FORECASTING THE ELECTRICITY CONSUMPTIONS OF PLN UP3 CENGKARENG USING DEEP LEARNING

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***Abstract*— The consumption of electrical energy for the community every year has increased including the electricity consumption of PLN UP3 Cengkareng customers. Therefore, PLN UP3 Cengkareng must supply electricity to customers in all categories such as Social Category, Household Category, Business Category, Industry Category and Government Category. With customer needs that continue to increase, it is necessary to forecast future electricity needs, so that PLN UP3 Cengkareng can provide the required electrical power. For this reason, it is necessary to predict the electricity demand. This research was conducted to forecast the electricity demand of UP3 Cengkareng by using the DeepLearning Model Long Short-Term Memory (LSTM). The data set used in this study was taken from the PLN UP3 Cengkareng information system, for 10 years, the period from 2012 to 2021. Thedata used is divided into 2 categories, namely 70% training data and30% testing data. The results obtained from this prediction are 96,689, with an average neuron value of 32 and an epoch value of 10.**

***Keywords*— Deep Learning, Electricity Consumption, Long ShortTerm Memory, PLN, Prediction**

I. INTRODUCTION

Electricity consumption in Indonesia always increases every year in line with the improvements and progress that have been achieved in development in various fields, both in the economic, industrial and technological fields. According to this data, the government continues to strive to provide electricity supplies to the community at large costs to ensure the availability of affordable electricity for the community. Based on data from the DKI Jakarta Provincial Central Statistics Agency, the number of electricity customers in DKI Jakarta from 2013 to 2020 has increased significantly, so the need for electrical energy has also increased in the Jakarta area and its surroundings. In this research, the case study is the Cengkareng area, West Jakarta.

The reason is that the Cengkareng area, West Jakarta, has an increasing population and this has an impact on the need for electricity as well as to the development of industry, business and the construction of elite housing.

The expected result of this research is to be able to make a forecast to determine future electricity needs for the people of Cengkareng and its surroundings using Deep Learning with the LSTM method.

Research studies regarding special forecasting of electricity needs have been carried out by several previous researchers using the LSTM method, including research conducted by [20] Short-Term Load Forecasting of the Batu City Electricity System using Deep Learning Long Short-Term Memory (LSTM), with results LSTM method and ARIMA method, the use of the LSTM method provides better forecasting results than the use of the ARIMA method, namely simulation results with a training data proportion of 80% and testing data of 20% show greater RMSE and MAPE values than when using a training data proportion of 70 % and testing 30%, because on four days in September and November, and one day in October 2020, there was an increase in peak load.

Research conducted by [12] Predicting Electrical Energy Use in Residential Houses using LSTM, with results regarding the types of attributes that will be used and predictor model architecture. The correlation coefficient between the target and other selected attributes is more than 0.07. For this scenario, 13 types of attributes are used as input to the LSTM. Based on research, 8 neurons in LSTM with 7 lookbacks have the best performance. The error value on the test data is 60.992 respectively 28,278 for RMSE and MAE.

Research conducted by [19] Short Term Load Forecasting of the Batu City Electrical System Using Deep Learning LSTM, with better forecasting results than using the ARIMA method, except if loading anomalies occur which result in changes in the characteristics of the data used in the simulation.

Furthermore, this research uses Deep Learning with the LSTM method, with the value, amount and category of electricity sales data for the period January 2012 to December 2021, with 5 Electricity Customer Categories (Social, Household, Business, Industrial, Government), in 27 types electric power, various epoch-neuron values in the distribution of training: testing data 70%:30% and the model is used to predict the next month's electricity needs.

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II. LITERATURE REVIEW

A. Deep Learning

Deep Learning is a part of machine learning where the algorithm used is similar to the way the human brain works, therefore it is also called an artificial neural network. Deep Learning is the implementation of basic machine learning concepts that adapt artificial neural network algorithms with more layers. With more hidden layers used between the input layer and the output layer, the network is called deep neural nets.

B. Forecasting

Forecasting is the science of predicting something in the future. Predictions can be made using past data which is processed using prediction methods. The purpose of predictions is to be a reference for decision making about something that will happen in the future that has been predicted in the present.

C. Long Short-Term Memory (LSTM)

LSTM is a type of Recurrent Neural network (RNN) that learns and memorizes long-term pattern dependencies. The RNN loop network only uses one simple layer, namely the tanh layer as in Fig. 1.

