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Multivariat Predict Sales Data Using the Recurrent Neural Network (RNN) Method

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Abstrak

Penelitian ini bertujuan untuk mengembangkan model prediksi data penjualan yang akurat dan mendukung pengambilan keputusan di masa depan. Metode yang digunakan dalam penelitian ini meliputi analisis data historis penjualan dan penerapan teknik statistik dan pembelajaran mesin untuk mengidentifikasi pola dan tren yang dapat mempengaruhi kinerja penjualan. Data penjualan dari periode sebelumnya digunakan untuk melatih model prediksi, sedangkan data yang lebih baru digunakan untuk menguji dan memvalidasi performa model. Algoritma Recurrent Neural Network (RNN): penelitian ini memprediksi penjualan. Data yang digunakan adalah data penjualan tahun 2020 dengan parameter Jumlah penjualan per hari dalam empat bulan terakhir. Hasil yang diperoleh melalui pengujian beberapa skenario pelatihan dan pengujian implementasi algoritma dalam hal ini adalah nilai akurasi tertinggi sebesar 96,92% pada arsitektur jaringan tiga lapisan neuron input, tiga neuron lapisan tersembunyi, satu output, pembagian pelatihan, dan data uji 70:30, learning value rate 0,9 dan maksimal 900 epoch.

Kata kunci*— Peramalan, Jaringan Neural Berulang, prediksi multivariat*

Abstract

This research aims to develop an accurate sales data prediction model and support future decision-making. The methods used in this research involve analyzing historical sales data and applying statistical techniques and machine learning to identify patterns and trends that may influence sales performance. Sales data from previous periods is used to train the prediction model, while newer data is used to test and validate the model's performance. Recurrent Neural Network (RNN) Algorithm: this study predicts sales. The data used is sales data in 2020 with the parameter Number of sales per day in the last four months. The results obtained through testing several training scenarios and testing the implementation of the algorithm, in this case, is the highest accuracy value of 96.92% in the network architecture of three input neuron layers, three hidden layer neurons, one output, division of training, and test data 70: 30, learning value rate of 0.9 and a maximum of 900 epochs.

Keywords*— Forecasting, Recurrent Neural Network, multivariate prediction*

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1. INTRODUCTION

Prediction is a process of predicting conditions that will occur in the future based on existing data. An example of forecasting is sales results, which are used to determine the estimated sales volume so that appropriate decisions can be made based on existing data [1][2]. Sales prediction (forecasting) plays a vital role in planning and decision-making, especially in the production sector in the sales industry[3]. Production and operations management activities use demand forecasting in planning related to production planning[4].

Poor sales predictions will automatically lead to inadequate production planning. As a result, inventory becomes very high or vice versa, and sales are lost due to the unavailability of goods to be sold [5]. 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 [6]. This condition creates opportunities for competitors to enter, resulting in the loss of existing market opportunities (loss opportunity).

Prediction is a crucial element in decision-making because whether a decision is effective or not generally depends on several factors that we cannot see when the decision is made, which is based on existing and past data [7]. To be able to predict sales data, time series data from the past is needed, which can be analyzed so that patterns can be formed that can predict future conditions [8]. One method that can be used to predict sales data is to use the Recurrent Neural Network (RNN) model [9].

Recurrent Neural Network (RNN) has good processing time series data capabilities. Recurrent Neural Network (RNN) is a type of Neural Network architecture which, in carrying out the process, is called repeatedly to process input, which is usually sequential data [10]. Sequential data has characteristics where data samples are processed in a sequence (for example, time), and samples in the sequence are closely related to each other [11]. Time series sales data can be classified as sequential data because it is processed in a time sequence [12]. The contribution resulting from this research is that it can recognize patterns and trends that may change over time. RNN models can help predict data and adapt to changes, including changes in consumer trends, seasonal variability, or external factors that can influence sales. Another contribution is multivariate data analysis, particularly in sales forecasting. Applying the RNN method adds an analytical framework that can be used to understand relationships between variables and make more precise predictions.

