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A Comparison of Machine Learning and Deep Learning Methods for Temperatures Predictions on Java Island

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Abstract

Climate change is a global long-term change in temperatures and weather. Climate change is a worldwide issue that requires proper handling to reduce the negative impact on humans and the environment. Analyzing historical data is beneficial for studying climate change. Machine learning and deep learning methods are useful tools for data analysis. The goal of this paper is to find the best model for forecasting temperatures, a case study in Java Island. Java Island is the most densely island and the central economy and business in Indonesia. Climate change research in Java Island is important for sustainability. It runs several algorithms i.e., Gradient Boosting, AdaBoost, XGBoost, CatBoost, Light GBM, Random Forest, Support Vector Regression, Extreme Learning Machine, Long Short-Term Memory, Gated Recurrent Unit, Bidirectional Long Short-Term Memory, and Bidirectional Gated Recurrent Unit. The experiment uses a historical daily time series of temperatures from 1 January 1990 to 31 December 2024. In general, the experimental results show that Gradient Boosting produces the highest average coefficient of determination R^2 scores of 0.34 and the lowest Mean Absolute Error scores of 0.69. Long Short-Term Memory and Gated Recurrent Units are the deep learning models that also work well for forecasting. According to the experimental results, in some cases, machine learning models outperform deep learning models and vice versa.

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INTRODUCTION (CALISTO MT 10)

Climate change is a global long-term change in temperatures and weather (Santos & Bakhshoodeh, 2021; Abbass et al., 2022). Global warming and climate emergency are used as synonyms for climate change. Climate change affects humans and the environment, so it is one of the global problems that needs proper handling. Some of the effects of climate change are extreme weather, drought, flood, food, disease, and food security. A study found that the cost of extreme events caused by climate change is around US$143 billion per year (Newman & Noy, 2023). A study that applies a combination of projections of climate change models shows that increasing 3°C causes global average losses by 10% of global domestic product, especially in poorer and low-latitude countries (Waidelich et al., 2024).

In Indonesia, some research has been conducted on climate change studies. Recent studies have been analysing meteorological data from some regions in Indonesia and found that increasing temperatures and decreasing wind speeds are happening in some places (Handhayani, 2023; Handhayani & Rusdi, 2023; Andrian et al., 2024; Handhayani & Lewenusa, 2024). A study implementing K-Means Using Dynamic Time Warping to cluster cities in Java Island shows that some cities, Surabaya, Semarang, Jakarta, Bandung, Yogyakarta, and Serang, have increasing temperatures (Handhayani & Rusdi, 2023). An analysis of meteorological data in the East Indonesia region, implementing clustering methods to cluster cities based on daily time series meteorological data histories (Andrian et al., 2024). Several cities in Sumatra have an annual trend of increasing temperatures and decreasing wind speed (Handhayani & Lewenusa, 2024).

Machine learning and deep learning methods are powerful tools for climate change analysis (Milojevic-Dupont & Creutzig, 2021; Bamal et al., 2024; Ladi et al., 2022; Alonso-Robisco et al., 2024). Machine learning is a part of artificial intelligence that empowers computers and machines to learn like humans, and it can improve its performance through experience with more data. Deep learning is a branch of machine learning that utilizes multilayered neural networks to simulate the human brain's decision-making process. Machine learning and deep learning methods are applicable to supervised learning, unsupervised learning, and semi-supervised learning. Some machine learning methods for regression are Support Vector Regression (SVR) (Bansal et al., 2021), Random Forest Regression (Doz et al., 2023; Gaertner, 2024), Adaboost, XGBoost (Wen et al., 2022), Gradient Boosting (Di Persio & Fraccarolo, 2023), and Linear Regression (Yuan, 2023). Deep Learning methods for regression are Long-Short Term Memory (LSTM), Bidirectional Long-Short Term Memory (BiLSTM), Gated Recurrent Unit (GRU) (He et al., 2022), and Bidirectional Gated Recurrent Unit (BiGRU) (Chen et al., 2021).

