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Early Lightning Event Detection System Using the LSTM–GRU Architecture at Supadio Airport, Pontianak

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***Abstract* – Frequent thunderstorm activity around Supadio Airport, Pontianak, highlights the need for reliable lightning forecasting to support aviation safety and airport operations. In practice, most lightning systems are still used for detection rather than prediction, while many previous forecasting studies have relied on a single deep learning model, which may limit the ability to capture temporal patterns in meteorological data. Therefore, this study applied a hybrid Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) model to predict lightning occurrences using historical meteorological data from Supadio Airport. The main contribution of this study lies in the development of a hybrid LSTM–GRU framework for airport-scale lightning prediction using station-based historical meteorological data. This setting has received limited attention in previous studies and combined LSTM and GRU within a single framework to improve sequence learning while maintaining computational efficiency, in contrast to previous single-model approaches. The experimental results show that the proposed model achieved a testing accuracy of 0.6716, with an F1-score of 0.71 and a Recall of 0.78 for the dominant lightning class. Although the model still showed limited performance in detecting rare lightning events due to class imbalance, the overall results indicate that the LSTM–GRU model has strong potential as a basis for an airport-scale early warning system and may help support safer, more reliable flight operations.**

Keywords: hybrid LSTM-GRU, Supadio Airport, aviation safety, early warning system, lightning prediction.

I. INTRODUCTION

Ensuring the safety of passengers and flight crew is the central objective in aviation, and lightning remains one of the atmospheric hazards that can jeopardize this objective. Lightning strikes can disrupt navigation systems and damage aircraft components, making the ability to understand and anticipate lightning occurrences crucial for reducing operational risks [1]. Lightning itself is an electrical discharge produced by strong charge imbalances in the atmosphere, commonly categorized as intra-cloud (IC), cloud-to-cloud (CC), and cloud-to-ground (CG). Each type poses different operational challenges, and accurate knowledge of their intensity and spatial distribution helps inform safer flight routing. Moreover, reliable lightning information can reduce operational disturbances such as delays or diversions, which often translate into substantial economic losses for the aviation sector [2].

Indonesia's location along the equator places it within one of the most active convective regions globally, resulting in extremely frequent lightning. Kalimantan, in particular, consistently records some of the highest lightning densities in the country, often surpassing other regions in eastern Indonesia [3]. Studies across maritime Southeast Asia further show that the region experiences persistent lightning year-round. Airports situated in high-exposure zones—such as Supadio Airport—face elevated risks, underscoring the need for enhanced monitoring and prediction tools.

Modern airport lightning sensors, including those deployed at Supadio Airport, can capture detailed historical lightning records. However, these records are generally descriptive and lack predictive functionality. Meanwhile, conventional forecasting approaches such as Numerical Weather Prediction (NWP) frequently struggle with limited temporal and spatial granularity, making them insufficient to capture localized lightning behavior. These constraints demonstrate the importance of adopting a nowcasting approach based on deep learning methods, which can produce short-term, high-resolution lightning predictions from local meteorological variables [4].

Recent developments in Artificial Intelligence (AI), particularly in deep learning, have opened new opportunities for modeling sequential atmospheric data. While Recurrent Neural Networks (RNNs) were initially designed to handle time-dependent information, they suffer from the vanishing gradient issue when dealing with long sequences. More advanced variants, such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), were introduced to overcome these limitations through gating mechanisms that manage how information is retained and discarded [5]. LSTM excels in learning long-range dependencies, whereas GRU offers a more streamlined design with competitive performance and reduced computational cost [6].

Leveraging the strengths of both models, this study

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introduces a hybrid architecture that sequentially integrates LSTM and GRU. The LSTM component captures intricate temporal patterns from the meteorological inputs, while the GRU component refines these representations to produce efficient predictions [7]. Given the high lightning exposure around Supadio Airport and the limitations of traditional forecasting methods, this research aims to develop and assess the performance of the Hybrid LSTM–GRU model for predicting intra-cloud lightning. The proposed framework is expected to provide valuable support for operational decisions and enhance aviation safety across the Supadio Airport region.

