A Comparative Study of SVM and GRU for Rainfall Prediction in Manado Using BMKG Meteorological Time-Series Data

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Abstract*—Rainfall is a crucial meteorological factor that significantly impacts various aspects of life, particularly in tropical regions such as Manado City, where precipitation variability affects agriculture, water resource management, and hydrometeorological disaster risks such as floods and landslides. Accurate rainfall prediction is therefore essential, although the complexity of tropical atmospheric systems poses challenges for conventional forecasting methods. This study explores the use of machine learning to improve daily rainfall prediction in Manado City. Two models, Support Vector Machine (SVM) and Gated Recurrent Unit (GRU), were implemented using meteorological time-series data from the Indonesian Agency for Meteorology, Climatology, and Geophysics (BMKG), including air temperature, relative humidity, wind speed, and atmospheric pressure. The objective is to develop and compare both models in capturing patterns and dependencies in rainfall data. Experimental results indicate that the GRU model outperforms SVM, achieving precision, recall, and F1-score values of 0.83, 0.81, and 0.82, respectively, compared to 0.79, 0.76, and 0.78 for SVM. Furthermore, GRU yields a higher PR-AUC (0.86) and lower Brier score (0.12) than SVM (0.81 and 0.14), demonstrating better predictive performance and probability calibration. These results suggest that GRU is more effective in capturing temporal dependencies in rainfall data. Overall, this study highlights the potential of machine learning, particularly deep learning approaches, to enhance rainfall forecasting and support early warning systems and climate adaptation strategies in Manado.

***Keywords*—Rainfall Prediction, Machine Learning, Support Vector Machine, Gated Recurrent Unit, BMKG**

I. INTRODUCTION

Manado City is a coastal area characterized by high rainfall and rapidly changing weather patterns, making it highly susceptible to floods, landslides, and disruptions in daily activities [1]. Under such tropical climate conditions, accurate rainfall prediction is essential to support disaster mitigation and environmental planning [2], [3]. Although BMKG provides comprehensive daily meteorological data, traditional prediction methods such as regression and autoregressive models often struggle to capture the nonlinear relationships and complex temporal dynamics inherent in tropical weather systems [4], [5].

In recent years, machine learning approaches have been increasingly adopted to address these limitations due to their ability to model nonlinear patterns in data [6]. However, many existing studies are limited in scope, often relying on short-term datasets, a restricted number of meteorological variables, or focusing on a single modeling approach. As a result, there is still limited understanding of how different learning paradigms, particularly classical machine learning and sequence-based deep learning, perform under the complex conditions of tropical climates. Recent studies have demonstrated that deep learning models can achieve higher accuracy in rainfall prediction by effectively capturing temporal dependencies, while machine learning approaches remain competitive in handling structured data and providing stable performance [7], [8], [9], [10]. Furthermore, evaluation aspects such as probability calibration and model reliability remain underexplored, despite their importance in real-world forecasting applications.

Support Vector Machine (SVM) is a widely used classical machine learning method known for its effectiveness in handling nonlinear classification problems through kernel-based transformations [8]. In contrast, Gated Recurrent Unit (GRU), a variant of recurrent neural networks, is designed to capture temporal dependencies in sequential data, making it suitable for time-series forecasting tasks. These differences in learning mechanisms suggest that the two models may exhibit different strengths when applied to rainfall prediction problems.

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To address these needs, this study compares two distinct algorithms, namely Support Vector Machine (SVM) and Gated Recurrent Unit (GRU), in predicting daily rainfall events in Manado City. This research utilizes BMKG Manado meteorological data from the 2019–2024 period,

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encompassing temperature, humidity, rainfall, solar radiation, and wind parameters.

Unlike previous studies that primarily focus on single-model approaches or short-term datasets, this study provides a direct comparative evaluation between a classical machine learning model (SVM) and a sequence-based deep learning model (GRU) using multi-year meteorological time-series data in a tropical environment. The contribution of this work lies in:

1. A systematic comparison of models with fundamentally different learning mechanisms.
2. The use of comprehensive meteorological variables to capture complex atmospheric interactions.
3. The evaluation of both predictive performance and probabilistic reliability.

