Solar Power Forecasting on Smart Micro Grid Using CNN-LSTM Ensemble Method

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***Abstract*—The use of solar Photovoltaic (PV) energy as an alternative renewable energy source has increased worldwide. Problems in solar PV systems are caused by intrinsic intermittency in solar radiation and other meteorological factors so the power generated from PV is uncertain and unstable. Therefore, a forecasting model using an Artificial Intelligence (AI) approach is needed to overcome the instability in the utilization of energy generated by solar PV, especially for distributed residential PV, which is operated and maintained independently. The purpose of this study is to develop an ensemble model on Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM) to provide predictions on the generation of energy in solar PV. Performance evaluation is carried out by comparing several forecasting models, namely Deep Neural Network (DNN), CNN, LSTM, and the proposed ensemble model using scenarios of three different input data combinations (S1, S2, S3). Based on the results of experiments and performance measurements, the model that is proposed to have very good overall performance, especially superior in the combination of {S1, S3}, {S2, S3} and {S1, S2, S3}. The combination of {S1, S3} gives the best results in this model, namely Mean Square Error (MSE) = 0.0934; Root Mean Square Error (RMSE) = 0.3057 better than LSTM. The combination of {S2, S3} with MSE = 0.1359; RMSE = 0.3687. The combination of {S1, S2, S3} is also quite good with MSE = 0.0951.**

***Keywords*—Convolutional Neural Network (CNN), Long Short Term Memory (LSTM), ensemble, forecasting, Smart Micro Grid (SMG)**

I. Introduction

The provision of sufficient and adequate energy is a global problem, considering the increasing demand for energy and the decreasing raw materials for energy generation. Strategic steps have begun to be taken, namely by using power plants that are sourced from renewable energy as a substitute for fossil fuels. The development and use of renewable energy is increasingly becoming very important. The use of renewable energy sources is currently being carried out in various countries as a form of contribution to overcoming the issue of global warming [1, 2]. This requires a process that is not short, and also the support of fossil energy sources is still very much needed, so integration between energy sources must be developed.

Smart grid implementation is carried out on a micro scale to meet the electricity needs of households and buildings through the integration of renewable energy sources such as solar energy or solar Photovoltaic (PV) so as not to be fully dependent on the national electricity network. However, the unstable nature of solar energy sources will cause uncertainty in the electricity produced and impact the provision of electricity to users. The solar PV monitoring system can be used to determine the amount of electricity produced by PV, weather conditions, and panel conditions and to predict future PV electricity production using the Artificial Intelligence (AI) method [3, 4].

Developing methods in solar PV monitoring applications is important to maintain the performance and efficiency of the PV system [5–8]. AI methods are used for data analysis to provide diagnostic and optimization services on the grid. The forecasting process using an AI approach is very important for utilizing PV systems [4, 9]. This study uses the Deep Neural Network (DNN) algorithm to handle the complexity of problems in solar PV systems, including uncertainty and non-linearity, which have an impact on the increasingly complex structure of the energy data produced [10] and accelerate control and decision-making [7, 11]. Furthermore, the use of Internet of Things (IoT) technology is used to accelerate information processing and improve performance in monitoring systems [12–15].

This study aims to develop the forecasting model to improve the accuracy of predictions on energy generation from PV. Development of the Convolutional Neural Network-Long Short Term Memory (CNN-LSTM) ensemble model to provide future accurate prediction on renewable energy generation. Furthermore, the results of the LSTM model performance are compared with other algorithms, including DNN, CNN, and LSTM. This

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research has several major contributions in the field of renewable energy forecasting, including:

(1) Development of CNN-LSTM ensemble model for PV power prediction;
(2) Optimizing on CNN-LSTM ensemble model;
(3) Evaluation with various input data combinations;
(4) Data preprocessing for time-series forecasting.

This paper is structured into several parts, including Section I provides the introduction, Section II presents the literature review, Section III explains the method, Section IV describes the experiments and results, and Section V offers the conclusion.

II. Related Works

Several previous studies used statistical models based on regression equations, namely Autoregressive Integrated Moving Average (ARIMA) [16–18]. However, this model cannot be used in non-linear relationships. The Support Vector Machine (SVM) method [19] and ensemble methods [20, 21] of various non-linear regression models are used to overcome the regression model. However, these models rely on predetermined parameters and predetermined non-linear mappings [22]. The AI model based on neural network technology is the main model for power forecasting in PV systems. This model has advantages in solving complex nonlinear problems. Aslam *et al.* [23] developed a power forecasting model for the next day using the deep learning method based on a 2-stage mechanism on the LSTM architecture and the Bayesian optimization method applied to obtain the optimal combination of hyperparameters in the deep learning model. However, this model has complex computation, so the convergence process is slow.

Guo *et al.* [21] developed a PV power prediction method using a Stacking ensemble-based learning model consisting of several algorithms, including eXtreme Gradient Boosting (XGBoost), Random Forest (RF), Support Vector Regression (SVR), Light Gradient Boosting Machine (LGBM) and CatBoost. The test results showed that the ensemble method consisting of XGBoost, CatBoost, LGBM, RF provided the most accurate results. However, the performance results of the ensemble learning method will be affected by electricity data that has a complex random pattern and is difficult to adjust precisely [24]. So it requires a deep learning method or deep learning, which has advantages in non-linear data analysis.

Succetti *et al.* [25] developed a multivariate PV output power prediction model by comparing 4 DNN architectures. The test results proved that the multi-LSTM architecture has the highest accuracy. Agga *et al.* [26] developed two hybrid models using CNN-LSTM and ConvLSTM to predict PV generation power. The test results showed that the CNN-LSTM model gave more accurate results. However, this model requires long layers, which increases the computational complexity, and the accuracy of the model decreases when the prediction time is longer. Cervone *et al.* [27] developed the Artificial Neural Network (ANN) and Analog Ensemble (AnEn) method to predict PV power. The test results showed that the combination of AnEn+ANN gave the best results and was computationally efficient when applied to parallel computing. However, this approach requires a historical dataset that matches the analog model because the model is compiled only once in this approach.

