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Original Article

Multimodal Machine Learning for Cloud-to-Ground Lightning Classification and Polarity Localization in Tropical Thunderstorm

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Abstract *- Accurate classification and localization of Cloud-to-Ground (CG) lightning are essential for the development of reliable early warning systems in tropical regions and the improvement of thunderstorm monitoring. This study proposes a multimodal machine learning framework for CG lightning classification and polarity-based localization with synchronized atmospheric and electromagnetic measurements collected in Melaka, Malaysia, in 2024. The framework includes electric field waveform from PicoScope, CAPPI radar reflectivity images and Himawari infrared cloud images, which contain the electrical discharge characteristics and storm structure information. A dataset comprising 2,799 synchronized lightning events was analyzed using two independent learning approaches; a Convolutional Neural Network (CNN) and a feature-engineered XGBoost model. In addition to the lightning classification, a polarity-based localization approach is proposed. This approach is based on the Magnetic Direction Finder (MDF) where the prediction and interpretation of the North-South (NS) and East-West (EW) magnetic field polarities are used to find the location of the discharge quadrant. The CG classification accuracy was 99.24% for CNN and 99.91% for XGBoost with three-modality fusion. In polarity prediction, CNN achieved 88.25% accuracy, while XGBoost improved significantly from 26.29% with a single-modality input to 87.34% with multimodal integration. These findings underline the importance of a multimodal approach to lay a solid basis for the fusion of heterogeneous atmospheric and electromagnetic data and to improve the accuracy and robustness of lightning intelligence systems.*

Keywords *- Cloud-to-Ground lightning, Convolutional Neural Network, Magnetic direction finder, Multimodal machine learning, Polarity-based localization, XGBoost model.*

1. Introduction

Lightning represents a significant atmospheric hazard that can affect infrastructure, aviation, power systems and human safety [1]. Accurate classification of lightning type as well as reliable localization of discharge position is important for scientific understanding and operational warning system [2, 3].

Lightning classification enables different discharge categories to be distinguished, including Cloud-to-Ground (CG), Intra-Cloud (IC) and Cloud-to-Cloud (CC) events [4]. Each type of lightning has specific electrical signatures and propagation characteristics which are indicative of the charge distribution and the storm dynamics [5, 6]. The correct classification of lightning events is useful for understanding the storm electrification processes and for improving the reliability of early warning systems [7]. Classification differentiates the types of discharge, and localization allows to identify the exact geographical location of each event, so that it can be related directly to the infrastructure affected and to storm cells [8, 9]. This information is helpful for early warning systems, risk mitigation, and post-event damage monitoring since it enables accurate identification of the damaged assets and a better understanding of the reasons of failure.

There are various techniques proposed for lightning classification and localization, which aim to improve the detection accuracy and reliability. The standard technology for lightning-location systems is typically based on electromagnetic measurements using, for example, Time-of-Arrival (TOA), Time-Difference-of-Arrival (TDOA), and Magnetic Direction Finding (MDF) [10, 11]. They use a distributed sensor network to estimate the strike location through the signal propagation time and also the analysis of the polarity of the magnetic field [12]. Currently, signal pattern analysis, threshold-based algorithms, and statistical feature extraction are the main methods used to classify lightning [13, 14]. The methods aim to identify the difference between various types of lightning strikes by looking at waveforms' peak amplitude, polarity, pulse width, rise time, and frequency content [15]. These methods have provided reliable results in a controlled environment; however, their performance is often affected by the factors of signal noise, propagation effects and complexity of thunderstorm environments [16]. Current lightning detection systems, on the other hand, often treat classification and localization as two separate tasks, which restricts their ability to exploit the correlation between lightning characteristics, spatial distribution and storm structure, particularly in complex meteorological conditions [17, 18].

In addition, remote sensing platforms provide additional observations that contribute to the study of the structure and evolution of thunderstorms. Weather radar provides detailed information on convective core intensity, hydrometeor distribution and precipitation structure, which are closely associated with storm electrification and lightning initiation [19]. Meanwhile, the satellite observations in infrared channels bring details about cloud top properties and about the spatial structure of the convective systems, which may lead to further signals about the storm development and lightning activity [20]. Such remote sensing observations have been broadly used in the mesoscale lightning forecast and storm nowcasting. However, these remote sensing observations are normally used to describe the storm patterns and are not usually combined with ground-based electromagnetic measurements to analyze and classify the individual lightning events. This limits the ability to combine the electrical characteristics of the lightning discharge with the related storm environment.

