.1450	00:00:08

Table 2 Cable Sales cross validation results

Fold Ke-	Epoch 50		
	MAE	RMSE	Time Taken
1	0.0100	0.0207	00:00:09
2	0.0074	0.0145	00:00:11
3	0.0133	0.0330	00:00:25
4	0.0055	0.0106	00:00:11
5	0.0023	0.0033	00:00:11

3. 2 Results of the Long Short Term Memory Method

The best neuron parameters obtained in the training process will be tested to predict and get testing data results.

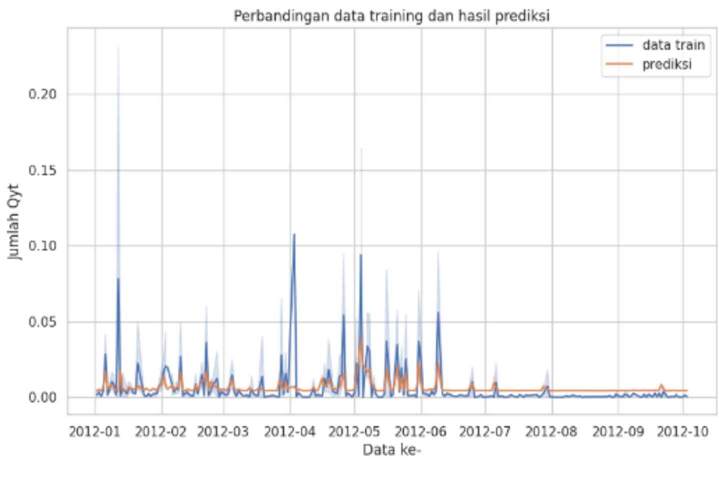

Figure 7 Comparison Chart of Training Data and Lamp Sales Prediction Results

The test results using training data can be seen in Figures 4 and 5. Comparison of Training Data and Prediction Results: the graph in blue is the result of training data predictions of 80% of the total data, and the graph in orange is the result of predictions obtained in testing training data. Then, in Figures 6 and 7, there is a comparison of Testing Data and Prediction Results; namely, the blue graph is the result of testing data predictions of 20% of the total data, and the orange graph is the result of predictions obtained from testing data testing.

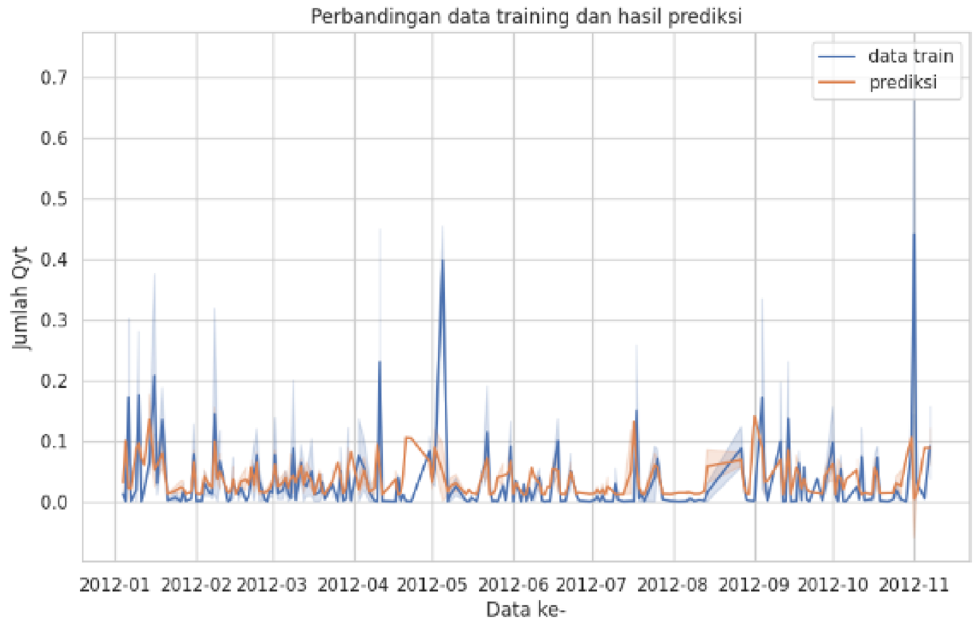

Figure 8 Comparison Chart of Training Data and Cable Sales Prediction Results

Convolutional layers in the ConvLSTM are responsible for extracting spatial features from the input data. These layers apply convolutional operations, which help the model identify patterns and relationships in the data that are spread across different spatial dimensions. This is especially useful in tasks where the data has a grid-like or image-like structure, such as sales data across multiple store locations. ConvLSTM models can consist of multiple layers, enabling a hierarchical approach to feature extraction and sequence modeling. Deeper architectures allow for the learning of more abstract and complex representations of the data, which is particularly beneficial for capturing intricate patterns in sales data.