In this paper, experiments were carried out by applying ensemble models to the CNN and LSTM methods which of course have a different perspective from that carried out in [26]. The CNN LSTM ensemble model is more flexible and accurate because it combines multiple models and can be used on varying data. The novelty of this research is the development of a model combining several forecasting algorithms through the use of ensemble models on CNN and LSTM algorithms. The research gaps come from [27] which has limitations in decreasing accuracy when using varying data. Through this proposed ensemble model, the experimental results prove that the CNN and LSTM ensemble models have higher accuracy compared to other algorithms.

III. Methods

Smart Micro Grid (SMG) consists of renewable solar energy sources and IoT platforms for remote monitoring [28, 29]. The operation and function of solar PV systems can be affected by various factors, such as environment, temperature, irradiation and others so that its accuracy and performance can be improved by using a solar PV monitoring system. The architecture of the PV monitoring system can be divided into 5 parts, including data acquisition, data processing, visualization, application and data storage. The data acquisition section is used to collect various data from various sensors, such as voltage, current, temperature, humidity, radiation, and others. The data obtained is then sent to the data processing section via data communication media, Wi-Fi. Furthermore, the data will be stored on a device such as a data logger, then analyzed and sent to the data visualization section. The proposed IoT-based PV performance monitoring system can be shown in Fig. 1.

The solar power forecasting on SMG is carried out in several stages as shown in Fig. 2, including the stages of data monitoring, data analytics, forecasting, optimization. The applications developed consist of prediction and forecasting of electric power generation. This PV performance monitoring system plays an important role in improving network stability and availability. The use of PV as an energy generator depends on the solar radiation received by the solar panels. In addition, it also depends on the ambient temperature and weather conditions and the geographical location of the PV panels. For this reason, the modeling of the forecasting process refers to weather conditions which then become weather parameters in the form of time series data.

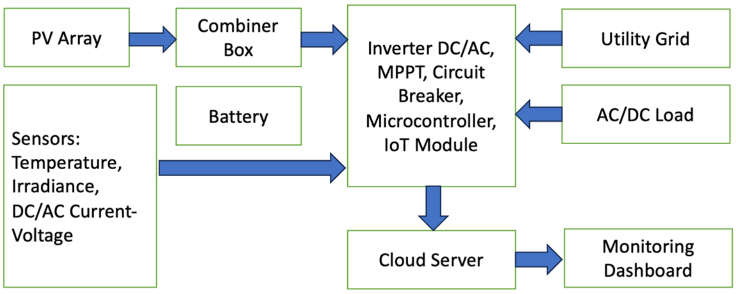


Fig. 1. PV smart micro grid performance monitoring system.

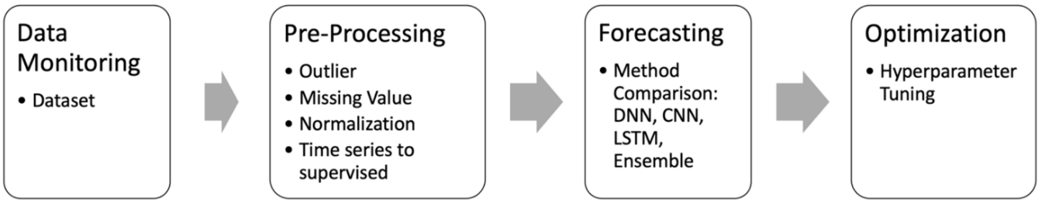


Fig. 2. Solar power forecasting stages.

The deep learning model was developed using Neural Network (NN) through modification of LSTM architecture as a Learning model to provide future accurate prediction in PV generation. The prediction problem can be formulated as follows: historical weather time series data in the form ($x_1, x_2, ..., x_n$), where n is the number of weather parameters. To predict the solar PV power in the day-ahead category, the initial step is to determine the mapping function between historical weather data and solar PV power prediction, namely:

$$\hat{S} = f(n_1, n_2, \dots, n)$$

The Machine Learning (ML) used in this study is NN with modifications to the LSTM network to improve prediction accuracy. The NN architecture has an input layer, a hidden layer, and an output layer. The basic architecture of NN is then changed into a DNN architecture with LSTM memory developed from the basic architecture of a Recurrent Neural Network (RNN). Several hidden layers, including LSTM memory units, are added to this architecture. RNN uses temporal information as input data and can create recurrent connections between neurons.

LSTM has memory cells in its neurons that have the ability to store information. Information entering and leaving the neuron memory cells is controlled by three gates, namely the input gate, the output gate, and the forget gate. Each of these gates receives the same input from the input neuron and also has an activation function. The activation function used in this forecasting process can be the tanh activation function and the Rectified Linear Unit (ReLU) activation function. Fig. 3 shows the basic LSTM network in NN with univariate data. The LSTM network is used as a prediction model in RNN, which can learn long-term dependencies between data so that it can connect past information with the present.