This research uses a dataset from kaggle. Kaggle is one of the world's famous Data Science and Machine Learning sites whose dataset can be downloaded in CSV format [13]. Kaggle is not just a collection of datasets but consists of the largest data community. Quite a few companies have analysis problems, but they don't have the resources of skilled Data Scientists. Kaggle Data Science is beneficial as a place for research.

2. METHOD

2.1 Methodology

In general, the steps in the sales data prediction process using Recurrent Neural Network (RNN) are as follows:

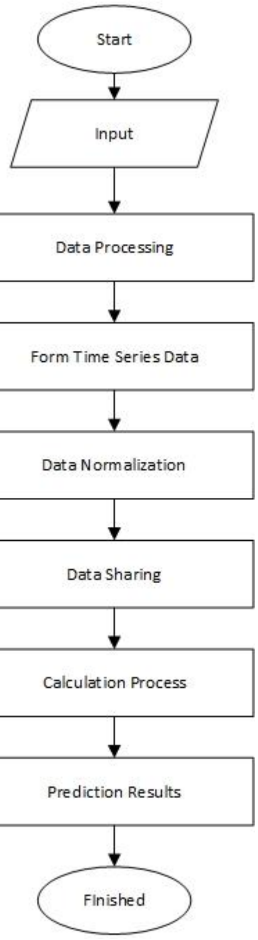


Figure 1. Research Stages

2. 2 Data Preprocessing

Preprocessing in research includes data normalization. Before processing, the input data will be normalized. Data normalization is carried out so that the network output matches the activation function used [14]. The data used in this research was taken from Kaggle. The total data used is 12 data, namely sales data for the last four months of 2020. The following is an example of sales data in 2020.

Table 1. Sales Dataset

Sales dataset	
Date	**Sales amount**
11/02/2020	130
12/02/2020	269
13/02/2020	252
14/02/2020	0
15/02/2020	15
16/02/2020	176
17/02/2020	0
18/02/2020	416
19/02/2020	301
20/02/2020	239
21/02/2020	204
22/02/2020	2
…	...

2. 2.1 Forming Time Series Data

The sales data in Table 1 is converted into time series data with input variables and target variables [15]. The initial step in the process of creating sales data prediction time series data is to create a data series from day 1 to day 12, initialed with X1, and the output is from day 2 to day 11, initialed with Y. The time series data can be seen in Table 2 as follows.

Table 2. Time Series Data

Time Series Data Sales Data			
No.	**Date**	**X1**	**Y**
1	11/02/2020	130	269
2	12/02/2020	269	252
3	13/02/2020	252	0
4	14/02/2020	0	15
5	15/02/2020	15	176
6	16/02/2020	176	0
7	17/02/2020	0	416
8	18/02/2020	416	301
9	19/02/2020	301	239
10	20/02/2020	239	204
11	21/02/2020	204	2
...	...	…	...

2. 2.2 Data Normalization

The time series data in Table 2 is normalized according to the range between 0 and 1 to adjust the activation function [16]. The normalization technique used uses min-max scaling. The following is a normalization calculation using the min-max scaling normalization formula.

$$X_n = X_0 - X_{min} / X_{max} - X_{min}$$

Information :

x : normalized data

x′ : data after normalization

min : minimum value of all data

max : the maximum value of all data

X_{max} = 416
X_{min} = 0

Date 11 = [(130 – 0) / (416 – 0] = 0,3125

Date 12 = [(269 – 0) / (416 - 0)] = 0,6466

This normalization will be carried out continuously from the 11th to the 22nd so that the normalization results can be seen in Table 3 as follows:

Table 3. Time Series Data Normalization Results

Time Series Data Normalization			
Date	***X1***	***X1´***	**Y´**
11/02/2020	130	0,3125	0,6466
12/02/2020	269	0,6466	0,6057
13/02/2020	252	0,6057	0
14/02/2020	0	0	0,0360
15/02/2020	15	0,0360	0,4230
16/02/2020	176	0,4230	0
17/02/2020	0	0	1
18/02/2020	416	1	0,7235
19/02/2020	301	0,7235	0,5745
20/02/2020	239	0,5745	0,4903
21/02/2020	204	0,4903	0,0048
22/02/2020	2	0,0048	