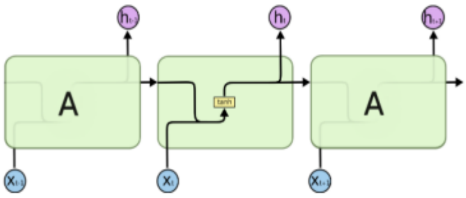

Fig. 1. Recurring module in RNN with one layer (Smagulova dan James. 2019)

Meanwhile, LSTM has 4 loop layers as in Fig. 2.

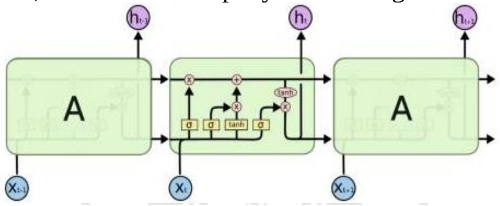

Fig. 2. Recurrence of four layers in LSTM (Smagulova dan James. 2019)

D. Data Normalization

Data Normalization is the rescaling of data from the original quantities and all values in the range between 0 and 1. To carry out normalization, the maximum and minimum values of the observed data must be known or can be accurately estimated.

In this research, Min Max Scaller was used to carry out normalization which is expressed by the formula:

$$y = \frac{x - min}{max - min} \quad (1)$$

Where:

y = normalization result value
min = minimum value of all data
x = input value
max = maximum value of all data

E. Modeling

To build the model and train the LSTM model, several parameters are used, namely:

1. Epoch (e)
   The number of epochs is a hyperparameter that determines how many or how many times a deep learning algorithm processes the entire data set. One epoch means that each sample in the training dataset has the opportunity to update the internal model parameters. An epoch of one or more batches (Jason Brownlee.2019).
2. Neurons (n)
   The number of neurons is a parameter that determines the layers in the hidden layer, where each neuron has several gates that regulate the memory of each neuron. The number of neurons is usually associated with the accuracy of the results obtained.

F. Root Mean Square Error (RMSE)

The evaluation method used is RMSE. RMSE is a measurement method by measuring the difference in value from a model's prediction as an estimate of the observed value. RMSE is the result of the square root of Mean Square Error (MSE).

The accuracy of the measurement error estimation method is characterized by the smallest RMSE value. The RMSE formula commonly used is as follows:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(A_t - F_t)^2}{n}} \quad (2)$$

Where:
At = Actual data value
n = Amount data
Ft = Value of forecasting result
∑ = *Summation* (add up all the values)

III. RESEARCH METHOD

Metodologi Penelitian yang digunakan di penelitian ini adalah metodologi Data Mining CRISP-DM (Cross Industry Standard Process for Data Mining). CRISP-DM sebagai pemecah masalah yang umum untuk bisnis dan penelitian. This methodology consists of six stages, which can be explained as follows and are shown in Fig. 3.

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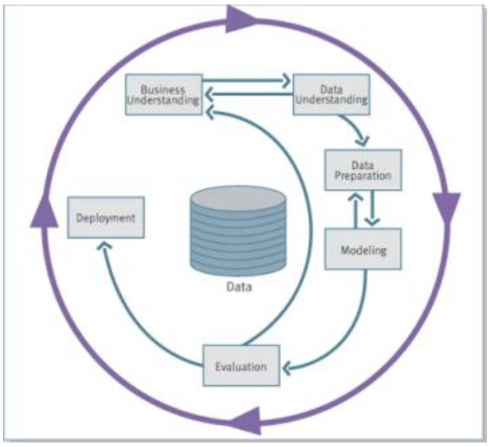

Fig. 3. Process CRISP-DM (Larose, 2014)

The research design was prepared by applying the CRISP-DM methodology, and was described into the following stages:

1. Business Understanding
   Understanding the need for electricity and the problems that need to be resolved, by analyzing the importance of information about the condition of electricity demand in the form of predictions of this need based on existing data.
2. Data Understanding
   It is concluded that the quality of the source data is sufficient, to find information (data) that supports the formation of research hypotheses, by:
   a) Data Collection
      Data containing Electricity Sales obtained from recorded data or electricity sales reports.
   b) Data Analysis and Validation
      Carrying out data analysis to facilitate understanding of the data and validating the data is done by assessing the suitability of the data to the research problem.
3. Data Processing
   Validating the data is conducted by assessing the suitability of the data to the research problem. From the data analysis carried out, it is assessed whether the data collected is in line with expectations, both in terms of quantity, attributes and quality, by means of Data Normalization. The term 'Normalization' is rescaling (rescaling) the data from the original amount so that all values are within range between 0 and 1.
4. Modeling
   Implementation of Deep Learning algorithms to create models from prepared data. The modeling target is to find the best model obtained using processed data. In this research, the algorithm used to produce the model is determined, namely deep learning LSTM. To build a model, the training process uses training data and applies parameters to obtain an LSTM model. To build the model and train the LSTM model, several parameters are used, namely the number of epochs and the number of neurons.
5. Evaluation
   The evaluation method used is RMSE. The accuracy of the measurement error estimation method is characterized by the smallest RMSE value.
6. Deployment
   Models that have gone through performance evaluation results are then saved in a certain file format and can be implemented in the form of an application. In this research, the web application can display graphs of electric power values and prediction results.

The research data that will be carried out uses the PLN UP3 Cengkareng Customer dataset. This dataset contains 3,240 Electricity Sales data consisting of 5 categories, namely social, household, business, industry, government. Some of the datasets used can be seen in Table I.

TABLE I. Sampel of Dataset

Tahun	**Bulan**	**Jenis**	**Jumlah Kwh**
2012	1	B-1 / 450 VA I	41.348
		B-1 / 900 VA I	115.609
		B-1 / 1.300 VA	411.521
		B-1 / 2.200 VA	3.347.105
		B-2 / 6.600 VA and above	11.991.144

Algorithm Design
In this research, several stages were carried out, namely problem analysis, data collection, data normalization, data preparation, data sharing, model evaluation model formation, model deployment and analysis results. These stages are depicted in the flow diagram in Fig. 4.

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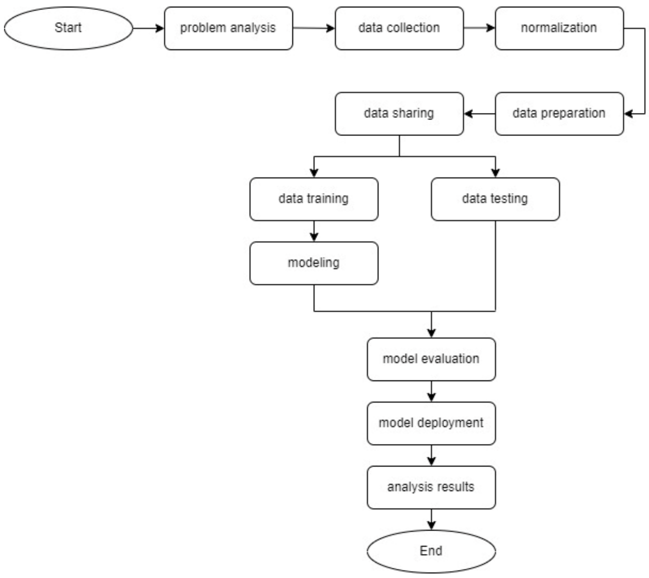


Fig. 4. Research Steps

The data used is electricity sales data, then data processing is carried out, namely the data normalization process, data sharing, namely training data and test data. Training data is used to find out the optimal model so that it can be tested later. Data testing is carried out to test using an optimal model from the results of training data which uses varying neuron and epoch values. Next, build an evaluation model which is carried out by applying the optimal parameters produced to the entire dataset, namely data on 5 categories of electricity customers with 27 types of electricity. After going through the training and testing process, the RMSE value is calculated and the model is also used to forecast electricity needs.

IV. RESULTS AND DISCUSSION

1. Data Source

The data obtained is the total sales of electricity which consists of social, household, business, industry and government from January 2012 to December 2021 obtained from Electricity Sales in the PLN UP3 Cengkareng Commercial Section. Total data owned is for 10 years with a total of 120 months. From all available data, there are 27 types of electricity which are written in electricity sales data in the form of kWh available in Table II.