Java Island is part of Indonesia's territory and is the most densely populated. Some cities on Java Island developed into central districts for education, economy, and industry. In the agricultural sector, Java Island is central to paddy production, which is the primary food source for Indonesians (Ishak et al., 2024). Analyzing temperatures on Java Island is crucial for understanding climate change in this region. Deep Learning is a sophisticated model for supervised learning jobs. The research question is whether deep learning models completely outperform conventional machine learning models for forecasting temperatures from time series data. The goal of this paper is to analyze the performance of machine learning and deep learning methods for forecasting temperatures in Java Island. It is beneficial to identify the most suitable model for temperature prediction. This paper uses historical time series temperature data from 14 cities on Java Island.

RESEARCH METHODS

The research workflow is described in Figure 1. It contains data collection, data preprocessing, model training, and model evaluation. The data is the historical daily time series temperatures collected from trustworthy sources. It collects data from several places in Java Island. The preprocessing step contains feature selection and missing values handling. It uses minimum, maximum, and average temperatures for experiments. Missing values handling is a step in examining the missing data and filling it up to create the completed data. It implements the forward and backward functions from standard Python to fill up the missing data. The output from this step is completed data. The data is then divided into the training sets and the testing sets. The training sets are used to train the models. It runs machine learning algorithms (Gradient Boosting (GB), Ada Boost, XG Boost, Cat Boost, Light GBM, Random Forest, Support Vector Regression, and Extreme Learning Machine) and deep learning algorithms (Long Short-Term Memory, Gated Recurrent Unit, Bidirectional Long Short-Term Memory, and Bidirectional Gated Recurrent Unit). The trained model is evaluated using testing sets. The performance of those algorithms is measured using Mean Absolute Error, Root Mean Squared Error, Mean Absolute Percentage Error, and Coefficient of Determination.

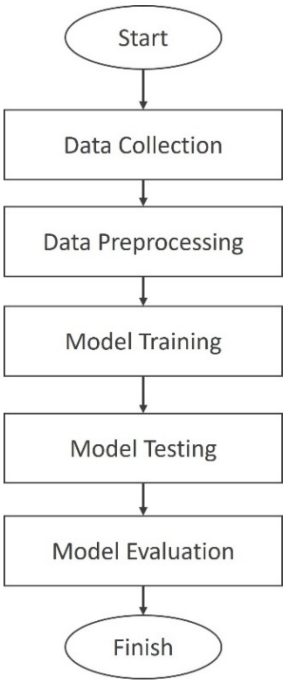

Figure 1. Research workflow

Some machine learning methods for forecasting are Gradient Boosting (GB), Ada Boost, XG Boost, Cat Boost, Random Forest, Support Vector Regression, and Extreme Machine Learning (ELM). Deep learning methods for forecasting are Long Short-Term Memory (LSTM), Bidirectional Long Short-Term Memory (BiLSTM), Gated Recurrent Unit (GRU), and Bidirectional Gated Recurrent Unit (BiGRU).

Gradient Boosting (GB) regression is a gradient-based boosting algorithm designed for regression problems (Mahamat et al., 2024). Let M be an ensemble of weak learners and let weak learners be $h_m(x)$ on (X, r). The Gradient Boosting regressor can be defined using equations (1), (2), and (3) (Mahamat et al., 2024).

$$r_i = y_i - \hat{y}_{i-1} \quad (1)$$

Update ensemble

$$\hat{y}_i = \hat{y}_{i-1} + \alpha * h_m(x_i) \quad (2)$$

$$\text{Prediction } \hat{y} = \sum[\alpha_m * h_m(X)] \quad (3)$$

Extreme gradient boosting (XGBoost) implements gradient boosting machines (gbm) for supervised learning problems (Ibrahem Ahmed Osman et al., 2021). The decision tree is the basis for AdaBoost and Random Forest. Adaptive Boosting (AdaBoost) runs recursively training-based models on different versions of data (Özen, 2024). For every iteration, AdaBoost updates the weights of the training data based on the error rate from the lower-level model. A machine learning approach that increases the accuracy and robustness of prediction by combining the outputs of many models is called ensemble learning (Özen, 2024). Random forest is a particular type of ensemble learning algorithm. Random Forest Regression implements many decision trees trained on a random subset of data (Özen, 2024; Sopany et al., 2025). CatBoost is developed from the Gradient Boosting algorithm (Hancock & Khoshgoftaar, 2020). It started with Bootstrap sampling. Different training datasets are formed by rows of data that are selected with replacement. Light Gradient Boosting Machine (Light GBM) is another version of the Gradient Boosted Decision Tree algorithm (Hancock & Khoshgoftaar, 2020).