II. Methodology

A. Research Methodology

This study employs a quantitative research approach, integrating direct field data acquisition, application-based data retrieval, and raw data processing. Lightning data were collected directly from the Lightning Detector system, accessible only through its dedicated PC, and exported in comma-separated values (CSV) format. The original per-second measurements were consolidated into daily datasets for further analysis. Data pre-processing included filtering missing or corrupted entries, which commonly occur due to communication interruptions between the sensor and the server. Model development and experimentation were conducted using the open-source Anaconda Navigator environment with Jupyter Notebook to implement the LSTM–GRU architecture. 80% of the dataset was allocated for training, with the remaining 20% used for testing and validation. Subsequent trend and correlation analyses were performed to examine long-term lightning activity patterns, which support~~s~~ model forecasting capabilities using a 10% validation split.

The research workflow consists of several stages: literature review, data acquisition, pre-processing, modeling, evaluation, and reporting. Time-series lightning data spanning 2022–2024 were restricted within a 30 km radius around Supadio Airport to focus on the operationally relevant airspace. The data were then aggregated into 10-minute and daily intervals and classified into multiple lightning-type categories (0, 1, 2, and combined) to support detailed prediction tasks. The modeling process began with LSTM, followed by GRU, and then a hybrid LSTM–GRU model if individual architectures did not meet the minimum prediction accuracy threshold of 65%. Additional optimization techniques, including feature reduction, temporal adjustments, and lag-based enhancements, were applied when necessary. The prediction process was considered successful once the model achieved or exceeded the 65% accuracy requirement, after which the study proceeded to documentation and publication.

B. Literature Review

Lightning forecasting has evolved considerably from conventional observation-based and empirical approaches toward data-driven methods, particularly machine learning and deep learning. This shift is largely motivated by the need for models that can more effectively capture nonlinear relationships and the rapidly varying dynamics of atmospheric processes. Recent review studies have highlighted the growing importance of deep learning in lightning prediction, emphasizing its ability to model the spatial and temporal complexity associated with convective weather systems [8]-[11].

The literature also shows that the selection of meteorological predictors strongly influences forecasting performance. Routinely observed surface variables, including temperature, humidity, atmospheric pressure, rainfall, and wind-related parameters, have been reported to provide meaningful predictive information for short-term lightning warning. In addition, several studies have identified physically relevant variables such as Convective Available Potential Energy (CAPE), cloud thickness, and precipitation intensity as important indicators of lightning occurrence. These findings confirm that historical meteorological observations remain a relevant and operationally practical data source for local-scale lightning prediction, especially in settings where radar and satellite products are not consistently available [12]-[15].

Recent advances in deep learning have enabled lightning prediction using a wide range of observational sources, including satellite imagery, radar products, atmospheric electric field measurements, and multisource data combinations. Previous studies have demonstrated that geostationary satellite observations can directly support lightning forecasting, while multisource frameworks generally provide better short-term predictive performance than single-source approaches. In parallel, semantic-segmentation-based models, artificial neural networks, and probabilistic methods have been applied to improve the representation of both cloud-to-ground and intra-cloud lightning events. Collectively, these studies indicate that deep learning offers strong capability for extracting lightning-related patterns from complex atmospheric datasets [16]-[22].

Another important direction in recent research is the development of hybrid and enhanced neural architectures to improve prediction accuracy while maintaining computational efficiency. Several studies have reported that hybrid AI frameworks, graph-based recurrent models, and recurrent convolutional networks can outperform conventional baseline approaches. In the context of sequential meteorological data, recurrent architectures such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are particularly relevant because they are designed to learn temporal dependencies. LSTM is widely recognized for its effectiveness in capturing long-range temporal relationships, whereas GRU offers a more compact structure and lower computational burden during model training [23]-[27], [10].