Machine learning algorithms are widely used to mimic complex non-linear connections between meteorological parameters and lightning incidence in atmospheric research [21-23]. Convolutional Neural Networks (CNNs) have demonstrated their ability to extract spatial characteristics from radar and satellite data for thunderstorm monitoring and lightning detection [24]. On the other hand, Extreme Gradient Boosting algorithms (XGBoost) have shown its ability in processing structured meteorological features and providing interpretable predictions of lightning activity together with atmospheric electrification processes [25]. Hybrid methods that mix feature extraction based on deep learning with ensemble learning based on trees have also shown better results in difficult environmental forecast tasks [26].

Even with these improvements, most of the studies that have been done so far use either image-based deep learning or machine learning models that are based on tabular meteorological variables. They do not combine electromagnetic waveform measurements and remote sensing observations into a single framework in order to well explain the individual lightning events. Thus, the electrical signature of a single discharge is not fully studied in concert with conditions that prevailed in the environment of the event.

Lightning classification and localization were often treated as separate tasks in previous studies. Lightning is generally classified based on its waveform characteristics, while its localization is frequently determined by interpreting polarity using MDF principles. The physical relationship between electromagnetic discharge signatures measured by ground-based sensors and the related storm structures identified by radar and satellite platforms is not taken into consideration by this separation [16]. Thus, there is a significant research gap in the integration of electromagnetic measurement with radar and satellite observation in the analysis lightning event. Unlike existing studies that mainly use these sensing modalities separately, their integration for individual lightning events remains limited.

This study introduces a physics-guided multimodal artificial intelligence framework for Cloud-to-Ground (CG) lightning classification and polarity localization that combines synchronized electric field waveforms, CAPPI radar reflectivity, and Himawari-9 Cloud-Top Height (CTH) measurements to overcome the limitations from previous studies. The framework processes complementary electrical and meteorological information by using two machine learning models, namely a Convolutional Neural Network (CNN) and a feature-engineered XGBoost model. Then, the predicted magnetic field polarities are combined according to the Magnetic Direction Finder (MDF) principle to determine the lightning discharge quadrant.

The contributions of this work are:

1. A multimodal lightning analysis framework combining synchronised electric field waveforms, CAPPI radar reflectivity, and Himawari-9 CTH observations to improve CG lightning characterisation.
2. A unified prediction framework for CG lightning classification and magnetic polarity estimation, with polarity predictions combined by MDF principle for quadrant localization.
3. A comparative evaluation of CNN and XGBoost using the same multimodal inputs, showing the effectiveness of multimodal feature fusion, especially for polarity localization.

The article is organized as follows. Section 2 reviews the existing studies on lightning classification, localization, and machine learning approaches. Section 3 outlines the suggested technique, which includes multimodal data collecting and synchronization, feature extraction, model designs, polarity determination, and an assessment mechanism. Section 4 presents experimental data and analysis, along with remarks. Section 5 concludes the paper and discusses future work.

2. Literature Review

2.1. Lightning Classification

Lightning has been traditionally being classified with the used of electrical and electromagnetic characteristics of lightning radiation signals. Different waveform characteristics will be shown according to different types of lightning discharges in order to differentiate between discharge categories. Therefore, many studies have focused on analysed signal pattern, threshold-based methods and statistical feature extraction for lightning classification [13, 14]. Features such as peak amplitude, pulse width, polarity, rising time and frequency content are useful in deriving information to discriminate different lightning events [15]. Wavelet-based analysis has also been applied on magnetic field signals to discriminate between different lightning events [14].

Recently, lightning signal identification and differentiation were also studied through machine-learning techniques. A self-supervised neural-network based lightning signal recognition scheme, which learns useful lightning representations from the lightning observations, was proposed by Lu et al. [13]. This study reveals the capability of representation learning for discharge discrimination. VLF/LF electric-field radiation waveforms were studied by Sun et al. [16], where learning-based lightning discrimination was effective. Generally, with appropriate data representation, lightning patterns can also be learned directly from waveforms through deep-learning models, instead of relying on predefined lightning descriptors. Therefore, deep-learning models using CNN-based architecture have been studied to recognize lightning signals based on the electric field waveform observations [31]. This opens an opportunity to characterize lightning patterns learnt from the input signals through the CNN feature representations and offers a more automatic lightning recognition procedure compared to the manual feature selection.