2. 2.3 Data Sharing

The amount of data used is 12 data, namely sales data for the last four months, data in the form of sales from Kaggle [17]. For example, manual calculations in this research use sales data in February 2020, where there were the most sales. Of the 11 data, 80% will be used for training data, and 20% will be used for testing data, where the amount of training data is 11 x 80% = 9 data which is the amount of data to be used in training data and 11 x 20% = 2 data which is the amount of data to use for test data. The data distribution of 80%:20% in this study can be seen in Table 3.4 and Table 3.5 below.

Table 4. Training Data 80%

No	X1	Y
1	0,3125	0,6466
2	0,6466	0,6057
3	0,6057	0,0000
4	0,0000	0,0360
5	0,0360	0,4230
6	0,4230	0,0000
7	0,0000	1,0000
8	1,0000	0,7235
9	0,7235	0,5745

Table 5. Training Data 20%

No	X1	Y
1	0,0870	0,3478
2	0,3478	0,1739

The purpose of dividing training data and test data is so that the learning algorithm can learn from patterns that have been obtained from the results of the training process, which will be implemented in the testing data[18][19]. The training and testing process using the RNN method will continue until an optimal model is obtained.

2.3 Method Analysis

The next stage is method analysis. The method used in this research is Recurrent Neural Network (RNN). The architecture of the Recurrent Neural Network Method can be seen in Figure 2 below.

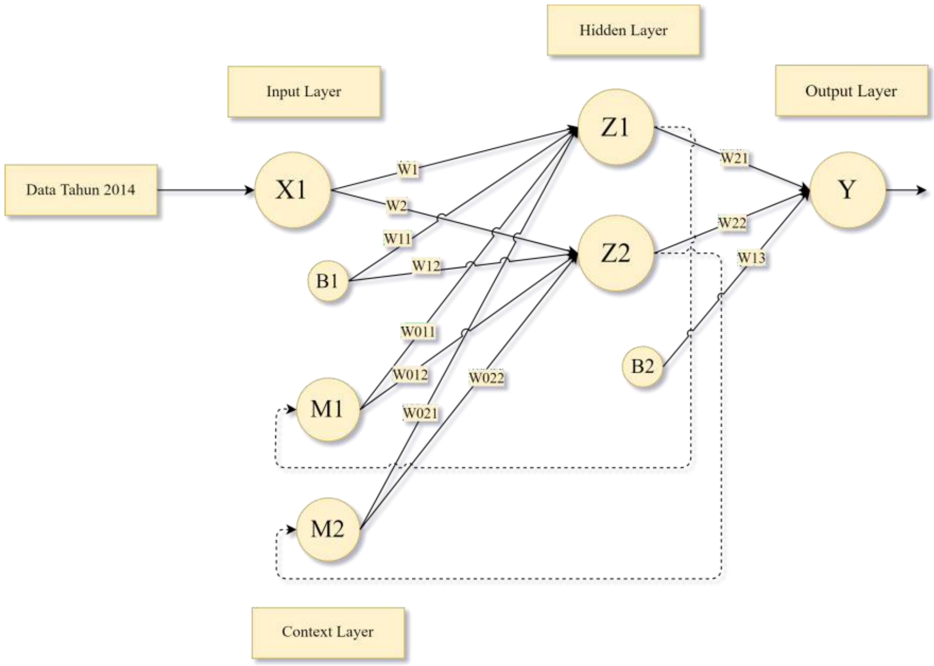


Figure 2. Recurrent Neural Network Architecture

a. The input data is sales data for 2020 from the 11th to the 22nd of February, which is then initialized with X1. Meanwhile, B1 is the initialization for the bias value from the input to the hidden layer, and B2 is the initialization for the bias value from the hidden layer to the output layer. Input variables can be seen in Table 6 below.