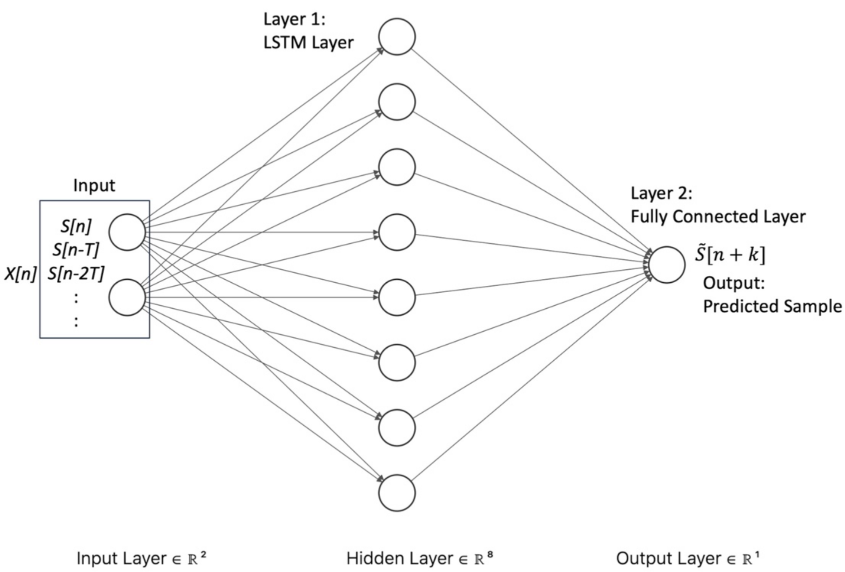


Fig. 3. Basic architecture of Long Short Term Memory (LSTM) in Neural Network (NN) with univariate data.

$S = \{S[n]\}, n > 0$, represents the sample in the form of a time series to be predicted. n, represents the current sample and the previous time. Thus, $S[n+K]$, $K > 0$ represents the sample to be predicted. Furthermore, $\tilde{S}[n+K]$ represents the result obtained from the parameter S. The input vector $x[n]$ containing the previous data sample in the time series can be expressed in Eq. (1) and the predicted result $\tilde{S}[n+K]$ is expressed in Eq. (2). f_m contains the parameters used in the learning process while $\mathfrak{T}_{n-1}$ is associated with the internal conditions of the RNN architecture, namely the LSTM layer as the hidden layer [25].

$$x[n] = \left[S[n], S[n-T], \ldots . S[n-(D-1)T]\right]^t \quad (1)$$

$$\tilde{S}[n+K] = f_u(x[n];\, \mathfrak{T}_{n-1}) \quad (2)$$

$$\tilde{S}_{m=1:M}[n+K] = f_m(x^m[n];\, \mathfrak{T}_{n-1}) \quad (3)$$

The forecasting model in this study will use multivariate time series data that can provide broader generalization capabilities compared to univariate. So that the time series model on the sample used becomes $S_m = \{S_m[n]\}$, $q = 1, 2, \ldots, M$, where M represents the number of time series samples specified and m represents the input parameters currently used. If the time series sample has $M = 2$ then the two time series samples are $S_1[n]$ and $S_2[n]$. Next, set the number of previous D samples used in each time series for the next prediction process. The input sequence is encapsulated using the embedding technique on all-time series that will be used for the multivariate prediction process as shown in Fig. 4 shows the time series input data on the basic LSTM network in the NN architecture. Then Eqs. (4)–(6) shows time series input sequence in multivariate data.

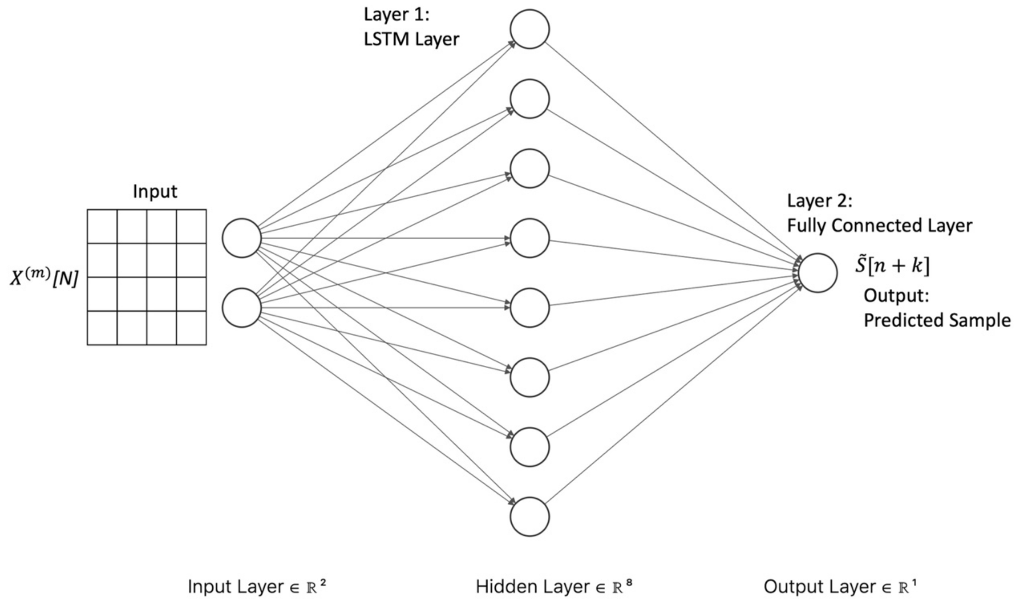


Fig. 4. Time series input data on the basic LSTM network in the NN architecture.

The prediction result formula $\tilde{S}[n+K]$ in the multivariate model is stated in Eq. (3).

$$x_1^{(c)}[n] = \left[S_1[n], S_1[n-T], \ldots . S_1[n-D-1]\right], \quad (4)$$

$$x_2^{(c)}[n] = \left[S_2[n], S_2[n-T], \ldots . S_2[n-D-1]\right], \quad (5)$$

$$x_M^{(c)}[n] = \left[S_M[n], S_M[n-T], \ldots . S_M[n-D-1]\right], \quad (6)$$

Furthermore, the prediction result formula $\tilde{S}[n+K]$ in the multivariate model from Fig. 4 is stated in Eq. (7).

$$\tilde{S}_1[n+K] = f_c\left(x_1^{(c)}[n], x_2^{(c)}[n], \ldots, x_M^{(c)}[n];\, \mathfrak{T}_{n-1}\right) \quad (7)$$

Optimization of hyperparameter settings is most appropriately done on this architecture. Some of the parameters that will be optimized include batch size, lookback, learning rate, encoder number, decoder number, encoder activation function, and decoder activation function. The learning process uses the ensemble model to provide more accurate estimation results. Fig. 5 is the ensemble structure used in this study.