Despite these advances, a clear research gap remains in airport-scale lightning forecasting based on station-derived historical meteorological data. Much of the existing literature has focused on radar-based systems, satellite-driven approaches, or broader regional applications, whereas comparatively little attention has been paid to operational lightning prediction in airport environments. Moreover, the reliance on single-model architectures in several previous studies suggests that further improvement is still needed in capturing complex temporal patterns without compromising computational efficiency [8], [9], [11], [26], [27]. Therefore, this study applies a hybrid LSTM–GRU model to historical meteorological data from Supadio Airport. By combining the temporal learning strength of LSTM with the computational efficiency of GRU, the proposed approach is expected to provide a more robust basis for local lightning early warning in support of aviation safety and airport operations [8], [12], [23].

III. Results and Discussion

In this study, the results are organized into three datasets one for each quarterly period, along with a combined pattern classification for the years 2022, 2023, and 2024. These datasets are then compared and visualized in a single, comprehensive graph, with category labels a through h corresponding to the defined lightning-type combinations. This comparative visualization supports the development of the early warning system by revealing temporal and categorical variations in lightning activity across the three-year observation period.

To initiate the analysis, the processed lightning dataset for the year 2022–2024 period was examined using quarterly and category-based classification. The following figure presents the evaluation results using the combined LSTM and GRU architecture on the collected lightning data. The dataset was classified into several categories: a, b, and c representing single-strike types; d, e, and f representing combination-strike types; g representing complex strike patterns; and h representing all remaining strike types not covered by the previously defined categories. This categorization enables a structured assessment of the model's ability to recognize different lightning characteristics and detect early-warning patterns across varying strike behaviors.

Figure 1 presents the quarterly distribution of lightning activity in 2022 for type_0, type_1, and type_2. Temporal analysis of the dataset using quarterly stratification reveals clear, structured seasonal patterns. The first quarter (January–March) recorded a combined activity total of 10,506 units, representing 12.1% of the annual activity, with measurable events occurring over 37 days. The second quarter (April–June) shows a significant increase, reaching 26,358 units (30.4% of the annual total) distributed across 57 active days. The third quarter (July–September) reached its peak with a total of 40,227 units, accounting for 46.4% of the yearly activity and spanning 45 active days. The fourth quarter (October–December) shows a sharp decline, totaling 9,634 units (11.1% of the annual activity) recorded over 32 active days. Figure 1 illustrates the lightning activity distribution for each type during the 2022 quarterly period.

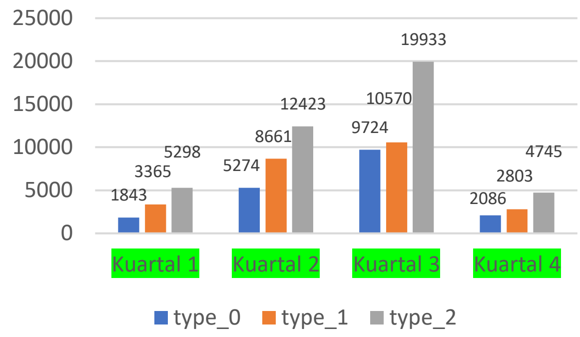

Figure 1. Quarterly Distribution of Lightning Activity in 2022

Figure 2 shows the distribution of lightning activity combination types recorded in 2022. The combination-type pattern consisting of types a, b, c, d, e, f, g, and h shows that type h which represents lightning events occurring beyond a 30-kilometer radius from the observation point, dominates the 2022 dataset. Out of 365 observation days, 194 days recorded lightning occurrences outside the 30-kilometer range, accounting for 53.15% of the entire year. This dominance indicates that regional lightning activity is more frequently detected at greater distances than events within the 30-kilometer observation zone, suggesting that the monitored area experiences relatively calm conditions for nearby lightning. In contrast, distant lightning activity persists year-round. It is important to note that category h does not contribute numerically to type_0, type_1, or type_2 values, as these parameters only record lightning events within a 30-kilometer radius. Therefore, the 194 days classified as type h represent days without measurable lightning within the observation zone but with detectable lightning activity outside it. This pattern provides essential insight into the persistence of regional lightning that may not be directly observed by the local measurement system.