Support Vector Regression (SVR) is a variant of the Support Vector Machine (SVM) algorithm that works for regression problems (Handhayani et al., 2024; Purba et al., 2025). Several kernel functions, i.e., Linear kernel, RBF kernel, and Polynomial kernel.

A neural network is an algorithm developed to imitate the structure of biological neural networks in the nerve system of the human brain. A neural network is a foundation for some algorithms, e.g., extreme learning machines, long short-term memory, and gated recurrent units. A neural network consists of neurons, connections, and weights. An extreme learning machine (ELM) is a neural network algorithm that implements a single hidden-layer feedforward neural network (Wang et al., 2022). ELM sets random values to the weights between the input and hidden layers, as well as the biases in the hidden layer. It uses a nonlinear activation function in the hidden layer.

Long Short-Term Memory (LSTM) is an efficient gradient-based method (Handhayani, 2023). LSTM refers to a standard recurrent neural network (RNN) that has long-term memory and short-term memory. Bidirectional Long Short-Term Memory (BiLSTM) is a neural network that contains two LSTM layers. BiLSTM connects two hidden layers that are opposite into a single output. BiLSTM utilizes pre- and postcontext by processing the information from two directions using two separate hidden layers.

A gated recurrent unit (GRU) is a type of neural network that implements a gating mechanism (Handhayani, 2023). A Bidirectional Gated Recurrent Unit (BiGRU) contains two GRUs that handle the input in a forward direction, and the other in a backward direction (Duan et al., 2023).

Coefficient of determination, mean absolute error (MAE), and root mean square error (RMSE) are used to evaluate the performance of the regressor (Handhayani, 2023; Handhayani et al., 2022; Chicco et al., 2021). The best value of R^2 is $+1$, and the worst value is $-\infty$. MAE and RMSE have the best value are 0 and the worst value is $+\infty$.

RESULTS AND DISCUSSION

The dataset is historical time series data from 1 January 1990 to 31 December 2024. The dataset is collected from the Indonesian Meteorology, Climatology, and Geophysics Agency. The dataset contains minimum temperatures, maximum temperatures, and average temperatures in degrees Celsius. The data is collected from 14 cities across Java Island and its surrounding areas, including Bandung, Banyuwangi, Malang, Bogor, Cilacap, Gresik, Jakarta, Majalengka, Nganjuk, Semarang, Sumenep, Tangerang, Tangerang Selatan, and Tegal. The dataset is divided into a training set and a testing set. The training set contains data from 1 January 1990 to 31 December 2023, and the testing set consists of data from 1 January 2024 to 31 December 2024.

Different models work differently for each dataset from each city. Figures 2, 3, and 4 illustrate the forecasting results using the best model. Note that the best model for each variable in each city is different. For minimum temperature predictions, Gradient Boosting (GB) performs the best for Bandung, Gresik, Jakarta, Majalengka, and Nganjuk. ELM works well for Banyuwangi, Malang, Semarang, Sumenep, and Tangerang. GRU and BiGRU have the best performance for Bogor and Cilacap, respectively. The deep learning models (LSTM, GRU, and BiGRU) are powerful when predicting the maximum temperatures. Light GBM is suitable for forecasting minimum, maximum, and average temperatures in Tangerang Selatan.

Table 1. The Average Values of Evaluation Metrics for Each Algorithm

No	Algorithm	MAE	RMSE	R^2	Running Time
1	SVR Linear	0.79	0.98	0.13	0.54
2	SVR RBF	0.82	1.03	0.06	0.76
3	Gradient Boosting	0.69	0.89	0.34	6.30
4	XG Boost	0.75	0.97	0.22	0.20
5	Ada Boost	0.83	1.03	0.10	1.01
6	Cat Boost	0.92	1.11	-0.06	2.74
7	Light GBM	0.70	0.90	0.33	0.16
8	Random Forest	0.80	0.99	0.17	1.50
9	ELM	0.87	1.05	-0.04	0.02
10	LSTM	0.75	0.95	0.22	24.07
11	BiLSTM	0.83	1.03	0.06	21.07
12	GRU	0.75	0.95	0.22	22.97
13	BiGRU	0.79	0.98	0.14	19.78