However, most of the studies on lightning classification are mainly focused on the characteristics of electromagnetic signals. Waveform information provides important features of the discharge level, but does not fully characterize the surrounding atmospheric environment where the lightning event occurs. Factors related to storm structure and convective development may provide further information in the understanding of lightning events. Therefore, the combination of electromagnetic waveform features with other meteorological observations still requires further investigation.

2.2. Lightning Localization

Lightning localization methods aim at localizing lightning discharges from electromagnetic observations and are typically implemented with an array of sensors by studying the signal arrival characteristics. The TOA and TDOA lightning localization methods use signal propagation time differences to estimate lightning positions from observations received in spatially distributed sensors [10]. On the other hand, a lightning discharge can be located by studying the measured magnetic field components using the MDF method. A number of recent studies have focused on the enhancements of lightning localization performances achieved from optimized processing techniques and sensor configurations. The Capon algorithm was used in a direction-of-arrival-based lightning position system in conjunction with the MDF method, proposed by Han et al. [3]. A number of research also studied the Particle Swarm Optimization (PSO) for choosing an appropriate set of monitoring stations [12]. Ground-based lightning-location systems have also been proposed to facilitate lightning discharge mapping and monitoring [9]. These studies show that lightning localization relies not only on electromagnetic signal properties, but also on the setup and processing of the measurement systems.

Additionally, Lu et al. proposed a method to identify the lightning location based on three-dimensional weather radar data, indicating that radar observations have potential to identify spatial characteristics associated with the lightning occurrence [19]. Deep-learning approaches with multisource spatial data have also been employed for the monitoring of lightning location [8]. However, current methods mostly handle localization as a separate task from lightning classification, where electrical waveform characteristics are mostly used to identify discharge types, and spatial information for locating lightning. This is why the electrical characteristics of one single discharge are not studied simultaneously with its atmospheric and spatial information.

2.3. Machine Learning of Lightning Analysis

The application of machine learning has grown rapidly in lightning research to model the linkages between lightning activity and the atmospheric environment. Machine-learning methods were used to predict lightning occurrence based on meteorological parameters by Mostajabi et al. [25]. A deep-learning method for cloud-to-ground lightning location and frequency prediction was proposed by Li et al. [22]. Also, hybrid machine-learning methods were explored for thunderstorm and lightning prediction [26], demonstrating the potential of data-driven approaches for lightning analysis. The capabilities of different machine learning algorithms are complementary depending on the input data. Deep-learning models are able to learn complex representations from high-dimensional data, whereas feature-based models like XGBoost work best on structured variables.

In general, the literature has demonstrated the effectiveness of machine learning for lightning classification and localization. However, information obtained from different sources has typically been analyzed separately or for different prediction objectives. Therefore, there is a need to integrate electrical and atmospheric information for both lightning classification and localization, as these data sources may provide complementary information on the characteristics of the lightning discharge and its surrounding atmospheric conditions. Such integration can provide a more comprehensive representation of individual lightning events by jointly considering discharge-level and atmospheric characteristics. Hence, a multimodal approach combining electromagnetic waveforms with atmospheric observations has the potential to improve the performance of lightning classification and localization.