Table 6. Input Variables

Variables X1	
Date	**Number of Sales**
11/02/2020	130
12/02/2020	269
13/02/2020	252
14/02/2020	0
15/02/2020	15
16/02/2020	176
17/02/2020	0
18/02/2020	416
19/02/2020	301
20/02/2020	239

21/02/2020	204

a) The input value will be normalized first before being input. Then, it will be passed to the hidden layer. Next, from the hidden layer to the context layer and back again to the hidden layer. In the picture above, Z is symbolized as a neuron in the hidden layer, and M is represented as the context layer.
b) Each neuron in the input layer and output layer will be connected to the hidden layer via weights and a binary sigmoid activation function.
c) After that, each parameter is given a value, including the weight value w1, weight value w21, and bias value, then the calculation process is carried out.
d) The output weight produced from the hidden layer will be passed to the output layer, which consists of 1 output initialized with the letter Y.

3. RESULTS AND DISCUSSION

The following are the results of the Python program displayed from Google Colabs using the Python programming language in classifying lighting product data that has been completed and produced output by the expectations of the study site.

1	DATA PENJUALAN PT. TERANG ABADI RAYA							
2	JANUARI-DESEMBER 2021							
3	Tanggal	Kode Barang	Nama Barang	Qty	Konversi	Qty Konver	Harga	
35	2-Jan-12	1BVSC2-U.014D	LAMPU VE 14W-2U VISICOM/72	36	1	36	23,000.00	
36	2-Jan-12	1BVSC4-U.036D	LAMPU VE 36W-4U VISICOM/48	24	1	24	68,500.00	
37	2-Jan-12	1BVSCSPL.036D	LAMPU VR 36W VISICOM (SPIRAL)/48	24	1	24	82,000.00	
38	2-Jan-12	1BVSCSPT.020D	LAMPU VR-20W/T3 VISICOM (SPIRAL)	24	1	24	32,000.00	
41	2-Jan-12	1BACEC75.005B	LAMPU C7,5 ACE BIRU	50	1	50	850	
42	2-Jan-12	1BACEC75.005D	LAMPU C7,5 ACE CLEAR	100	1	100	750	
43	2-Jan-12	1BACEC75.005H	LAMPU C7,5 ACE HIJAU	50	1	50	850	
44	2-Jan-12	1BBESC75.005M	LAMPU C7,5 BESS MERAH	50	1	50	850	
45	2-Jan-12	1BACEC75.005D	LAMPU C7,5 ACE CLEAR	2,000.00	1	2,000.00	725	
46	2-Jan-12	1BSAN3-U.032D	LAMPU NEW SUNNYCO SO-32W 3U	12	1	12	37,000.00	
47	2-Jan-12	1BVSC2-U.011D	LAMPU VE 11W-2U VISICOM/72	24	1	24	17,325.00	
48	2-Jan-12	1BVSC2-U.011W	LAMPU VE 11W-2U VISICOM (WW)/72	24	1	24	17,944.00	
49	2-Jan-12	1BVSC3-U.018D	LAMPU VE 18W-3U VISICOM/72	24	1	24	22,275.00	
50	2-Jan-12	1BVSC3-U.018W	LAMPU VE 18W-3U VISICOM (WW)/72	24	1	24	22,894.00	

Figure 3. Dataset table before labeling totaling 12,275.

In Figure 3, there is a visual dataset before it is labeled and a visual dataset that has been marked, which will be displayed in table form in Excel, to which the raw Excel dataset is attached.

After labeling and displaying the data that was previously hidden in columns or tables, the tagged data was obtained as many as 12,290. The following is a dataset that has been labeled in the form of a visual table. This can be seen in Table 4.