TABLE II. Data Source

No	Jenis Tenaga Listrik	Tahun	Bln	Jum Baris
1	social_s2_450_va	2012-2021	1-12	120
2	social _s2_900_va	2012-2021	1-12	120
3	social _s2_1300_va	2012-2021	1-12	120
4	social _s2_2200_va	2012-2021	1-12	120
5	social _s2_3500_va	2012-2021	1-12	120
6	household_r1_450_va	2012-2021	1-12	120
7	household _r1_900_va	2012-2021	1-12	120
8	household _r1_1300_va	2012-2021	1-12	120
9	household _r1_2200_va	2012-2021	1-12	120
10	household _r2_3500_va	2012-2021	1-12	120
11	household _r3_6600_va	2012-2021	1-12	120
12	business_b1_450_va	2012-2021	1-12	120
13	business _b1_900_va	2012-2021	1-12	120
14	business _b1_1300_va	2012-2021	1-12	120
15	business _b1_2200_va	2012-2021	1-12	120
16	business _b2_6600_va	2012-2021	1-12	120
17	industry_i1_1300_va	2012-2021	1-12	120
18	industry _i1_2200_va	2012-2021	1-12	120
19	industry _i1_3500_va	2012-2021	1-12	120
20	industry _i2_14_kva	2012-2021	1-12	120
21	industry _i3_200_kva	2012-2021	1-12	120
22	goverment_p1_450_va	2012-2021	1-12	120
23	goverment _p1_900_va	2012-2021	1-12	120
24	goverment _p1_1300_va	2012-2021	1-12	120
25	goverment _p1_2200_va	2012-2021	1-12	120
26	goverment _p1_6600_va	2012-2021	1-12	120
27	P3	2012-2021	1-12	120

2. Normalization

The following is data that will be normalized as an example of calculations for normalization, using formula (1). Example of normalization calculation using the formula above:

Line 1:
x = 3.347.105
Max = 4.807.092
Min = 2.812.802

$$y = \frac{3.347.105 - 2.812.802}{4.807.092 - 2.812.802} = \frac{534.303}{1.994.290} = 0.2679164 \quad (3)$$

Line 2:
x = 3.220.093
Max = 4.807.092
Min = 2.812.802

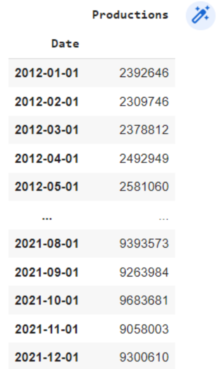
$$y = \frac{3.347.105 - 2.812.802}{4.807.092 - 2.812.802} = \frac{407.2910}{1.994.290} = 0.20422857 \quad (4)$$

Line 120:
x = 4.556.271
Max = 4.807.092
Min = 2.812.802

$$y = \frac{4.556.271 - 2812.802}{4.807.092 - 2.812.802} = \frac{1.753.469}{1994.290} = 0.87924474 \quad (5)$$

3. Data Preparing

In the data preparation process, the normalized data is created in the form of a CSV file and this data will be accessed using Google Colab. Data stored on Google Drive. After the data has been successfully input into the application, it is necessary to check whether the correct data has been read, for example in the first 5 data and the last 5 data, namely 5 types of customer categories with a total of 27 types of electricity and the results from matplotlib for the entire data for 10 years as following.



Date	Productions
2012-01-01	2392646
2012-02-01	2309746
2012-03-01	2378812
2012-04-01	2492949
2012-05-01	2581060
...	...
2021-08-01	9393573
2021-09-01	9263984
2021-10-01	9683681
2021-11-01	9058003
2021-12-01	9300610

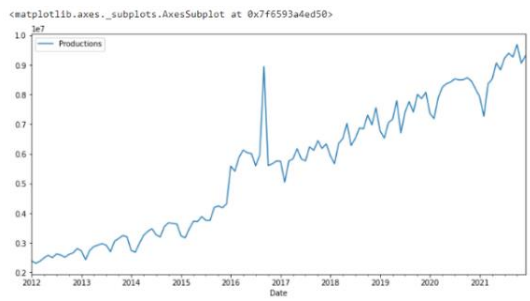


Fig. 5. Data Table and Data Graph

4. Data Sharing

The data is divided into 2 parts, namely: into training data 70% and testing data 30%.

5. Data Training

The Data Training Process can be seen in Table 5 and Fig.5, by displaying 1 data sample using the R-3 6600 VA Household category, the RMSE value is used to assess model results or optimal model performance. The Epoch (e) and Neuron (n) values are determined to vary as model training parameters. In this research, all data was trained with a combination of neuron values of 16, 32, 64,128 and 256, while the epoch combination was 10, with a training data ratio of 70%.