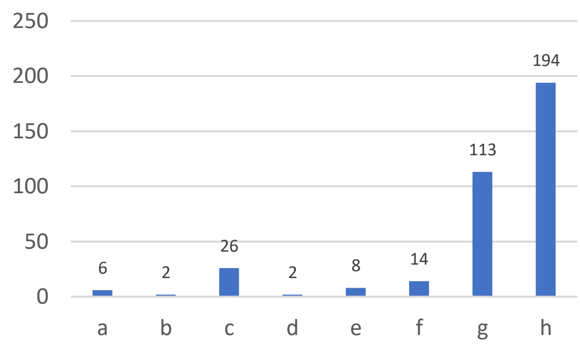

Figure 2. Distribution of Lightning Activity Combination in 2022

Figure 3 illustrates the quarterly lightning activity distribution in 2023. The quarterly distribution in 2023 exhibits a distinct pattern, characterized by a progressive increase toward the fourth quarter. In the first quarter, type_0 recorded 3,240 units, type_1 5,855 units, and type_2 reached 7,882 units, with daily averages of 36.00 units, 65.06 units, and 87.58 units, respectively. These values represent increases of 43% for type_0, 42.53% for type_1, and 32.78% for type_2 compared to the first quarter of 2022.

The second quarter showed further increases, with type_0 reaching 7,368 units, type_1 totaling 8,954 units, and type_2 recording 14,214 units. The daily averages rose to 80.97, 98.40, and 156.20 units, respectively. Despite this upward trend compared to the previous quarter, the second-quarter values in 2023 remained lower than those observed in the third quarter of 2022.

The third quarter recorded the highest values, with type_0 reaching 18,452 units (up 47.30% than the previous year), type_1 totaling 14,922 units (up 29.16%), and type_2 reaching 36,842 units (up 45.89%). The corresponding daily averages were 200.57, 162.20, and 400.46 units. Notably, type_2 exhibited a particularly high daily average of 400.46 units.

The fourth quarter maintained consistently high values, with type_0 totaling 10,676 units, type_1 reaching 14,258 units, and type_2 recording 23,173 units. In contrast to 2022, which experienced a sharp decline in the fourth quarter, 2023 maintained high intensity through the end of the year, with daily averages of 116.04, 154.98 and 251.88 units, respectively.

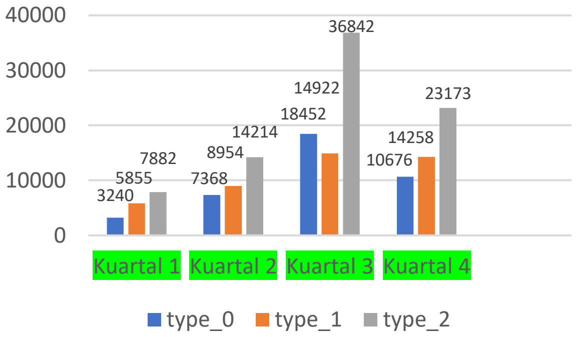

Figure 3. Quarterly Distribution of Lightning Activity in 2023

Figure 4 presents the distribution of lightning activity combination types in 2023. The combined type patterns consist of types a, b, c, d, e, f, g, and h. Type h, which represents lightning detections occurring beyond a 30-kilometer radius from the observation point, was recorded on 137 days out of the 365 observation days in 2023, accounting for 37.53% of the year. This proportion shows a highly significant decrease of 15.62 percentage points from 2022 (53.15%) and is also lower than the 2024 figure (46.99%). The year 2023 recorded the lowest value among the three analyzed years, indicating a fundamental change in the dynamics of regional lightning activity.