1		Tanggal	ode Baran	ama Baran	Qty	Konversi	ty Konver	Harga	label
2	0	2012-01-02 00:00:00	1CVSCISO	ISOLASI 3/	1000	1	1000	5500	Laris
3	1	2012-01-02 00:00:00	1AVSCNYI	NYM 2X1,	8	10	80	2151530	Laris
4	2	2012-01-02 00:00:00	1AVSCNYI	NYM 3X1,	100	1	100	287050	Laris
5	3	2012-01-02 00:00:00	1AVSCNYI	NYM 3X2,	100	1	100	419810	Laris
6	4	2012-01-02 00:00:00	1AVSCNYI	NYM 3X2,	50	2	100	839620	Laris
7	5	2012-01-02 00:00:00	1AVSCNYI	NYM 4X2,	7	2	14	2100000	Laris
8	6	2012-01-02 00:00:00	1AVSCNYZ	NYZ 2X23	120	0.9	108	175600	Laris
9	7	2012-01-02 00:00:00	1ASICNYM	NYM 2X2,	30	1	30	600000	Laris
10	8	2012-01-02 00:00:00	1ABESNYA	NYA 1,5X7	486	1	486	24500	Laris
11	9	2012-01-02 00:00:00	1ABESNYA	NYA 1,5X7	17	1	17	24500	Laris
12	10	2012-01-02 00:00:00	1ABESNYA	NYA 1,5X7	7	1	7	24500	Tidak Laris
13	11	2012-01-02 00:00:00	1AACENYA	NYA 1,5X7	306	1	306	47500	Laris
14	12	2012-01-02 00:00:00	1AACENYA	NYA 1,5X7	4	1	4	47500	Tidak Laris
15	13	2012-01-02 00:00:00	1ASICNYM	NYM 2X2,	20	1	20	600000	Laris
16	14	2012-01-02 00:00:00	1ASICNYM	NYM 3X2,	30	1	30	800000	Laris
17	15	2012-01-02 00:00:00	1AVSCNYI	NYM 3X2,	50	1	50	800000	Laris
18	16	2012-01-02 00:00:00	1EVSCKLD	KALENDEF	1	1	1	0	Tidak Laris
19	17	2012-01-02 00:00:00	1ASICNYM	NYM 2X2,	42	1	42	600000	Laris
20	18	2012-01-02 00:00:00	1BHEM2-U	PLC HEMA	750	1	750	3800	Laris
21	19	2012-01-02 00:00:00	1BHEM2-U	PLC HEMA	750	1	750	3800	Laris
22	20	2012-01-02 00:00:00	1BHEM2-U	PLC HEMA	750	1	750	3800	Laris
23	21	2012-01-02 00:00:00	1BHEM2-U	PLC HEMA	750	1	750	3800	Laris
24	22	2012-01-02 00:00:00	1ASANHYI	NYM HYO	10	2	20	165000	Laris

Figure 4. Dataset table after 12,290 labels.

Then, the initial process carried out is the Excel dataset import page, where on this page, the dataset import is carried out using pandas. If some columns or attributes are not used, for example, only have a NULL value, then the column can be deleted. Only those that have a value are used because not all The data have value in the dataset. The function of na del df is to delete data that has no value.

```
[ ] import pandas as pd

    df = pd.read_excel('/content/laporan penjualan PT. Terang Abadi Raya.xlsx',header=2)
```

```
[ ] df.head()
```

	Tanggal	Kode Barang	Nama Barang	Qty	Konversi	Qty Konversi	Harga	Unnamed: 7	Unnamed: 8	
0	2012-01-02	1CVSCISO.0034	ISOLASI 3/4 "X7MMX20M NACHI TAPE/120	1000	1.0	1000.0	5500.0	NaN	NaN	NaN
1	2012-01-02	1AVSCNYM.210E	NYM 2X1,5X500M VISICOM./1	8	10.0	80.0	2151530.0	NaN	NaN	NaN
2	2012-01-02	1AVSCNYM.310A	NYM 3X1,5X50M VISICOM/2	100	1.0	100.0	287050.0	NaN	NaN	NaN
3	2012-01-02	1AVSCNYM.320A	NYM 3X2,5X50M VISICOM/2	100	1.0	100.0	419810.0	NaN	NaN	NaN
4	2012-01-02	1AVSCNYM.320B	NYM 3X2,5X100M VISICOM/1	50	2.0	100.0	839620.0	NaN	NaN	NaN

```
[ ] del df['Unnamed: 7']
    del df['Unnamed: 8']
    del df[' ']
```