TABLE III. Proses Data Training RT R-3 6600 VA

The amount (n)	The amount (e)	RMSE
16	10	44013199.77
32	10	25535890.67
64	10	41122765.07
128	**10**	**7504461.12**
256	10	11286318.94

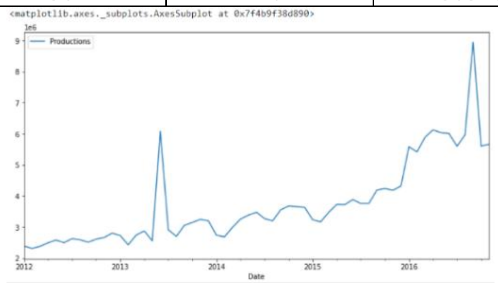


Fig. 6. RT R-3 6600 VA Training Data Process Graph with n= 128 and e=10

6. Formation of Data Testing

Data Testing is carried out to test using an optimal model from the results of Training Data. Testing data can be seen in Fig. 7 below:

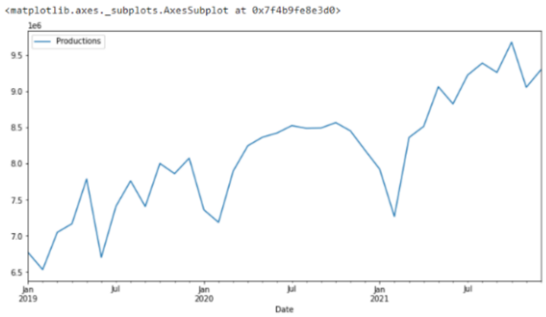


Fig. 7. Graph of Testing Data Formation for RT R-3 6600 VA Data Testing

Next, the model is used to predict using testing data. By obtaining the optimal model (smallest RMS value), then testing it with testing data, to determine the accuracy value. The following is the process and results of testing using the optimal model on neuron 128 and epoch 10, which can be seen from Table 4 and Fig.8 below: Next, the model is used to predict using testing data. By obtaining the optimal model (smallest RMS value), then testing it with testing data, to determine the accuracy value. The following is the process and results of testing using the optimal model on neuron 128 and epoch 10, which can be seen from Table IV and Fig. 8 below:

TABLE IV. Proses Data *Testing* RT R-3 6600 VA

The amount (n)	The amount (e)	RMSE
128	10	577277.94

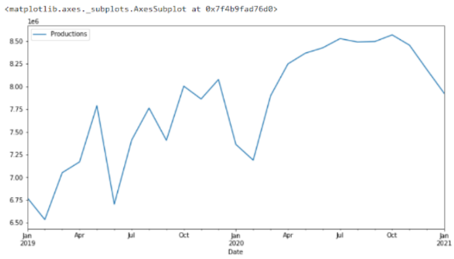


Fig. 8. Graph of RT R-3 6600 VA Data Testing Results with n= 128 and e=10

7. Model Evaluation

Model evaluation is carried out by applying the optimal parameters produced to the entire dataset, namely to data on 5 types of electricity customers with 27 categories as follows:

1. Types of Social Customers with 5 categories, namely: 450 VA, 900 VA, 1300 VA, 2200 VA, 3500 VA.
2. Types of Household Customers with 6 categories, namely: 450 VA, 900 VA, 1300 VA, 2200 VA, 3500 VA, 6600 VA.
3. Types of Business Customers with 5 categories, namely: 450 VA, B-1 900 VA, 1300 VA, 2200 VA, 6600 VA.
4. Types of Industrial Customers with 5 categories, namely: 1300 VA, 2200 VA, 3500 VA, 14 KVA, 200 KVA.
5. Types of Government Customers with 6 categories, namely: 450 VA, 900 VA, 1300 VA, 2200 VA, 6600, P3.

After going through the training and testing process, each model is obtained. The following are the results for 27 types of electricity customers with each category. Apart from that, the model is also obtained to make predictions for the next month's electricity needs.