The shift in the distribution of type h in 2023 exhibits a pattern opposite to that of 2022. Specifically, 2023 marks a pivotal point in the transition from a system dominated by regional-scale lightning activity (type h) toward a more balanced system characterized by increased local lightning activity (type g). In 2023, type g was observed on 172 days (47.12%), surpassing type h for the first time and becoming the dominant category. Figure 4 presents the lightning data for each combined type in 2023.

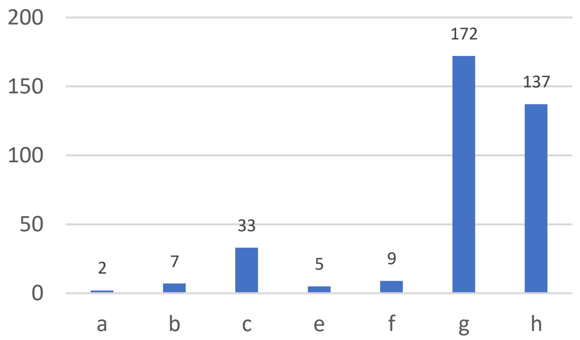

Figure 4. Distribution of Lightning Activity Combination in 2023

Figure 5 shows the quarterly distribution of lightning activity in 2024. The quarterly distribution in 2024 exhibits a consistent, progressive decline throughout the year. The first quarter recorded the highest values, with type_0 totaling 5,496 units, type_1 9,728 units, and type_2 reaching 12,555 units. The corresponding daily averages for this period were 60.40 units, 106.90 units, and 137.97 units, respectively. Although these values were 69.60% lower for type_0 and 41.58% lower for type_1 compared to the first quarter of 2023, type_2 still exhibited a relatively high level of intensity.

The second quarter showed a decline, with type_0 reaching 4,500 units (a 38.93% decrease from Q1), type_1 totaling 4,173 units (a 53.40% decrease), and type_2 recording 8,032 units (a 43.49% decrease). Daily averages decreased to 49.45, 45.86, and 88.26 units, respectively. The most pronounced reduction occurred in type_1, indicating a specific change in its characteristics.

In the third quarter, type_0 recorded 3,905 units, type_1 3,777 units, and type_2 reached 8,277 units, with daily averages of 42.45, 41.05, and 89.97 units, respectively. Compared to the third quarter of 2023, type_0 and type_1 declined by 78.83% and 74.69%, respectively, indicating a highly significant change in conditions. However, type_2 maintained relatively stable values compared to the previous quarter.

The fourth quarter exhibited the most drastic decline, with type_0 totaling 2,364 units, type_1 only 1,029 units, and type_2 reaching 3,458 units. Daily averages reached their lowest levels of 25.70, 11.18, and 37.59 units, respectively. This decline contrasts sharply with the fourth quarter of 2023, which still showed high intensity. The progressive decline throughout 2024 indicates fundamental changes in conditions that consistently influenced the observed phenomenon.

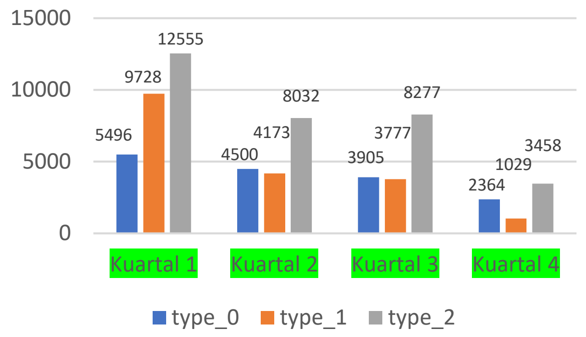

Figure 5. Quarterly Distribution of Lightning Activity in 2024

Figure 6 illustrates the distribution of lightning activity combination types in 2024. The combined type patterns consist of types a, b, c, d, e, f, g, and h. Type h, which represents lightning detections occurring beyond a 30-kilometer radius from the observation center, was recorded on 172 days out of 366 observation days in 2024, accounting for 46.99% of the year. This proportion represents a significant decrease of 6.16 percentage points compared to 2022, which recorded 53.15%. This decline implies a shift in regional lightning activity patterns, with a relative increase in lightning occurrences within the 30-kilometer observation range (category g), which rose from 30.96% to 42.35%.