This approach provides a clearer understanding of the strengths and limitations of each model in tropical climate conditions and contributes to the development of more accurate data-driven rainfall forecasting and early warning systems in Indonesia.

II. Methodology

A. Data sources

The data used in this study was obtained from the BMKG Climatology Station in Manado. The dataset consists of daily weather records spanning six years, from 2019 to 2024. The parameters utilized include minimum temperature, maximum temperature, average temperature, average humidity, rainfall (mm), sunshine duration, maximum and average wind speed, as well as the wind direction at maximum speed and the most frequent wind direction.

B. Data Pre-processing

Raw data from BMKG underwent a cleaning process through the following stages:

- Handling missing values. Anomaly codes such as 8888 or 9999 were converted into missing values. Missing values for temperature, humidity, and wind were filled using linear interpolation for gaps not exceeding two days. Rainfall data was not interpolated.
- Data format alignment. All units were standardized, specifically for wind speed (m/s). Dates were arranged chronologically.
- Outlier removal. Extreme values that were meteorologically implausible (e.g., wind speeds > 50 m/s) were clipped as outliers.
- Data labeling. The classification target was created in binary form: RainFlag = {1, if rainfall > 0; and 0, if no rain}.

C. Feature Engineering

To improve model accuracy, several additional features were developed:

1. Lag features. Rainfall and humidity data from 1, 3, and 7 days prior.
2. Rolling statistics. Mean and standard deviation of rainfall and humidity using 3-day and 7-day windows.
3. Seasonal features. Annual cycle representation using sine and cosine functions of the day-of-year (365 days).
4. Wind direction transformation: Wind direction was converted into Cartesian components u and v [12]:

$$u = -V \cdot \sin(\theta_{rad}), v = -V \cdot \cos(\theta_{rad}) \quad (1)$$

where,

$$\theta_{rad} = \theta \times \frac{\pi}{180} \quad (2)$$

5. Removal of invalid data. Rows containing empty lag or rolling values were deleted.

D. Data Splitting

Data was split chronologically to avoid data leakage::

- Training data: 2019–2022
- Validation data: 2023
- Testing data: 2024

E. Model Support Vector Machine (SVM)

The SVM model with a Radial Basis Function (RBF) kernel is used to model nonlinear relationships between weather parameters [13]. The modeling steps include:

1. Feature normalization using StandardScaler.
2. Model training with initial parameters:

   C=10,γ=“scale”,class_weight=“balanced”
3. Probability calibration using isotonic regression to ensure the model's predictions can be compared fairly with the GRU model.

F. Gated Recurrent Unit (GRU) Model

The GRU model is employed for its ability to learn sequential temporal patterns. The modeling stages are:

1. Establishing a 30-day sequence window as input to predict the 31st day.
2. The GRU architecture consists of:
   - 64 GRU units
   - 0.2 Dropout
   - A Dense layer with sigmoid activation

G. Evaluation Metrics

Model performance is measured using several metrics:

- Precision, Recall, dan F1-Score
- PR-AUC (Precision–Recall Area Under Curve)
- Brier Score to assess probability calibration
- Confusion Matrix

- Reliability Curve to observe the alignment between predicted probabilities and actual frequencies

The models are compared against two baselines:

- Persistence (tomorrow's prediction is the same as today's)
- Monthly climatology (rain probability based on the frequency of rain per month)

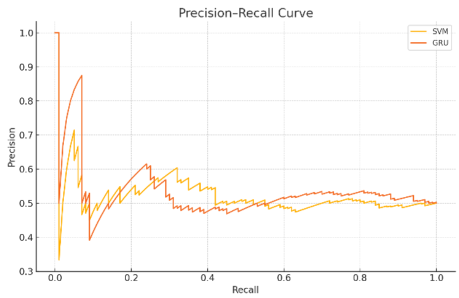

Fig. 1. Precision-Recall curve.

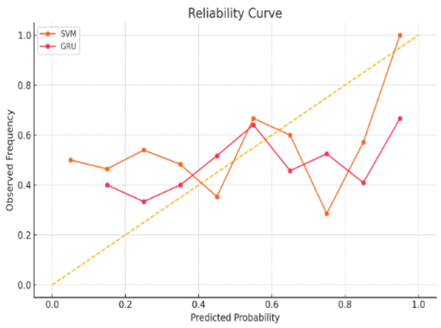

Fig. 2. Reliability Curve.