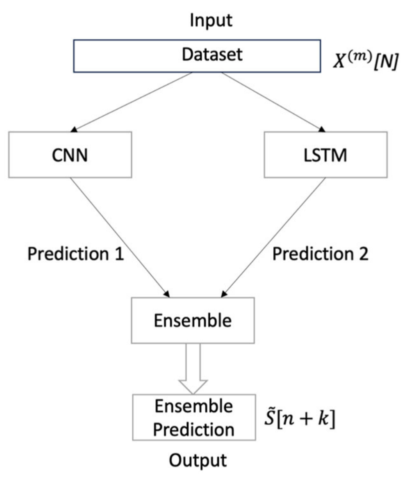


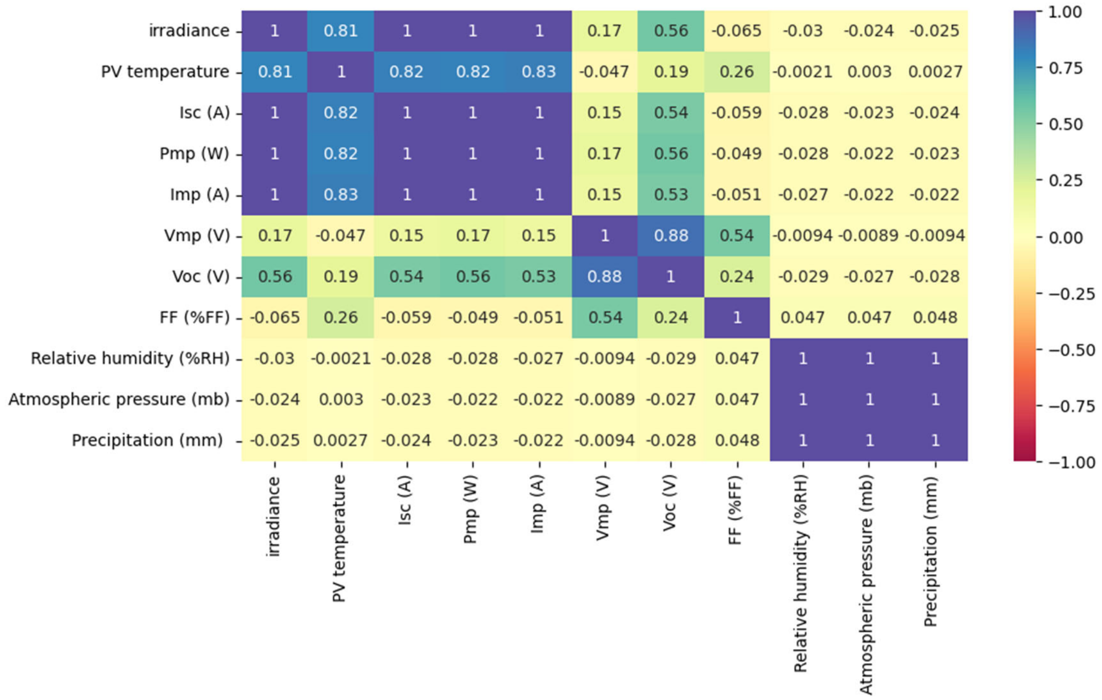
Fig. 5. Ensemble structure in CNN and LSTM architectures.

The CNN-LSTM ensemble method is chosen as the primary approach for solar PV power forecasting in smart micro grids compared to other models including attention mechanism-based models such as Transformer or Attention-LSTM [30]. The combination of these two methods in the CNN-LSTM ensemble allows the model to handle complex patterns in solar energy data that have high fluctuations and non-linear properties. Furthermore, CNN and LSTM have lower complexity compared to Transformer or Attention-based models that require more data for good generalization.

To evaluate the performance of the proposed algorithm, we conducted several experimental simulations to predict future solar power generation. The ML algorithm is implemented using Keras API for Python with the framework used, namely TensorFlow. This study uses two evaluation measurements to compare the prediction accuracy of the algorithms used, namely Mean Absolute Average (MAE), Mean Square Error (MSE) and Root Mean Square Error (RMSE). The measurement of the algorithm's performance accuracy is carried out through the following scenarios: Initial experiments use public datasets to measure the performance evaluation of the proposed algorithm. This public dataset consists of voltage-current (V-I) curve data and environmental meteorological data for PV modules. The measurement of prediction accuracy is carried out by comparing several learning algorithms used.

IV. Experimental and Results

The PV system on the smart micro grid uses a capacity of 1000 wp, consisting of 10 solar panel modules, each with a capacity of 100 wp. The 2000W/24 VDC grid tie inverter device as a DC to AC power converter from the solar panel which will be used to serve the electricity supply for the load in on grid mode. The 2000W/24 VDC off grid inverter device as a DC to AC power converter from the battery to be used to supply electricity to the load in off grid mode. Furthermore, the 100A/48 VDC MPPT solar charger controller is used as a solar charge controller on the battery [28, 29]. Initial experiments used a public dataset to measure the performance evaluation of the proposed algorithm [31]. This public dataset consists of several measured parameters and in this study 11 parameters were taken to analyze the correlation as shown in Fig. 6.