Figure 5. Dataset Import Process

This page is the process of training a model, testing the model using test data and then calculating its accuracy.

```
[ ] from sklearn.neighbors import KNeighborsClassifier

    model = KNeighborsClassifier(n_neighbors=3)
    model.fit(X_train,y_train)

    KNeighborsClassifier(n_neighbors=3)
```

```
    from sklearn import metrics

    y_pred = model.predict(X_test)
    print("Accuracy:",metrics.accuracy_score(y_test, y_pred))

    Accuracy: 0.7685646811860404
```

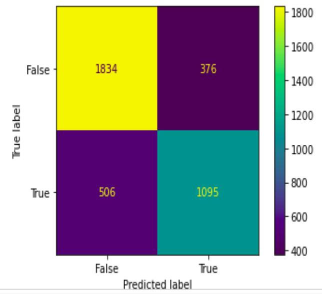
Figure 6. Train the KNN Model.

This page is the process of calculating True Positive, True Negative, False Positive, and False Negative values to calculate other confusion matrix values, then calculate different confusion matrix values.

```
from sklearn.metrics import  confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt
from sklearn import metrics

y_pred = model.predict(X_test)
confusion_matrix = confusion_matrix(y_test, y_pred)

cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = confusion_matrix, display_labels = [False, True])
cm_display.plot()
plt.show()
```




```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

       Laris       0.78      0.83      0.81      2210
 Tidak Laris       0.74      0.68      0.71      1601

    accuracy                           0.77      3811
   macro avg       0.76      0.76      0.76      3811
weighted avg       0.77      0.77      0.77      3811
```

Figure 7. Confusion Matrix Value

This page is the process after getting good test results. The model can be exported.

```
import pickle

filename = '/content/KNN_PT Terang Abadi Raya.pkl'
pickle.dump(model, open(filename, 'wb'))
```

Figure 8. Model results

This page is the result of the classification of goods labels for best-selling lighting products, which can be seen comprehensively for items that are categorized as best-selling after being successfully classified into two categories.

```
df[df['label']=='Laris']
```

	Tanggal	Kode Barang	Nama Barang	Qty	Konversi	Qty Konversi	Harga	label
0	2012-01-02	1CVSCISO.0034	ISOLASI 3/4 "X7MMX20M NACHI TAPE/120	1000	1.0	1000.0	5500.0	Laris
1	2012-01-02	1AVSCNYM.210E	NYM 2X1,5X500M VISICOM./1	8	10.0	80.0	2151530.0	Laris
2	2012-01-02	1AVSCNYM.310A	NYM 3X1,5X50M VISICOM/2	100	1.0	100.0	287050.0	Laris
3	2012-01-02	1AVSCNYM.320A	NYM 3X2,5X50M VISICOM/2	100	1.0	100.0	419810.0	Laris
4	2012-01-02	1AVSCNYM.320B	NYM 3X2,5X100M VISICOM/1	50	2.0	100.0	839620.0	Laris
...	...	...	...	...	...	...	...	...
19270	2012-12-29	1AVSCT-V.RG6D	KABEL TV RG-6U 305M VISICOM GRADE	64	1.0	64.0	340000.0	Laris
19271	2012-12-29	1BVSC3-U.028D	LAMPU VE 28W-3U VISICOM/72	7200	1.0	7200.0	23285.0	Laris
19272	2012-12-29	1CCMTFIT.0504	FITING GANTUNG T 504	9000	1.0	9000.0	750.0	Laris
19273	2012-12-29	1BHEM2-U.018D	PLC HEMAT 18W-2U/50	3000	1.0	3000.0	3250.0	Laris
19274	2012-12-29	1BHEM2-U.020D	PLC HEMAT 20W-2U/100	6050	1.0	6050.0	3250.0	Laris

12420 rows × 8 columns

Figure 9. Best-Selling Product Classification Results

This page results from the K-Nearest Neighbor (K-NN) classification of labels for non-selling lighting products, which can be seen comprehensively for items categorized as not selling after they have been successfully classified.

```
[ ] df[df['label']=='Tidak Laris']
```