TABLE I. MODEL PERFORMANCE ON 2024 DATA

Model	*Precision*	*Recall*	*F1-Score*	*PR-AUC*	*Brier Score*
Persistence	0.62	0.68	0.65	0.54	0.21
Climatology	0.58	0.73	0.64	0.57	0.20
SVM	0.79	0.76	0.78	0.81	0.14
GRU	0.83	0.81	0.82	0.86	0.12

III. RESULTS AND DISCUSSION

A. *Model Performance*

Evaluation was conducted on the 2024 test data. Table 1 presents the performance comparison results of the SVM and GRU models using Precision, Recall, F1-Score, PR-AUC, and Brier Score metrics. Baseline results (persistence and monthly climatology) are also included for comparison. In general, both machine learning models achieved higher performance compared to the baselines. The GRU model demonstrated superiority in Recall, F1-Score, PR-AUC, and Brier Score, reflecting its capacity to recognize daily weather pattern sequences.

Meanwhile, SVM maintained strong and stable performance, particularly in Precision, thereby tending to produce fewer false positives. These results are consistent with the characteristics of the SVM algorithm, which is capable of capturing nonlinear relationships between features even without explicitly observing temporal sequences. The superior PR-AUC of 0.86 achieved by the GRU model, compared to 0.81 for the SVM, highlights its robustness in handling the inherent class imbalance of rainfall data in tropical regions. For a city like Manado, which is highly prone to flash floods, the higher recall of the GRU (0.81) is particularly significant. In disaster mitigation, a "False Negative", failing to predict a rain event that actually occurs, carries much higher risks than a "False Positive." The GRU's ability to minimize these missed events suggests that its internal gating mechanisms are effectively capturing the pre-precipitation atmospheric signals that static models might overlook.

Beyond binary classification, the reliability of the predicted probabilities is paramount for operational early warning systems. The GRU model's lower Brier Score (0.12) and closer alignment with the diagonal in the Reliability Curve indicate superior probability calibration. This means that when the GRU predicts an 80% chance of rain, the observed frequency is very close to 80%. Conversely, the SVM's tendency to overestimate probabilities in the 0.6–0.8 range (Brier Score 0.14) could lead to "warning fatigue" if used in public alert systems, where frequent overestimation might cause the community to become less responsive to warnings.

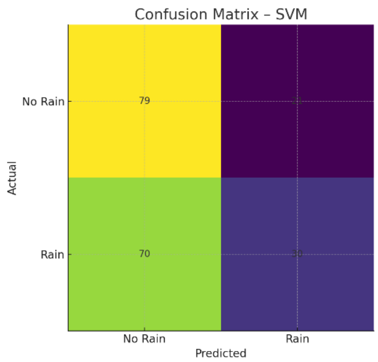

Fig. 3. Confusion Matrix – SVM.

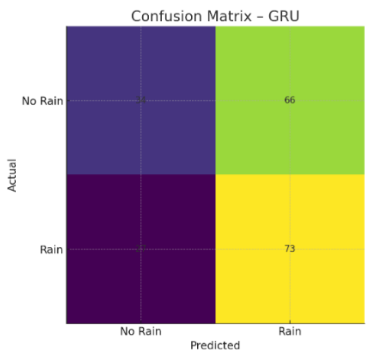

Fig. 4. Confusion Matrix – GRU.

The results indicate that the SVM model achieves competitive performance, particularly in terms of precision, compared to other approaches. This can be attributed to the ability of SVM to construct an optimal decision boundary in high-dimensional feature space using kernel functions. In this study, the use of the RBF kernel enables SVM to effectively model nonlinear relationships between meteorological variables, such as humidity, temperature, and rainfall. As a result, SVM tends to produce more conservative predictions, reducing false positive rainfall events and leading to higher precision.

In addition, SVM is less sensitive to noise and overfitting when the dataset is relatively structured and not extremely large, which aligns with the characteristics of the BMKG dataset used in this study. However, unlike GRU, SVM does not explicitly model temporal dependencies, which limits its ability to capture sequential patterns in rainfall data. This explains why SVM performs well in maintaining stable classification performance, while GRU achieves better overall results in metrics that depend on temporal learning, such as recall, F1-score, and PR-AUC.