	irradiance	PV temperature	Isc (A)	Pmp (W)	Imp (A)	Vmp (V)	Voc (V)	FF (%FF)	Relative humidity (%RH)	Atmospheric pressure (mb)	Precipitation (mm)
irradiance	1	0.81	1	1	1	0.17	0.56	-0.065	-0.03	-0.024	-0.025
PV temperature	0.81	1	0.82	0.82	0.83	-0.047	0.19	0.26	-0.0021	0.003	0.0027
Isc (A)	1	0.82	1	1	1	0.15	0.54	-0.059	-0.028	-0.023	-0.024
Pmp (W)	1	0.82	1	1	1	0.17	0.56	-0.049	-0.028	-0.022	-0.023
Imp (A)	1	0.83	1	1	1	0.15	0.53	-0.051	-0.027	-0.022	-0.022
Vmp (V)	0.17	-0.047	0.15	0.17	0.15	1	0.88	0.54	-0.0094	-0.0089	-0.0094
Voc (V)	0.56	0.19	0.54	0.56	0.53	0.88	1	0.24	-0.029	-0.027	-0.028
FF (%FF)	-0.065	0.26	-0.059	-0.049	-0.051	0.54	0.24	1	0.047	0.047	0.048
Relative humidity (%RH)	-0.03	-0.0021	-0.028	-0.028	-0.027	-0.0094	-0.029	0.047	1	1	1
Atmospheric pressure (mb)	-0.024	0.003	-0.023	-0.022	-0.022	-0.0089	-0.027	0.047	1	1	1
Precipitation (mm)	-0.025	0.0027	-0.024	-0.023	-0.022	-0.0094	-0.028	0.048	1	1	1

Fig. 6. Data correlation between the Pmp (W) parameter and other parameters.

The Pmp (W) parameter has a high correlation with the irradiance, PV temperature, Isc (A), and Imp (A) parameters, namely 1, 0.82, 1, 1, 1. If the values of the parameters increase, the value of the Pmp (W) parameter will also increase. Therefore, these parameters will be used in the forecasting process. In addition, the Pmp (W) parameter has a negative correlation with the FF (%FF), Relative Humidity (%RH), Atmospheric pressure (mb), and Precipitation (mm) parameters, namely −0.049, −0.028, −0.022, −0.023. This negative correlation results in the value of the Pmp (W) parameter having no relationship with changes in the values of these parameters. This public dataset consists of current-voltage (V-I) curve data: Maximum power, maximum current, and maximum voltage, and environmental meteorological data for PV modules: irradiance, and PV temperature, as shown in Fig. 7.

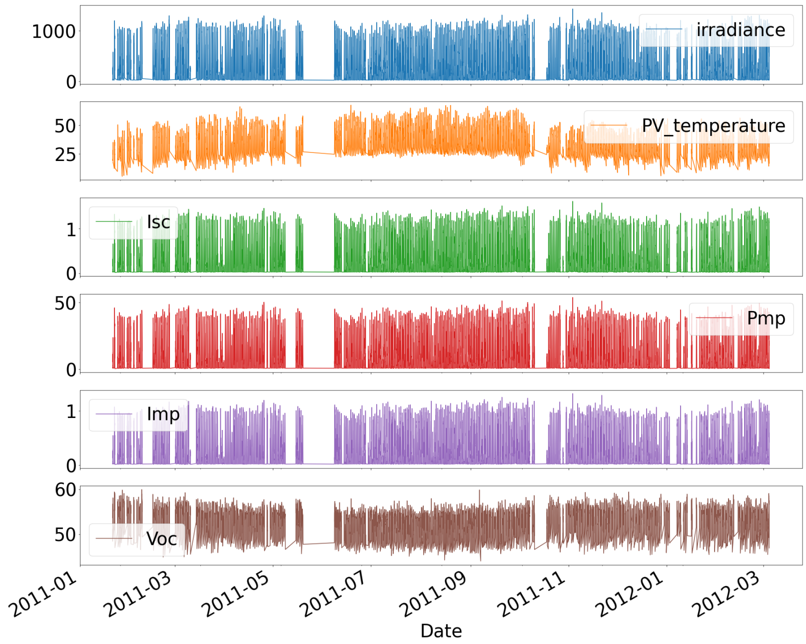


Fig. 7. Time series data: irradiance, PV temperature, maximum power, maximum current and maximum voltage.

The preparation of research data was carried out by identifying the emergence of abnormal values in the form of missing values and outlier values that can impact increasing error values in forecasting. Based on Fig. 8, which is a boxplot visualization, the results of the check show that no missing values were found, and there were outlier values in the Voc (V) data. To handle the presence of outliers, deletions were carried out on the data rows that were detected as outliers.

Outlier treatment on the Voc (V) variable is done using the IQR method—Replace the data points with the lower whisker (Q1 − 1.5 × IQR) or upper whisker (Q3 + 1.5 × IQR) value. The results of this process can be seen in the following Fig. 9. It can be seen that there are no outliers in the Voc (V) variable.

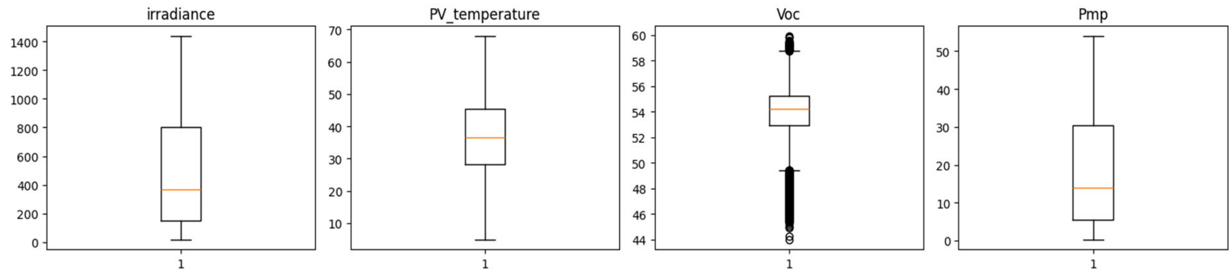


Fig. 8. Data distribution of each parameter and the emergence of outliers in Voc (V).