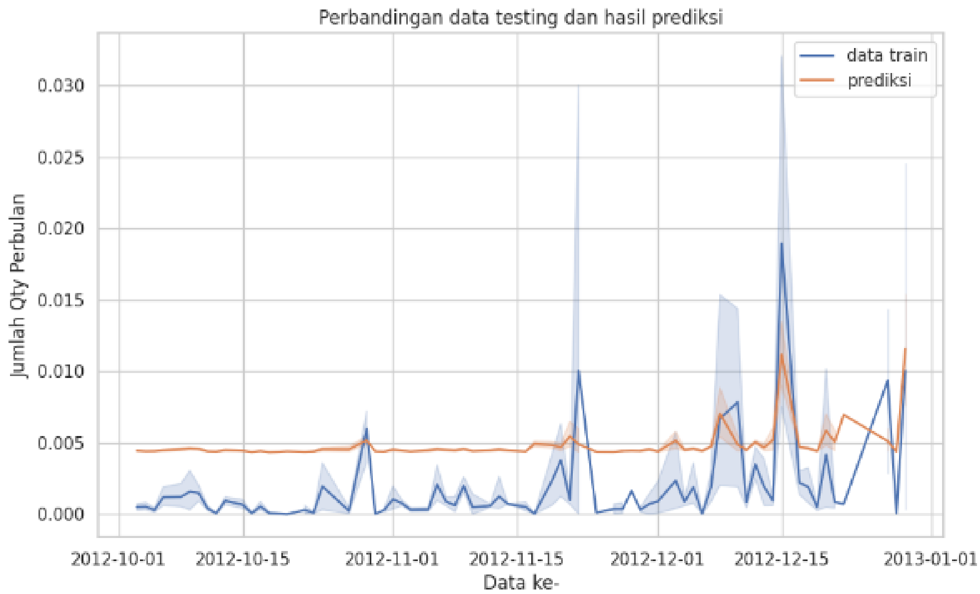

Figure 9 Comparison Chart of Testing Data and Lamp Sales Prediction Results

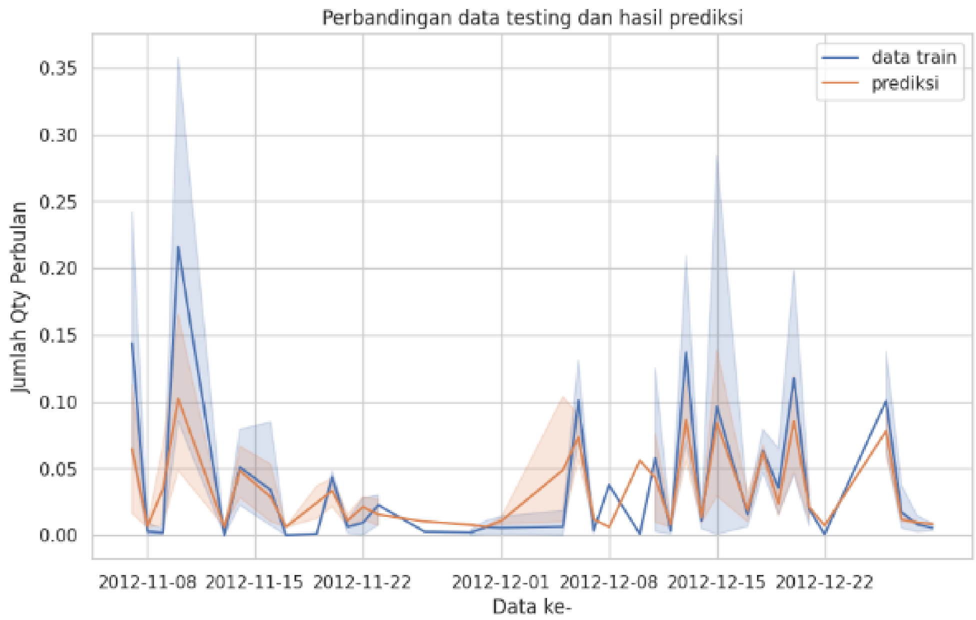

Figure 10 Comparison Chart of Testing Data and Cable Sales Prediction Results

3. 3 Hasil Perhitungan MAE dan MAPE

In this research, to measure prediction accuracy, it is calculated using Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) on training data and testing data. Table 4.15 shows the process of several training sessions for determining epoch values starting from 10, 50, 100, and 500. The MAE and MAPE values with the minor average were obtained at epoch ten, which shows that from the results of MAE and MAPE calculations in the data train forecasting, namely MAE is 0.1003 and MAPE of 23.9985%, while forecasting testing data, obtained MAE of 0.0923 and MAPE of 12.2182%. The results of the training show that the greater the amount of training data used, the smaller the error value obtained in the training so that the predictions will be more accurate.

Table 3 MAE and MAPE Calculations

Sale	Data Train		Data Test	
	MAE	MAPE %	MAE	MAPE %
Lampu	0.0602	44%	0.0841	47%
Kabel	0.1051	22%	0.1180	22%

3. 4 Prediction Results One Year Ahead

In this research, to measure prediction accuracy, it is calculated using Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) on training data and testing data. Table 4.15 shows the process of several training sessions for determining