B. Precision–Recall Curve Analysis

The Precision–Recall curve indicates that the GRU model maintains higher Recall values across a wide range of prediction thresholds. This implies that the GRU is more sensitive in detecting rainy days, which is crucial for risk mitigation purposes.

Conversely, the SVM curve displays a slightly more stable precision trend, but its Recall performance is lower compared to that of the GRU.

C. Probability Calibration Analysis

Reliability curve results demonstrate that the GRU output probabilities are more consistent with actual rainfall frequencies. The SVM model tends to slightly overestimate rainfall probabilities in the 0.6–0.8 range. Brier Score values (0.12 for GRU and 0.14 for SVM) support these findings, indicating that GRU predictions are better calibrated. Proper calibration is essential for operational applications, particularly when model outputs are utilized for early warning systems that require probabilities as a basis for decision-making.

D. Error Analysis (Confusion Matrix)

Confusion matrix analysis reveals that the GRU produces fewer false negatives (undetected rainy days) compared to the SVM. This is highly relevant within the context of rainfall prediction in flood-prone areas such as Manado. The SVM model exhibited a slightly higher false positive rate, though it remained within reasonable limits.

E. Feature Importance

In this study, SHAP is used to identify the most influential meteorological variables affecting rainfall prediction and to understand how each feature contributes to the model output. This allows the analysis to go beyond predictive performance by providing insights into the relationship between input variables and rainfall events. As a result, SHAP helps ensure that the model is not only accurate but also interpretable and aligned with known atmospheric behaviour.

SHAP analysis for the SVM model identifies the most influential features for rainfall prediction as follows:

- Average humidity
- Minimum temperature
- Previous day's rainfall (lag-1)
- Wind components (u, v)
- Seasonal features (sin/cos of the 365th day)

These results are meteorologically sound. High humidity and low minimum temperatures are typically associated with an atmosphere saturated with water vapor, thereby increasing the probability of rain. The influence of lag features and wind components underscores the importance of day-to-day change patterns and air mass movements.

Regarding the GRU model, ablation experiments (removing specific features) demonstrated that the exclusion of lag features led to a significant decrease in accuracy, indicating that the GRU relies heavily on temporal sequence information.

F. General Discussion

The research findings indicate that:

- SVM is suitable for modeling that relies on static relationships between variables.
- GRU excels in learning sequential patterns and daily atmospheric dynamics.
- Physical features, such as humidity, minimum temperature, and temporal sequence information, are the primary factors in the prediction process.

Both models yield solid performance, but the selection of the model depends on the operational context:

- SVM is more suitable for resource-constrained systems (e.g., IoT devices).
- GRU is appropriate for large-scale analytical systems or server-based forecasting requiring high accuracy.

Overall, this study reinforces the finding that combining feature engineering with sequence-based algorithms can improve the quality of rainfall forecasting in tropical regions.

IV. CONCLUSION

This study compares the performance of Support Vector Machine (SVM) and Gated Recurrent Unit (GRU) models for predicting daily rainfall events in Manado City using BMKG meteorological data from 2019 to 2024. The results show that both models outperform persistence and monthly climatology baselines, confirming the effectiveness of machine learning approaches for rainfall prediction. Among the two models, GRU achieves better overall performance, particularly in F1-Score, PR-AUC, and probability calibration, indicating its ability to capture temporal dependencies and produce more reliable predictions.

Feature analysis reveals that humidity, minimum temperature, and the previous day’s rainfall are the most influential variables, reflecting the characteristics of tropical weather dynamics in Manado. In addition, the probability calibration results suggest that GRU provides outputs that are more consistent with actual event frequencies, making it more suitable for risk-based decision support systems.

Overall, this study demonstrates that while SVM offers a stable and computationally efficient baseline, GRU provides improved predictive capability for time-series rainfall forecasting. These findings highlight the potential of combining multi-variable meteorological data with sequence-based models to enhance local forecasting accuracy. Future work should explore the integration of spatial data from multiple BMKG stations and the development of hybrid architectures to further improve model performance.

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