As in 2022, category h in 2024 did not contribute numerically to the type_0, type_1, or type_2 parameters, indicating that these three parameters exclusively record lightning events occurring within the 30-kilometer observation zone. Accordingly, the 172 days classified as category h represent days with detected regional lightning activity that occurred beyond the quantitative measurement capability of the local system. This shift from the dominance of category h toward a stronger balance with category g highlights a structural change in the spatial distribution of lightning activity.

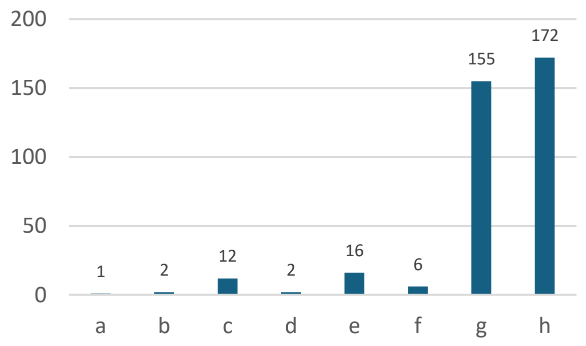

Figure 6. Distribution of Lightning Activity Combination in 2024

Figure 7 illustrates the percentage distribution of lightning strikes across categories a to h for the 2022–2024 period. Across categories a to h, the visualization shows that category h dominates with the highest contribution at 46%, followed by category g at 40%. Meanwhile, the remaining categories a, b, c, d, e, and f account for significantly smaller proportions, each ranging from 0% to 3%. This pattern indicates that most recorded lightning events fall within categories h and g, making these two types the primary representation of lightning characteristics at Supadio Airport over the three-year observation period.

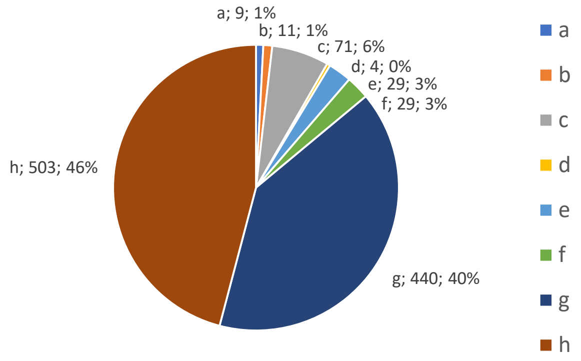

Figure 7. Percentage Distribution of Lightning Strikes by Category for 2022–2024

Figure 8 presents the grouped distribution of lightning strike classifications for the entire dataset. The classification of lightning events in this study is organized into a structured grouping system to enable clearer interpretation of patterns and detection outcomes. Lightning occurrences are categorized into multiple classes based on their characteristics, including single-stroke strikes, combination strokes, complex events, and other irregular patterns. This classification framework serves as the foundation for analyzing temporal trends, evaluating model performance, and understanding the distribution of lightning activity across the dataset. By grouping the events into well-defined categories, the study ensures that subsequent analyses—including model predictions, quarterly comparisons, and multi-year evaluations—are presented with improved clarity and scientific consistency.