epoch values starting from 10, 50, 100, and 500. The MAE and MAPE values with the minor average were obtained at epoch ten, which shows that from the results of MAE and MAPE calculations in the data train forecasting, namely MAE is 0.1003 and MAPE of 23.9985% while forecasting testing data, obtained MAE of 0.0923 and MAPE of 12.2182%. The results of the training show that the greater the amount of training data used, the smaller the error value obtained in the training so that the predictions will be more

Table 4 Prediction Results for the Next Year of Lamp Sales

Period	Predictions
1	0.005667
2	0.004735
3	0.004942
4	0.005318
5	0.005482
6	0.005481
7	0.005551
8	0.005612
9	0.005642
10	0.005661
11	0.005679
12	0.005692

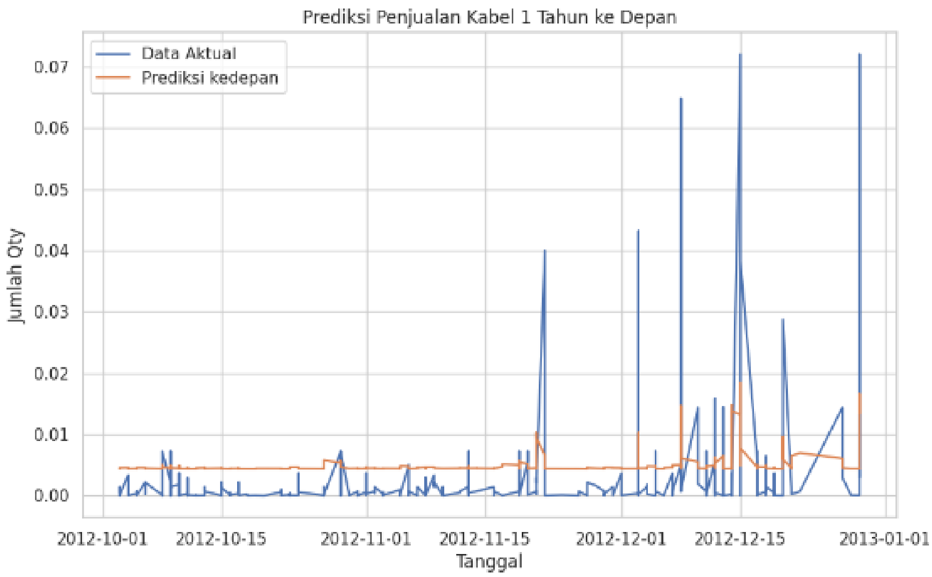

Figure 11 Graph of Lamp Sales Prediction Results for the Next Year

Table 5 Prediction Results for the Next Year of Cable Sales

Period	Predictions
1	0.015285
2	0.023153
3	0.031851
4	0.041574
5	0.049089
6	0.053657
7	0.056738
8	0.058763
9	0.060083
10	0.060949
11	0.061515
12	0.061885

ConvLSTM can effectively model the spatiotemporal patterns that influence sales figures. For instance, it can account for seasonality, regional variations, marketing campaigns, and other factors that affect sales. By combining spatial and temporal information, ConvLSTM can provide more accurate and context-aware predictions compared to traditional time series models or standalone CNNs or LSTMs.