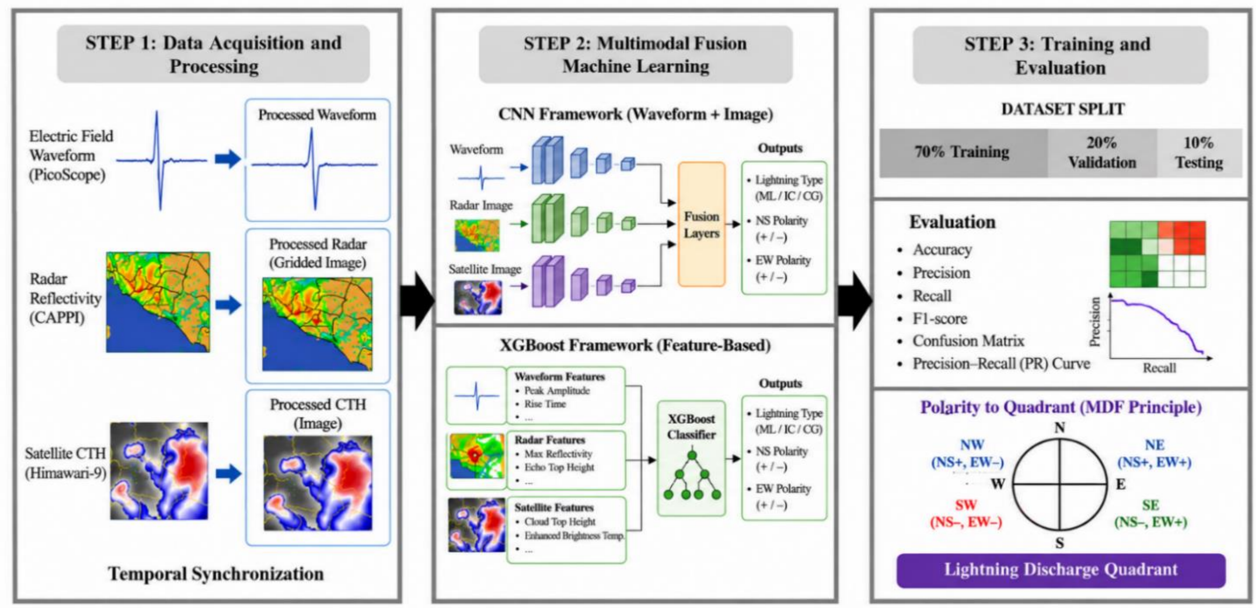


Fig. 1 Overall methodology of the proposed multimodal lightning analysis framework

3. Materials and Methods

3.1. Overall Methodology

The overall procedure (demonstrated in Figure 1) can be broken down into three phases. The first phase collected and preprocessed observations from the PicoScope-based electromagnetic measurement system, CAPPI radar reflectivity and Himawari-9 CTH products, respectively. Lightning measurements from each lightning event were temporally aligned for the three types of observations and transformed into the input format required for the learning models. The resultant multimodal datasets were further split into training, validation and testing datasets with a 70:20:10 ratio. The development of the two learning techniques from the synchronised observations was carried out in the second phase.

A CNN learning model was constructed to learn relevant features directly from the waveform, radar and satellite image observations using parallel convolutional branches. Simultaneously, an XGBoost learning model was constructed to learn feature representations using engineered descriptors created from the same set of three sensing observations. Lightning type identification and the prediction of North-South (NS) and East-West (EW) polarities of the magnetic field were carried out from the two learning models.The last phase assessed the learning models using the independent testing subset. Evaluation metrics, including accuracy, precision, recall, F1-score, confusion matrices and Precision-Recall (PR) curves, were applied to examine the lightning classification and magnetic-polarity prediction performance. The predicted NS and EW polarities were then interpreted following the Magnetic Direction Finder (MDF) principle to acquire the corresponding lightning discharge quadrant. This final procedure allows the performance in lightning classification and lightning-polarity-based localisation to be assessed.

3.2. Data Acquisition and Synchronization

The lightning measurements were made at Faculty of Electronic and Computer Engineering Technology (FTKEK), Universiti Teknikal Malaysia Melaka (UTeM), 2.314077°N, 102.318282°E, as shown in Figure 2. The lightning observation system comprises a fast-response electric field antenna and magnetic field sensor connected through a signal-conditioning buffer with decay constants of 13ms. The electric and magnetic field signals from lightning measurements were obtained through a PicoScope oscilloscope with a view to extracting relevant lightning-type classification features and magnetic-polarity identification features from the recorded lightning waveforms [27]. Weather radar observations were collected in the form of a CAPPI radar reflectivity product from the Malaysian Meteorological Department (MMD). CAPPI data represented a height of 2 km and were available every 10 min. The nearest CAPPI images to each lightning discharge time were extracted to characterize the surrounding precipitation and convective structures for each lightning event [28].