Table 2. The Best Models for Each City for Predicting the Minimum Temperatures

No	City	MAE	RMSE	R^2	Algorithm
1	Bandung	0.59	0.78	0.52	Gradient Boosting
2	Banyuwangi	0.67	0.83	0.35	Light GBM
3	Bogor	0.67	0.88	0.28	BiGRU
4	Cilacap	0.59	0.77	0.52	GRU
5	Gresik	0.79	1.00	0.36	Gradient Boosting
6	Jakarta	0.79	0.94	0.16	Gradient Boosting
7	Majalengka	0.73	1.00	0.20	Gradient Boosting
8	Malang	0.65	0.68	0.83	ELM
9	Nganjuk	0.67	0.87	0.30	Gradient Boosting
10	Semarang	0.69	0.87	0.41	Light GBM
11	Sumenep	0.74	0.93	0.88	Gradient Boosting
12	Tangerang	0.50	0.63	0.60	ELM
13	Tangerang Selatan	0.69	0.88	0.22	Light GBM
14	Tegal	0.61	0.55	0.51	SVR Linear

Table 3. The Best Models for Each City for Predicting the Maximum Temperatures

No	City	MAE	RMSE	R^2	Algorithm
1	Bandung	0.58	0.78	0.52	LSTM
2	Banyuwangi	0.59	0.76	0.45	GRU
3	Bogor	0.66	0.88	0.29	LSTM
4	Cilacap	0.63	0.79	0.49	GRU
5	Gresik	0.75	0.93	0.41	GRU
6	Jakarta	0.79	0.94	0.16	Gradient Boosting
7	Majalengka	0.71	0.97	0.26	LSTM
8	Malang	0.76	0.99	0.58	LSTM
9	Nganjuk	0.67	0.87	0.30	Gradient Boosting
10	Semarang	0.67	0.72	0.44	GRU
11	Sumenep	0.75	0.93	0.18	BiGRU
12	Tangerang	0.65	0.84	0.30	LSTM
13	Tangerang Selatan	0.69	0.88	0.22	Light GBM
14	Tegal	0.61	0.75	0.51	SVR Linear

Table 4. The best Models for Each City for Predicting the Average Temperatures

No	City	MAE	RMSE	R^2	Algorithm
1	Bandung	0.59	0.79	0.52	Gradient Boosting
2	Banyuwangi	0.61	0.77	0.44	GRU
3	Bogor	0.66	0.87	0.29	GRU
4	Cilacap	0.62	0.79	0.49	GRU
5	Gresik	0.77	0.97	0.39	LSTM
6	Jakarta	0.78	0.94	0.16	Light GBM
7	Majalengka	0.68	0.96	0.26	Light GBM
8	Malang	0.74	0.99	0.58	Light GBM
9	Nganjuk	0.67	0.87	0.29	Gradient Boosting
10	Semarang	0.69	0.85	0.41	LGBM
11	Sumenep	0.74	0.93	0.19	Gradient Boosting
12	Tangerang	0.66	0.84	0.29	LSTM
13	Tangerang Selatan	0.69	0.88	0.22	Light GBM
14	Tegal	0.59	0.74	0.52	GRU

Overall, Gradient Boosting (GB), LSTM, and GRU produce the highest R^2 for 9 experiments, respectively. ELM has 7 experiments, and Light GBM has 4 experiments with the highest R^2 scores. SVR Linear and BiGRU achieve the highest R^2 scores in two experiments. The best model for forecasting temperatures is beneficial for future climate projections. The experimental results indicate that deep learning models do not consistently outperform conventional machine learning models in forecasting temperatures. This study proves that the compatibility between the model and data cannot be generalized. The presence of deep learning models for regression problems complements the machine learning models. In some cases, machine learning and deep learning models possibly outperform each other.

The experiment was done individually for each city using the training and testing sets in the same hardware environment for fairness. This paper observes the performance of each proposed method for forecasting the minimum, maximum, and average temperatures to find the best model for each city. The running time is computed from the average running time of building the model, training, and prediction.