TABLE V. Summary of Result

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No	Types of Electric Power	n	e	Result
1	social_s2_450_va	128	10	4191.2346
2	social _s2_900_va	64	10	2366.6946
3	social _s2_1300_va	16	10	7564.091
4	social _s2_2200_va	16	10	274452.483
5	social _s2_3500_va	128	10	254339.864
6	household_r1_450_va	32	10	694601.161
7	household _r1_900_va	129	10	681093.581
8	household _r1_1300_va	32	10	1186076.459
9	household _r1_2200_va	64	10	1194763.983
10	household _r2_3500_va	128	10	1389531.185
11	household _r3_6600_va	128	10	577277.948
12	business_b1_450_va	256	10	3634.795
13	business _b1_900_va	32	10	13440.842
14	business _b1_1300_va	32	10	23727.551
15	business _b1_2200_va	256	10	272797.3665
16	business _b2_6600_va	16	10	1995866.289
17	industry_i1_1300_va	32	10	96.689
18	industry _i1_2200_va	32	10	559.664
19	industry _i1_3500_va	64	10	2284.352
20	industry _i2_14_kva	32	10	2210562.468
21	industry _i3_200_kva	16	10	40354122.66
22	goverment_p1_450_va	64	10	29.538
23	goverment _p1_900_va	64	10	333.226
24	goverment _p1_1300_va	128	10	2154.432
25	goverment _p1_2200_va	64	10	3978.941
26	goverment _p1_6600_va	16	10	31062.046
27	P3	16	10	82838.431

8. Deployment Model

In order that the model can be used in real time, which is the final stage of this research, the model is implemented into a web-based application as shown in Fig. 9 below:

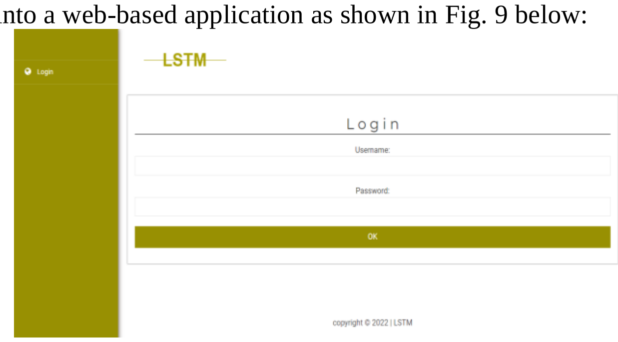


Fig. 9. Login page display

Next, the system will carry out validation, if correct it will be directed to the dashboard as shown in Fig.10 below:

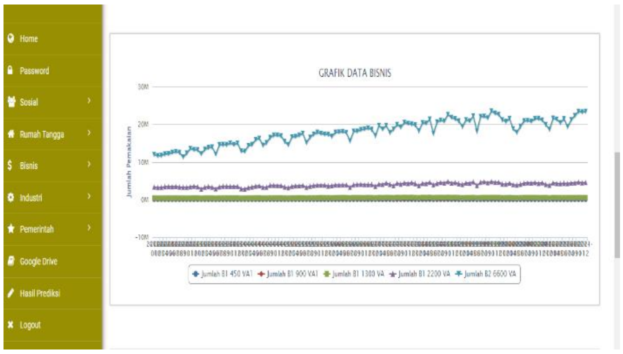
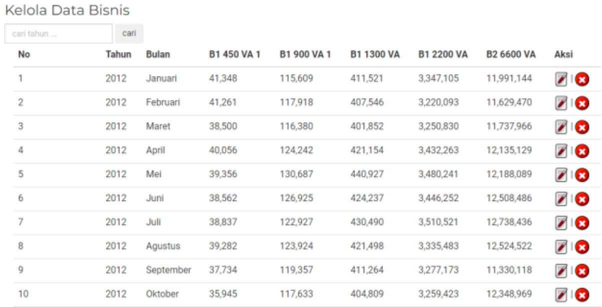


Fig. 10. Dashboard page

Admins can also manage data by searching data by year, making data changes directly through the application even to delete data