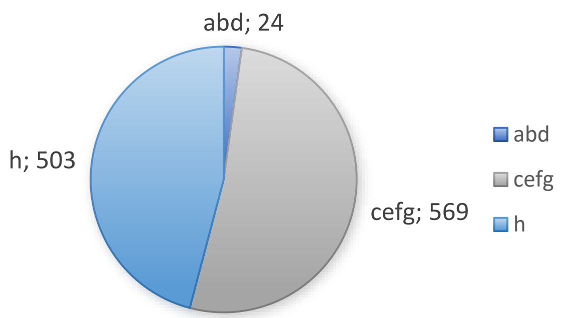

Figure 8. Lightning Strike classifications for 2022-2024

The distribution of lightning strike classifications across the dataset, grouped into three main categories: cefg, abd, and h. The cefg category accounts for the largest proportion, with 569 recorded events, indicating a dominant presence of combination and complex lightning patterns. The abc category, consisting of 24 events, accounts for a relatively small fraction and reflects the occurrence of single or less complex strike types. Meanwhile, category h comprises 503 events, representing all remaining lightning occurrences not classified within the defined groups. This grouping visualization provides a clear overview of the variability and frequency distribution of lightning events used in the analysis.

The feature set used in this study incorporates several temporal and lag-based variables designed to capture patterns in lightning occurrences across different time scales. The day_of_week, month, and day_of_year features represent weekly, monthly, and annual groupings, respectively, enabling the model to learn seasonality, periodic trends, and cyclical behavior associated with lightning activity. Additionally, the lag features lag_1, lag_2, and lag_7 correspond to lightning observations from 1, 2, and 7 days prior. These lagged values help the model identify short-term dependencies, delayed effects, and weekly repetition patterns within the data. The target_encoded feature represents the encoded target variable, capturing the statistical relationship between historical lightning categories and model inputs through supervised encoding. All selected features were then normalized using the MinMaxScaler to ensure consistent scaling and to improve the stability and convergence of the LSTM–GRU learning process.

The evaluation of the lightning prediction model using the Hybrid LSTM–GRU architecture resulted in a Test Accuracy of 0.6716, indicating that the model correctly classified 67.16% of all cases. However, the detailed assessment presented in the Classification Report reveals substantial variation in performance across classes. The model demonstrated strong predictive capability for the common lightning category, achieving a precision of 0.71, a recall of 0.78, and an F1-score of 0.74, which reflects its effectiveness in identifying frequently occurring lightning events. In contrast, the model's performance declined for the less_common class, which recorded an F1-score of 0.57 (precision 0.60, recall 0.54), indicating challenges in capturing patterns associated with less frequent lightning occurrences.

The lightning early-warning system is categorized into four operational alert levels. Level Green indicates minimal or safe lightning risk, allowing all airport operations, including flight activities, ground handling, and maintenance to proceed normally with continuous real-time monitoring. Level Yellow reflects an increasing lightning risk within the next three days, prompting heightened awareness and preparation among ground handling personnel, ATC, and maintenance units, along with expanded weather monitoring and equipment readiness checks. Level Orange signifies a high predicted lightning risk within the same timeframe, requiring operational restrictions on outdoor critical activities such as refueling, cargo handling, and pushback. At the same time, all apron personnel are instructed to seek shelter and limit aircraft marshaling. Level Red represents a very high or active lightning threat within a 30-km radius of the airport, necessitating the temporary suspension of aircraft movements, including takeoffs and landings, to ensure operational safety.

IV. Conclusion

The Hybrid Long Short-Term Memory–Gated Recurrent Unit (LSTM–GRU) model proposed for lightning forecasting at Supadio Airport showed encouraging results for airport-scale early warning purposes. The model achieved a test accuracy of 0.6716, an F1-score of 0.71 and a Recall of 0.78 for the dominant lightning category. This study highlights the advantage of combining LSTM and GRU to capture temporal relationships in historical meteorological data better while preserving computational efficiency in sequential modeling. The findings suggest that the model performs well at detecting frequent lightning events and offers practical benefits for enhancing aviation safety and supporting airport operational decisions. However, its ability to detect rare lightning events is still limited because of class imbalance in the dataset, indicating that future work should focus on data balancing and further model improvement to increase the reliability of the early warning system.

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