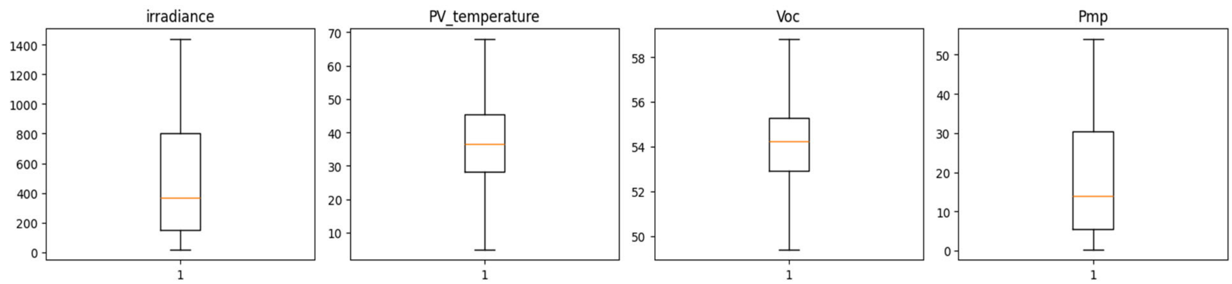


Fig. 9. Outlier treatment on the Voc (V) variable.

Resampling time series data for forecasting involves adjusting the data frequency to suit the forecasting model's requirements. Adjusting the frequency of the data from 10 minutes to daily by using the results of the average of the data per day. Cross validation for time series forecasting, which is inherently sequential, with past values influencing future values. Time series cross validation aims to ensure temporal order, where future data is used to predict past or current values. In this step, cross validation uses a sliding window technique. Data in each window will be tested in the next window.

TABLE I. SUMMARY OF MSE, MAE AND RMSE PERFORMANCE METRICS OF ALL FORECASTING MODELS

Model	Input	MSE	MAE	RMSE
Deep Neural Network (DNN)	S1, S2	0.1045	0.0189	0.3233
	S1, S3	0.1035	0.0178	0.3214
	S2, S3	0.1064	0.0201	0.3261
	S1, S2, S3	0.1008	0.0185	0.3175
Convolutional Neural Network (CNN)	S1, S2	0.1264	0.0265	0.3557
	S1, S3	0.1308	0.0283	0.3616
	S2, S3	0.1314	0.2928	0.3626
	S1, S2, S3	0.1255	0.0264	0.3544
Long Short Term Memory (LSTM)	S1, S2	0.1058	0.0192	0.3253
	S1, S3	0.0957	0.0158	0.3094
	S2, S3	0.1019	0.0175	0.3192
	S1, S2, S3	0.1073	0.0190	0.3276
Ensemble	S1, S2	0.1330	0.0296	0.3648
	S1, S3	0.0934	0.0169	0.3057
	S2, S3	0.1359	0.0311	0.3687
	S1, S2, S3	0.0951	0.1713	0.3084

Based on the experimental results and performance measurements of several forecasting models, including DNN, CNN, LSTM, and the proposed algorithm using scenarios of three different input data combinations (S1, S2, S3). Variations in input data will show the sensitivity of the model to the type of input data used. These inputs or features represent irradiance (S1), PV temperature (S2), and Voc (S3) then Pmp represent output or target.

A summary of the performance metrics MSE, MAE and RMSE of all forecasting models is shown in Table I. DNN performance is quite stable with MSE values ranging from 0.1008 – 0.1064. The MAE values (0.0178 – 0.0201) and RMSE (0.3175 – 0.3261) indicate that this model has a fairly small error. The combination of S1, S3 gives the best performance with MSE = 0.1035 and RMSE = 0.3214, while the combination of S2, S3 gives the worst results (MSE = 0.1064). CNN showed the worst performance compared to other models, with the highest MSE (0.1255 – 0.1314). MAE in the combination of S2, S3 is very high (0.2928). The combination of S1, S2 gave slightly better results (MSE = 0.1264, RMSE = 0.3557) than other combinations. LSTM is the best performing model, especially with the combination of S1, S3 which gives the lowest MSE (0.0957), the lowest MAE (0.0158), and the lowest RMSE (0.3094). The combination of S2, S3 is also quite good compared to other models, but still worse than the combination of S1, S3. Therefore, it can be concluded, ensemble model has very good performance overall, especially excelling on the combinations of {S2, S3} and {S1, S2, S3}. Ensemble model can be the best solution for PV energy production forecasting, provided that the right combination of inputs.

Based on Fig. 10, the DNN performance analysis shows that the MSE, MAE, and RMSE for training continue to decline steadily, indicating that the model is able to learn well but there is overfitting. In addition, the validation MAE and RMSE tend to stagnate. Fig. 11 shows the performance analysis of the CNN model. The MSE, MAE, and RMSE for training experience a stable decline. The validation error tends to be more volatile than DNN, especially in MAE and RMS. After about 50 epochs, the validation error did not experience significant improvement, indicating the possibility of the model experiencing underfitting. Furthermore, in Fig. 12, the LSTM performance analysis shows a more stable learning pattern than CNN and DNN. The MSE, MAE, and RMSE experience a faster and more stable decline in both training and validation. However, there is a slight increase in validation error at the end of training, possibly requiring early stopping. Fig. 13 shows the performance analysis of the ensemble model. The ensemble model has a faster error decline than other individual models. Validation error decreases faster than other models, indicating that the combination of CNN and LSTM helps improve prediction accuracy. Training and validation errors are more balanced than other models, indicating better generalization ability. MSE, MAE, and RMSE stabilize after about 40 epochs, indicating the model converges faster than other models that require more than 100 epochs.