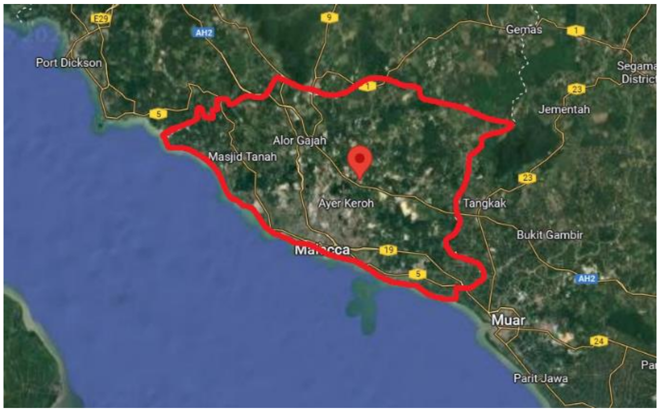


Fig. 2 The observation station at UTeM (2.314077°N, 102.318282°E) on a Google Map

Geostationary satellite observations were also obtained from MMD in the form of Himawari-9 infrared observations. These observations characterise the lightning-associated cloud structure and convective environment. The nearest Himawari-9 images to each lightning discharge time were extracted to ensure temporal consistency between the ground-based and radar observations. The three observations were then synchronised with each lightning event such that every waveform observation was matched with a radar image and a satellite image from a coincident period and a storm environment. This process yielded a multimodal dataset of lightning observations with a total of 2,799 lightning events, which was later prepared as a common input for the CNN and XGBoost models.

In addition to radar and ground-based observation, geostationary satellite data were obtained from the Malaysian Meteorological Department (MMD) in the form of Himawari-9 infrared imagery. The satellite data provides information of the cloud-top brightness temperature and spatial cloud structure over the Peninsular Malaysia region [29]. These satellite data provide large-scale context on convective development, cloud organization, and storm extent that cannot be fully learned from localized electromagnetic waveform measurements alone [30]. For each lightning event, the nearest Himawari-9 image to the recorded discharge time was chosen to temporally synchronize all input modalities.

The multimodal dataset was established by synchronizing the Himawari-9 satellite cloud images, CAPPI radar reflectivity images and PicoScope waveform data, which contained 2,799 lightning events. The dataset was then divided into training and testing sets, with a balanced representation of different lightning types to ensure consistent evaluation of the proposed multimodal learning approaches.

Temporal synchronization was used to determine that the waveform, radar and satellite observations were referring to the same lightning discharge event in the same storm system. The synchronized data set serves as the common input to CNN-based image learning and feature-engineered XGBoost classification described in the following sections.

3.3. Feature Extraction and Input Representation

The obtained waveform signals were transformed to image representations by extracting the central region of interest and resizing the resultant images to 224 × 224 pixels. Likewise, radar and satellite images were spatially extracted around the lightning discharge location and resampled to the same spatial resolution to guarantee consistent input dimensions across all modalities. This picture-like data enables CNN to learn discriminative features from the waveform morphology, temporal variations, and spatial properties of the radar and satellite observations. This waveform-to-image translation has been employed effectively in signal classification applications involving complicated temporal patterns [31].

The images were converted to greyscale and transformed into structured numerical descriptors for training XGBoost. Histogram distributions were calculated as

$$H(k) = \frac{\mathrm{n_k}}{\mathrm{N}} \tag{1}$$

Where $\mathrm{n_k}$ is the number of pixels in bin k. Gradient magnitude features were computed as

$$\mathrm{G} = \sqrt{(\frac{\partial \mathrm{I}}{\partial \mathrm{x}})^2 + (\frac{\partial \mathrm{I}}{\partial \mathrm{y}})^2} \tag{2}$$

The radial intensity and directional profiles were extracted to capture the geometry and orientation of the waveform. Radar and satellite images were extracted with similar histogram, gradient and block texture features, forming a fused feature vector with physical interpretability [32].

3.4. Framework Architecture

After feature preparation, two independent learning frameworks were implemented to evaluate the effectiveness of the multimodal fusion. CNN learns end-to-end features directly from multimodal images, in contrast to XGBoost, which relies on handcrafted descriptors extracted from waveform, radar and satellite observations. The two frameworks give the same results as in lightning classification and localization, which allows to compare directly their ability to classify.

3.4.1. Multimodal CNN Branch

Three parallel convolutional branches were constructed, each receiving waveform, radar, or satellite images. Each branch applied convolution operations defined as:

$$\mathrm{F}_l = \sigma(\mathrm{W}_l * \mathrm{F}_{l-1} + \mathrm{b}_l) \tag{3}$$

Where W_l represents learnable kernels and σ is the nonlinear activation function. Pooling layers reduced spatial resolution while retaining dominant features. Feature maps from the three branches were concatenated into,

$$F_{fusion} = [(F_{waveform} \,||\, F_{radar} \,||\, F_{satellite}) \quad (4)$$

This fused representation was then fed into fully connected layers with softmax activation for lightning type classification. The same phenomenon observed by heterogeneous sensors can be discriminated better using multimodal CNN fusion [33]. Figure 3 shows the overview of the CNN framework.