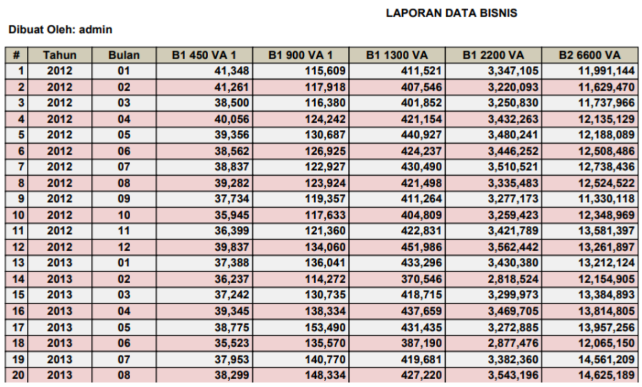

Kelola Data Bisnis

cari tahun ... cari

No	Tahun	Bulan	B1 450 VA 1	B1 900 VA 1	B1 1300 VA	B1 2200 VA	B2 6600 VA	Aksi
1	2012	Januari	41,348	115,609	411,521	3,347,105	11,991,144	
2	2012	Februari	41,261	117,918	407,546	3,220,093	11,629,470	
3	2012	Maret	38,500	116,380	401,852	3,250,830	11,737,966	
4	2012	April	40,056	124,242	421,154	3,432,263	12,135,129	
5	2012	Mei	39,356	130,687	440,927	3,480,241	12,188,089	
6	2012	Juni	38,562	126,925	424,237	3,446,252	12,508,486	
7	2012	Juli	38,837	122,927	430,490	3,510,521	12,738,436	
8	2012	Agustus	39,282	123,924	421,498	3,335,483	12,524,522	
9	2012	September	37,734	119,357	411,264	3,277,173	11,330,118	
10	2012	Oktober	35,945	117,633	404,809	3,259,423	12,348,969	

Fig. 11. Manage Data page

Admin can also print all data in PDF format for the purposes of making reports.


LAPORAN DATA BISNIS

Dibuat Oleh: admin

#	Tahun	Bulan	B1 450 VA 1	B1 900 VA 1	B1 1300 VA	B1 2200 VA	B2 6600 VA
1	2012	01	41,348	115,609	411,521	3,347,105	11,991,144
2	2012	02	41,261	117,918	407,546	3,220,093	11,629,470
3	2012	03	38,500	116,380	401,852	3,250,830	11,737,966
4	2012	04	40,056	124,242	421,154	3,432,263	12,135,129
5	2012	05	39,356	130,687	440,927	3,480,241	12,188,089
6	2012	06	38,562	126,925	424,237	3,446,252	12,508,486
7	2012	07	38,837	122,927	430,490	3,510,521	12,738,436
8	2012	08	39,282	123,924	421,498	3,335,483	12,524,522
9	2012	09	37,734	119,357	411,264	3,277,173	11,330,118
10	2012	10	35,945	117,633	404,809	3,259,423	12,348,969
11	2012	11	36,399	121,360	422,831	3,421,789	13,581,397
12	2012	12	39,837	134,060	451,986	3,562,442	13,261,897
13	2013	01	37,388	136,041	433,296	3,430,380	13,212,124
14	2013	02	36,237	114,272	370,546	2,818,524	12,154,905
15	2013	03	37,242	130,735	418,715	3,299,973	13,384,893
16	2013	04	39,345	138,334	437,659	3,469,705	13,814,805
17	2013	05	38,775	153,490	431,435	3,272,885	13,957,256
18	2013	06	35,523	135,570	387,190	2,877,476	12,065,150
19	2013	07	37,953	140,770	419,681	3,382,360	14,561,209
20	2013	08	38,299	148,334	427,220	3,543,196	14,625,189

Fig. 12. PDF Data Print Page Overall Data

Files stored on Google Drive can also be accessed directly via the integrated web application, so admins can also directly make changes to CSV files or source code in Python via Google Colab.

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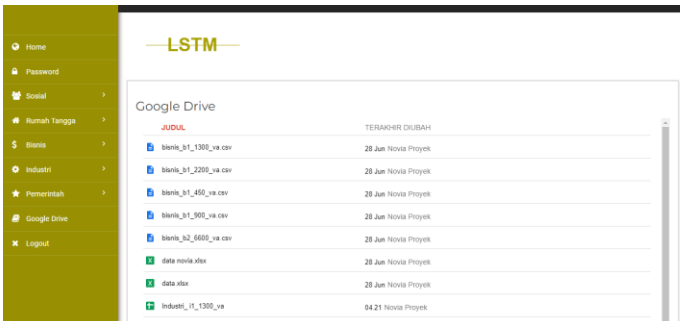

Fig. 13. Google Drive page

V. CONCLUSION

From this research, it can be concluded that the prediction of electricity needs in UP3 Cengkareng using the Deep Learning LSTM method obtained accurate prediction results.

The Deep Learning method is proven to be able to predict well the amount of electricity needed for PLN UP3 Cengkareng in the future with a neuron value of 32 and epoch 10 and the smallest value is 96,689, with the results being able to predict electricity needs in the following month.

From the smallest RMSE value, it can be seen that the prediction results have a significant accuracy value.

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