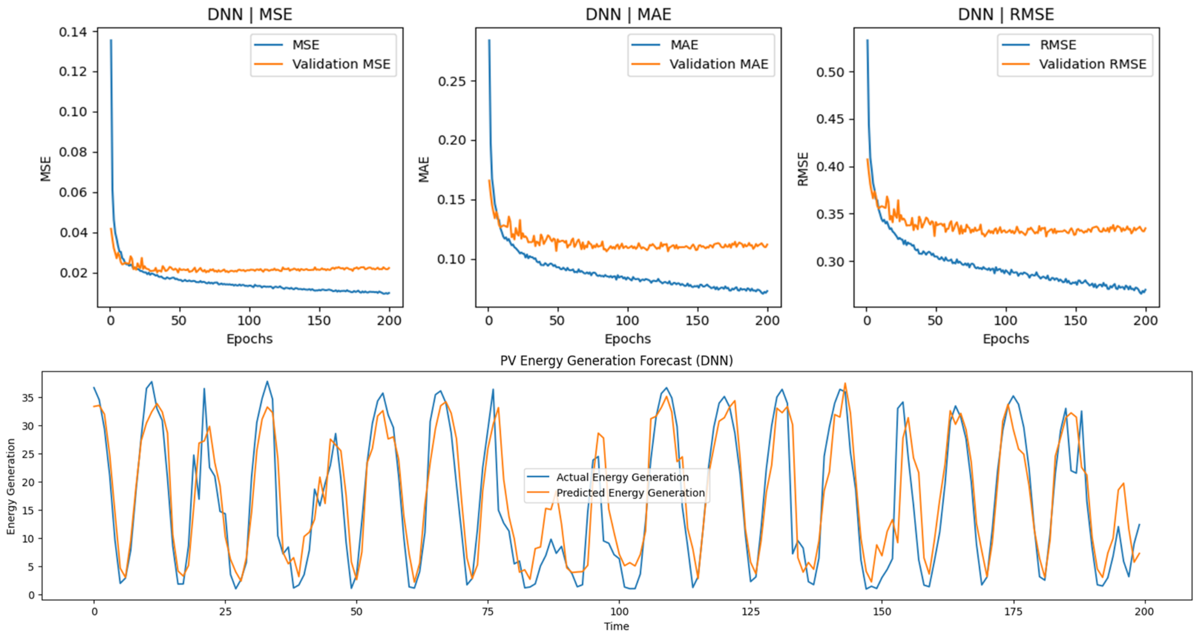


Fig. 10. Error values of DNN model {S1, S2, S3} and result of PV energy generation forecast (DNN).

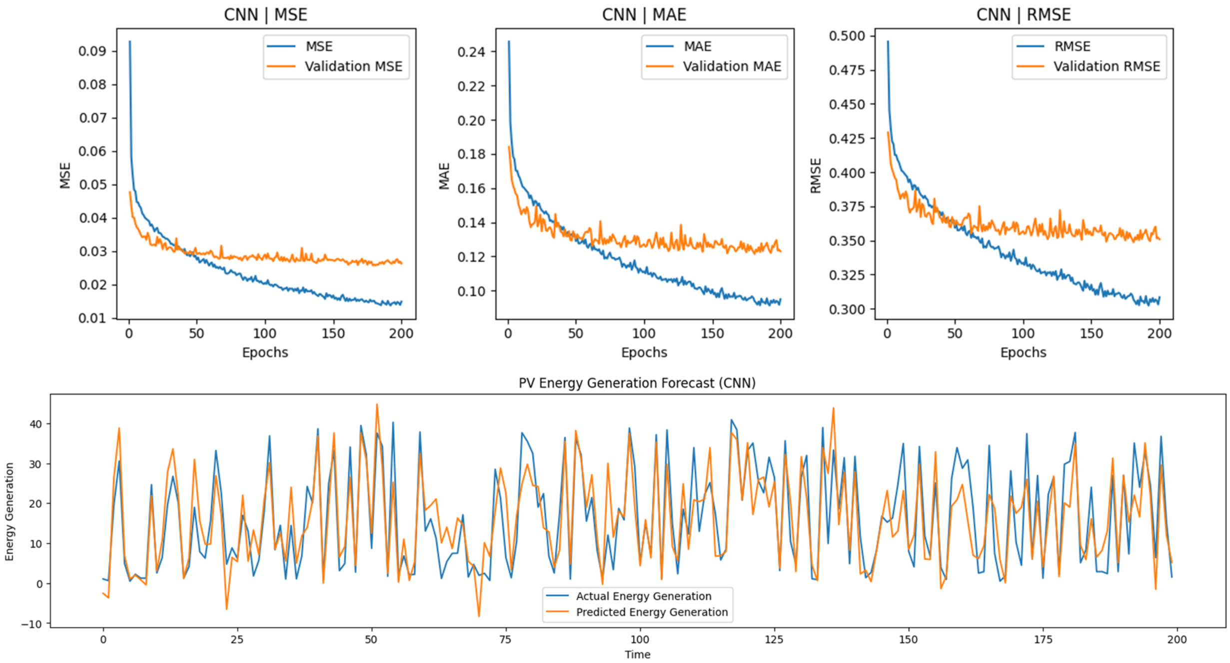


Fig. 11. Error values of CNN model {S1, S2, S3} and result of PV energy generation forecast (CNN).