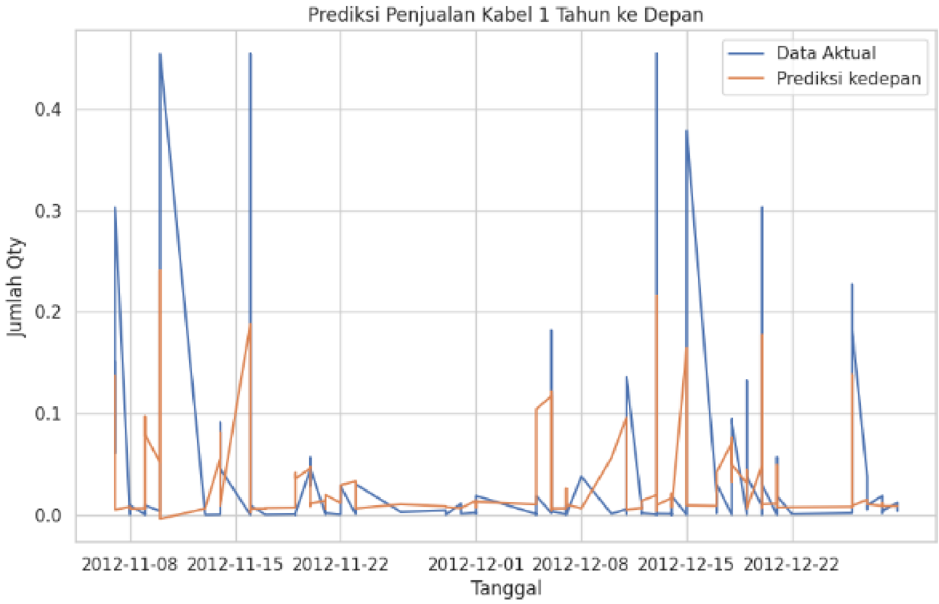

Figure 12 Graph of Cable Sales Prediction Results for the Next Year

4. CONCLUSIONS

Convolutional Long Short-Term Memory (C-LSTM) was successfully applied to predict PT Terang Abadi Raya product sales. Data on lamp and cable sales totaling 3,904 for lamp sales and 1,164 for cable sales were processed using the k-fold cross-validation method to eliminate data bias by dividing the data into five folds. The calculation results show that the smallest value was obtained at epoch 10, namely MAE 0.1051 and MAPE 22% in testing data for lamp sales. Meanwhile, the smallest value for cable sales was found at epoch 100, with MAE 0.0602 and MAPE 44% in testing data. The Long Short Term Memory method with several ten neurons produces the slightest error in the training process. By utilizing prediction models that have been tested, lamp and cable sales estimates are made for the following year. Lamp sales at the beginning of the year started at 0.005667 in January, then experienced fluctuations, reaching 0.005692 in December. Meanwhile, cable sales started at 0.015285 in January and ended at 0.061885 in December. The results of this research provide useful information for predicting product sales at PT Terang Abadi Raya based on analysis using Convolutional Long Short-Term Memory. the Convolutional Long Short-Term Memory (ConvLSTM) algorithm is a powerful and versatile neural network architecture for prediction tasks, especially when dealing with spatiotemporal data. Its key advantages lie in its ability to seamlessly combine the strengths of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, offering a holistic approach to capturing spatial and temporal dependencies in the data. When applied to sales prediction, ConvLSTM can enhance forecasting accuracy by considering not only the temporal aspect but also the spatial factors, such as store locations, regional variations, and other relevant features. It is particularly useful for businesses seeking to make data-driven decisions, optimize inventory management, and improve overall operational efficiency.

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