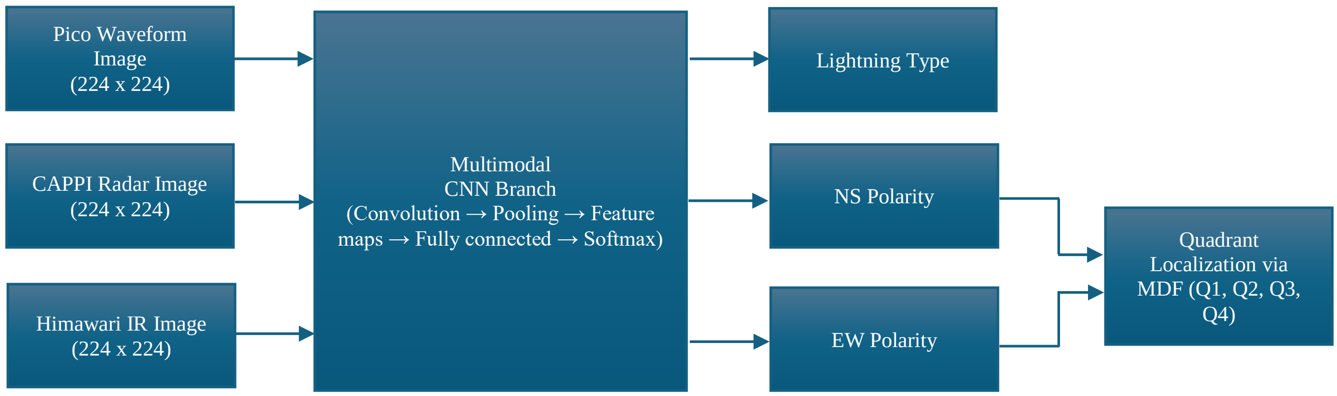


Fig. 3 Overview of CNN framework

3.4.2. Feature Engineered XGBoost Branch

The fused feature vector

$$X = [(X_{waveform}, X_{radar}, X_{satellite}) \quad (5)$$

was used to train XGBoost classifiers. XGBoost minimizes the regularized objective.

$$L = \sum_i l(y_i, \hat{y}_i) + \sum_i \Omega(f_k) \quad (6)$$

Where l is classification loss, and Ω penalizes tree complexity [34]. A multi-class model predicted lightning type, while two binary models predicted north-south and east-west polarities. Figure 4 illustrates the overview of the XGBoost framework.