The experiments run 13 algorithms, i.e., Support Vector Regression using Linear Kernel (SVR Linear), Support Vector Regression using RBF Kernel (SVR RBF), Gradient Boosting, Ada Boost, Cat Boost, XG Boost, Light GBM, Random Forest, ELM, LSTM, GRU, BiLSTM, and BiGRU. The best model is selected based on the MAE, MAPE, RMSE, and R^2 values. The best model has the lowest MAE, RMSE, and MAPE scores, as well as the highest R^2 score. According to the experimental results, the top 3 best machine learning models for forecasting temperatures are Gradient Boosting, Light GBM, and XG Boost. The best deep learning models are LSTM and GRU, where they have similar performance evaluation scores. Gradient Boosting outperforms other methods. Machine Learning algorithms always run faster than deep learning models. Comparing the running time during creating the model, training, and prediction, ELM runs fastest, and LSTM runs slowest. Machine Learning models for forecasting run faster than Deep Learning models. It is understandable because the Deep Learning models run iteratively to fit the weights to reach the lowest error. Figure 5 shows the annual trend of temperatures. The annual trend of minimum, maximum, and average temperatures from 1990 to 2024 in each city shows that an increasing trend occurs in some areas. The increasing trend of minimum temperatures occurred in Bogor, Cilacap, Gresik, Jakarta, Majalengka, Nganjuk, Semarang, Tangerang Selatan, and Tegal. Bandung, Malang, Bogor, Semarang, Sumenep, Tangerang, and Tegal have a rising trend of annual maximum temperatures. The trend of average temperatures increases in Bogor, Malang, Jakarta, Majalengka, Semarang, Sumenep, Tangerang, Tangerang Selatan, and Tegal. The consistent temperature increase is evidence of global warming.