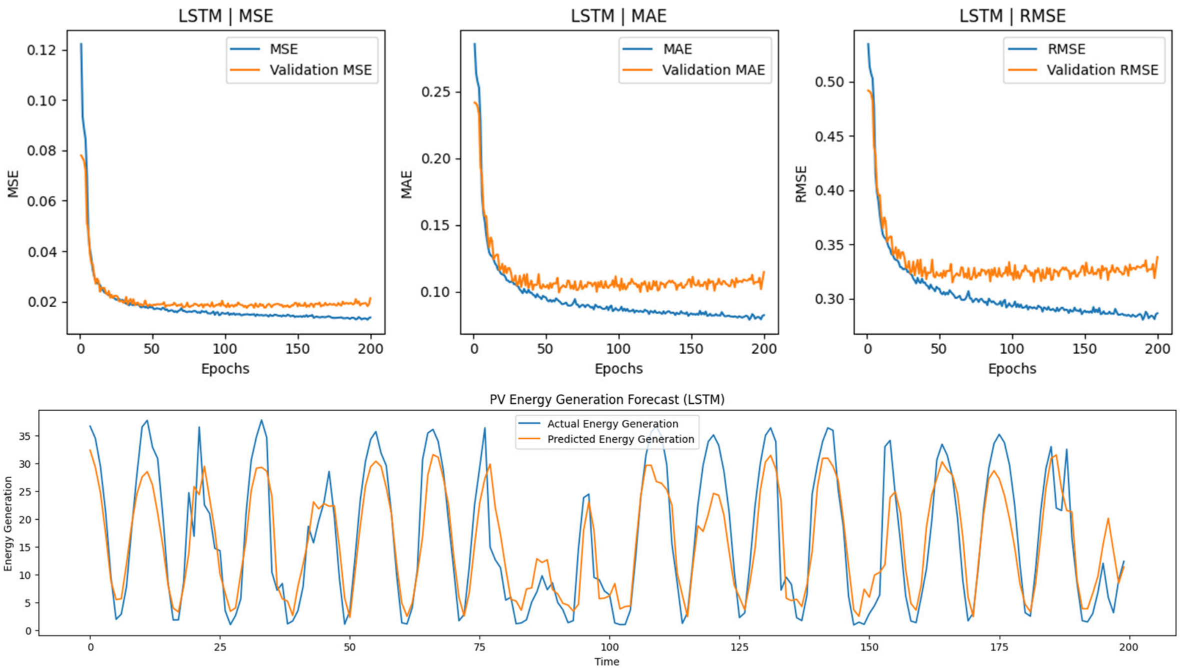
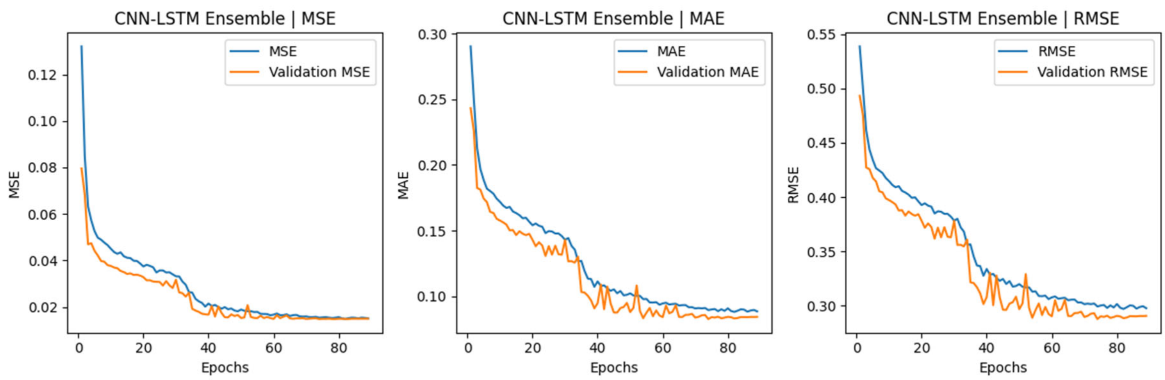


Fig. 12. Error values of LSTM model {S1, S2, S3} and result of PV energy generation forecast (LSTM).



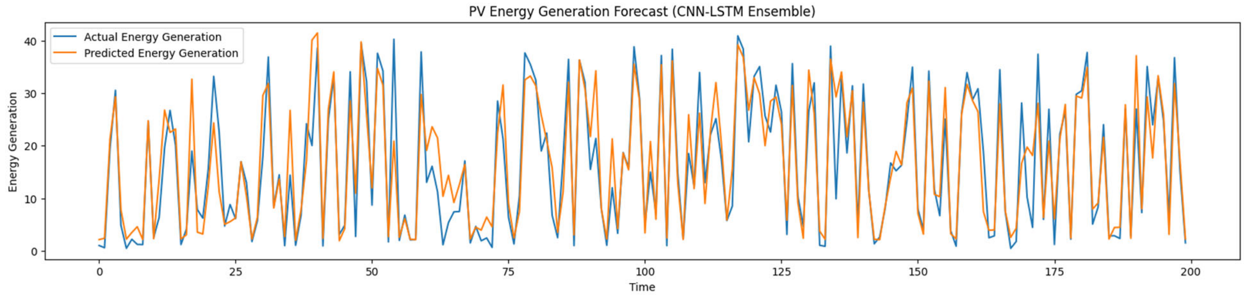


Fig. 13. Error values of CNN-LSTM ensemble model {S1, S2, S3} and result of PV energy generation forecast (CNN-LSTM ensemble).

V. Conclusion

This study developed an ensemble model using the CNN and LSTM architecture to provide Future Accurate Prediction on electricity usage and renewable energy generation. Experimental results show that the CNN-LSTM ensemble model has the best performance in predicting PV energy production, with the lowest MSE, MAE, and RMSE and the fastest convergence compared to other models. LSTM also shows good results, able to capture temporal patterns with better generalization than DNN and CNN. DNN is quite stable but suffers from overfitting, while CNN suffers from underfitting and is not suitable for time-series forecasting. The combination of S1, S3 inputs produces the best performance, especially in LSTM and ensemble Model. However, this paper only tested using one dataset so the model performance results are not yet generalizable. This paper will be further improved through testing with more varied datasets, using real-world datasets from various geographic conditions, because weather variability can affect model performance. hyperparameter tuning and additional hybrid techniques such as attention mechanism can be applied for further improvement.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

NI contributed to conducting experiments and testing and writing the article; PP contributed to supervising and validating the substance design of the article; HS contributed to checking and validating the results of the experiments, checking the writing; all authors had approved the final version.

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