	Tanggal	Kode Barang	Nama Barang	Qty	Konversi	Qty Konversi	Harga	label
10	2012-01-02	1ABESNYA.15NM	NYA 1,5X70M BESS (M-H)	7	1.0	7.0	24500.0	Tidak Laris
12	2012-01-02	1AACENYA.15NM	NYA 1,5X70M ACE (M-H)	4	1.0	4.0	47500.0	Tidak Laris
16	2012-01-02	1EVSCKLD.2011	KALENDER MEJA VISICOM 2021	1	1.0	1.0	0.0	Tidak Laris
25	2012-01-02	1AVSCNYM.210A	NYM 2X1,5X50M VISICOM/2	10	1.0	10.0	0.0	Tidak Laris
27	2012-01-02	1ASANHYM.275B	NYM HYO 2X0,75X100M SUNNYCO/5	5	2.0	10.0	165000.0	Tidak Laris
...	...	...	...	...	...	...	...	...
19285	2012-12-29	1EVSCKLD.001L	KALENDER GANT. VISICOM 2022	3	1.0	3.0	0.0	Tidak Laris
19286	2012-12-29	1EVSCKLD.001L	KALENDER GANT. VISICOM 2022	2	1.0	2.0	0.0	Tidak Laris
19287	2012-12-29	1EVSCKLD.001L	KALENDER GANT. VISICOM 2022	3	1.0	3.0	0.0	Tidak Laris
19288	2012-12-29	1EVSCKLD.001L	KALENDER GANT. VISICOM 2022	5	1.0	5.0	0.0	Tidak Laris
19289	2012-12-29	1EVSCKLD.001L	KALENDER GANT. VISICOM 2022	5	1.0	5.0	0.0	Tidak Laris

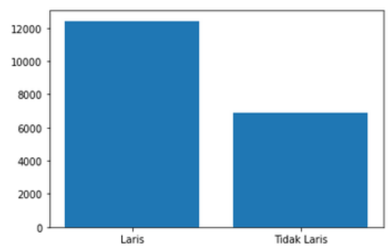
6870 rows × 8 columns

Figure 10. Classification Results for Non-Selling Products

This a page that displays product graphs in 2 label categories, namely the best-selling label and the not-best-selling label, where the best-selling lighting products have been successfully classified as 12,420 items categorized as selling well and as many as 6,870 items categorized as not selling well, from the total lighting product dataset. With a total of 19,290 data.

```
[9] import matplotlib.pyplot as plt

    x = ['Laris','Tidak Laris']
    y = valOfdf
    plt.bar(x,y)
    plt.show()
```




```
print(y)

[12420, 6870]
```

Figure 11. Graphic results for classification of lighting products.

Testing is carried out to observe execution results through test data and check the function of the system test results.

Table 5 Description of neural network parameter

Which was tested	**Process is displayedroses Ditampilkan**	**Results**
Import Datasets	Entering Dataset	In accordance
Determine Min Max of Unique Value	Carrying out the scaling process min max of price and Conversion Qty	In accordance
Split Data	The process carries out a proportion of 80% of the data for training and 20% data for tests	In accordance
Confussion Matrix	Calculate True Positive, True values Negative, False Positive, and False Negative to count Confusion Matrix	In accordance
Data Classification	Classify with The K-Nearest Neighbor (K-NN) method for lighting product products using a dataset in CSV format succeeded in displaying them in 2 categories, namely best-selling and not-selling, and a chart	In accordance

4. CONCLUSIONS

The conclusion of this research is to answer the problem formulation that has been presented, namely that the author succeeded in classifying 19,290 lighting products using the Python programming language using Google Collabs. Of the 19,290 items organized, the graphic results showed that 12,420 were categorized as best-selling items. , and as many as 6,870 were classified as not selling well.

Based on the conclusions of the results of the research that has been carried out, along with suggestions that the author can convey, for the sake of developing further research, this can be done by changing the type of distance used and can be created by increasing the amount of data and variables, so that better algorithm accuracy results can be obtained.

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