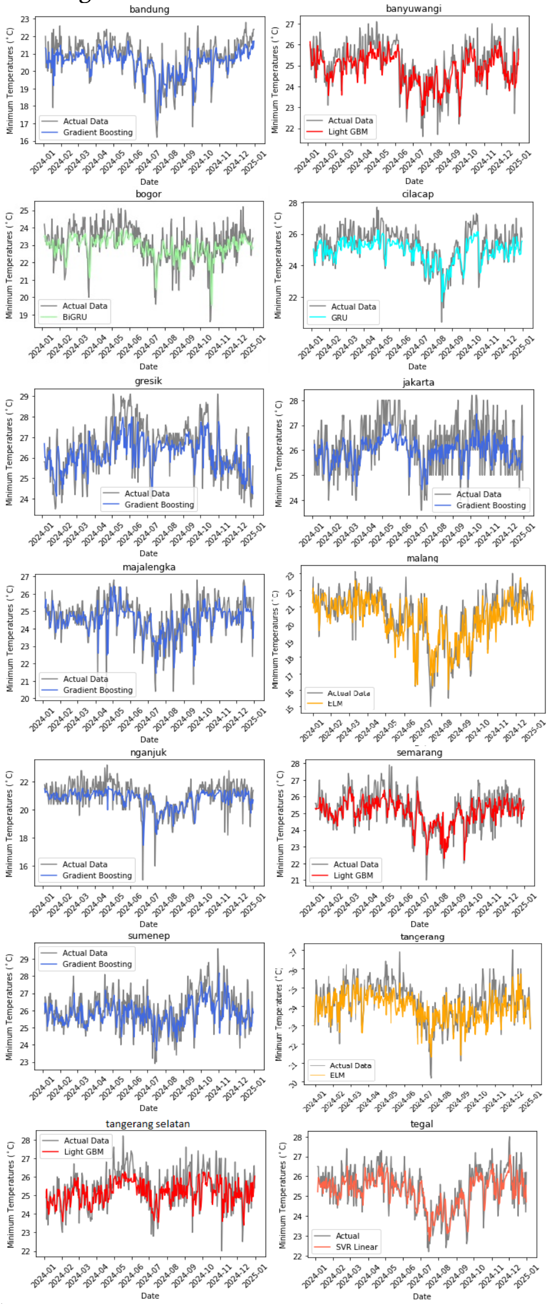

Figure 2. Forecasting minimum temperatures

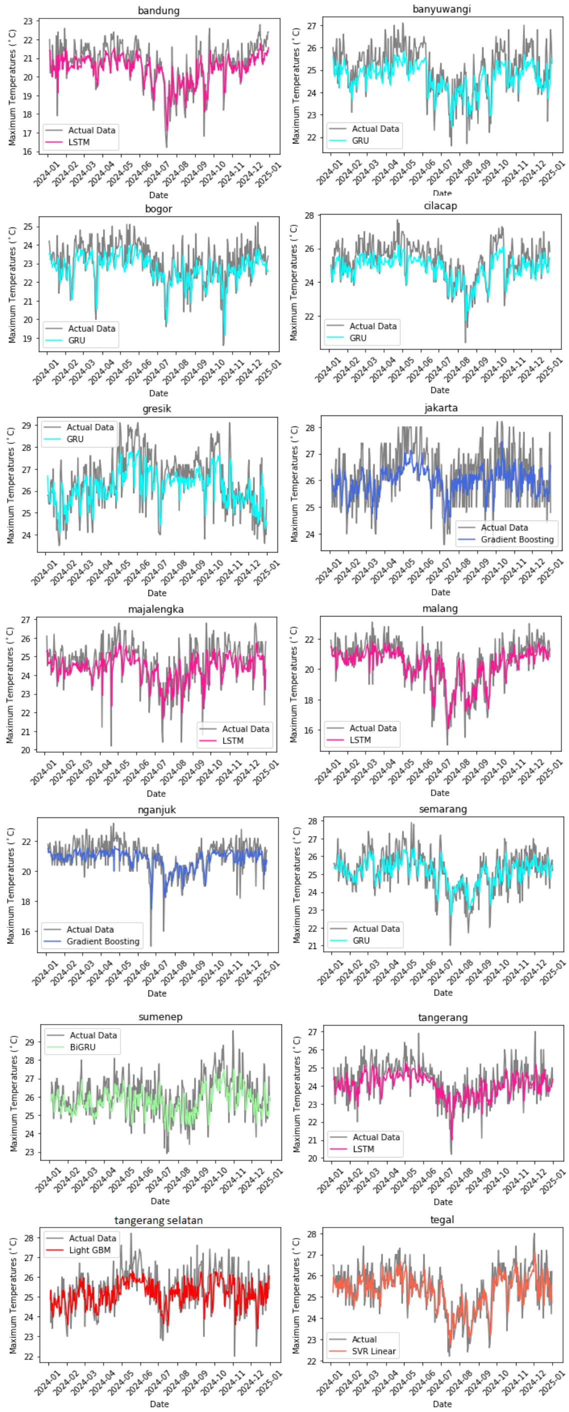

Figure 3. Forecasting maximum temperatures

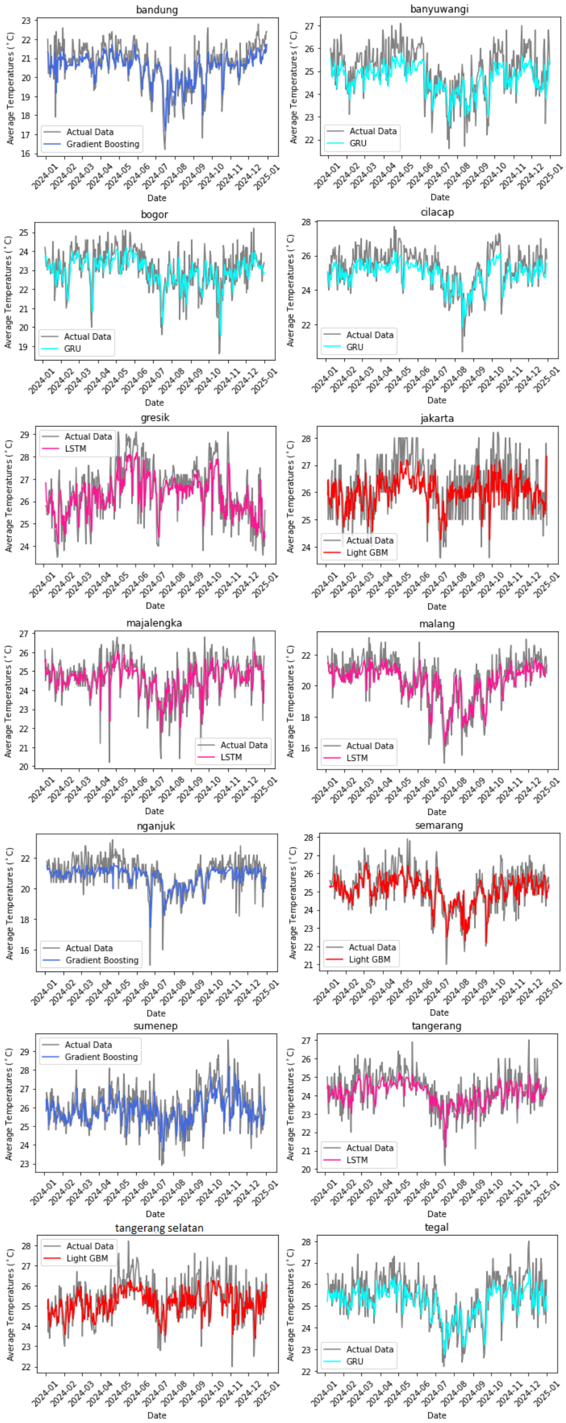

Figure 4. Forecasting average temperatures

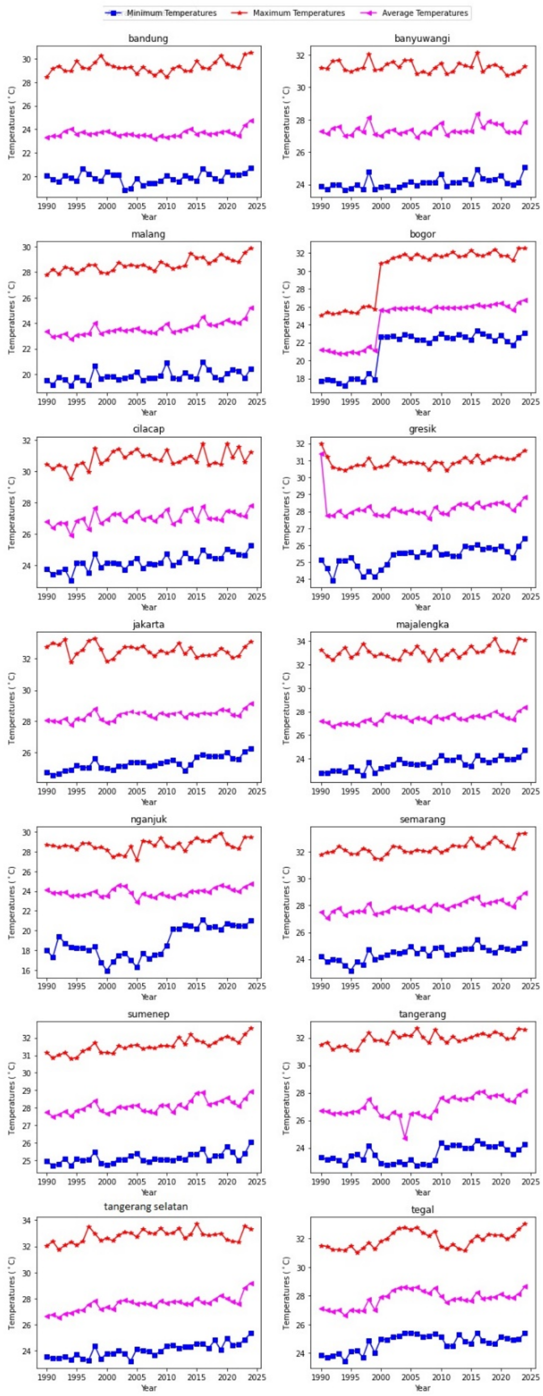

Figure 5. The annual trend of temperatures.

CONCLUSION

In conclusion, deep learning models complement machine learning models for solving regression problems. In some cases, the machine learning models outperform deep learning models and vice versa. In the study of forecasting temperatures in Java Island from 14 cities (Bandung, Banyuwangi, Malang, Bogor, Cilacap, Gresik, Jakarta, Majalengka, Nganjuk, Semarang, Sumenep, Tangerang, Tangerang Selatan, and Tegal), Gradient Boosting, LSTM, and GRU produced lower MAE, MAPE, and RMSE scores and obtained higher R^2 scores than other models. The optimal model, which produces a lower error score for forecasting temperatures in each city, is different. Overall, Machine Learning models run faster than Deep Learning models. For future research, it is important to apply integration analysis of other meteorological variables, e.g., precipitation, wind speed, and humidity, for a comprehensive study of climate change.

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