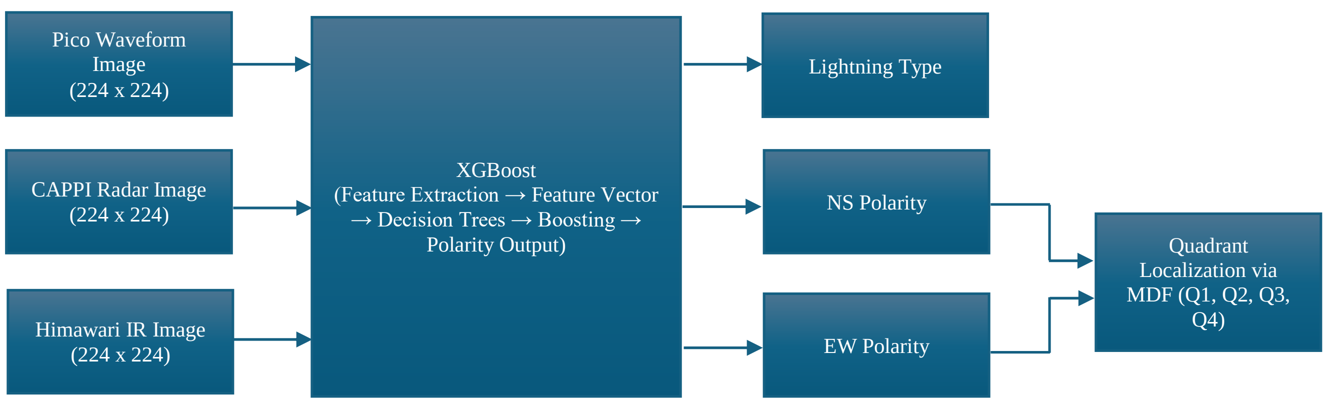


Fig. 4 Overview of XGBoost framework

3.5. Polarity and Quadrant Determination

The polarity classification objectives in this study are conducted by the Magnetic Direction Finding (MDF). The MDF locates lightning based upon a set of orthogonal measurements of the magnetic field. The conventional MDF configuration consists of an NS- and EW-loop antennas that measure the horizontal components of the magnetic field generated by lightning. The sign of the induced magnetic field from lightning is associated to the direction of the lightning current as well as the circulating direction of the induced magnetic field [35].

The MDF is divided in 4 quadrants: Q1, Q2, Q3 and Q4, as shown in Figure 6. The magnetic field associated with a current flowing through a conducting wire can be characterized with Ampère's law.

Maxwell–Ampère's law extended this relation by considering the contribution of a time-changing electric field to the magnetic field generation. Lightning discharge provides information of the direction and polarity of the measured magnetic field that helps to identify the discharge quadrant.

The magnetic field direction can be altered depending on where and in which direction lightning is occurring. A-CG discharge has upward-moving current and shows positive polarity in a so-called atmospheric sign convention, and a +CG discharge has downward-directed current and has opposite polarity to −CG. The magnetic- and electric-field measurements are thus acquired simultaneously to identify lightning-polarity.

The quadrant identification relys on the NS and EW magnetic-field components polarity. Figures 8 and 9 describe the +CG and −CG lightning flash examples. When a lightning flash hits in Q1, it shows +CG that leads to negative polarity for both the NS and the EW components, while - CG lightning hits the same quadrant with positive polarity for both the components.

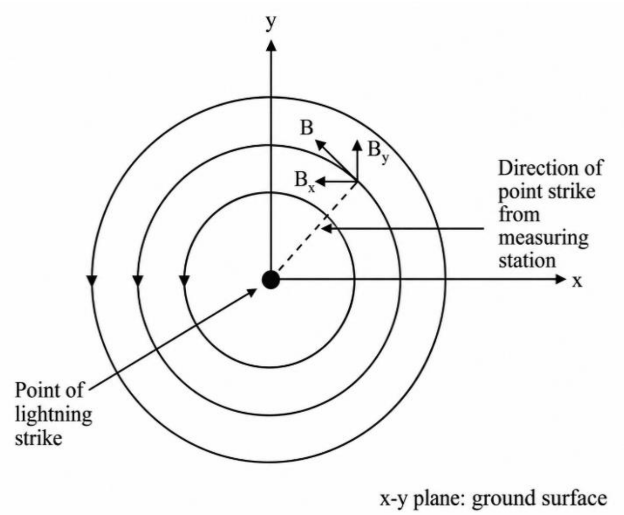


Fig. 5 Direction of magnetic fields based on a point (at center) of a lightning

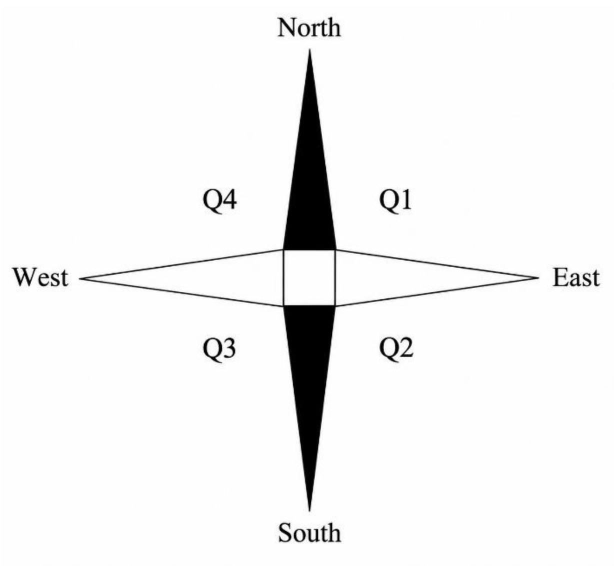


Fig. 6 Diagram of the quadrants based on the two-axis loop antenna of Magnetic Direction Finder (MDF)

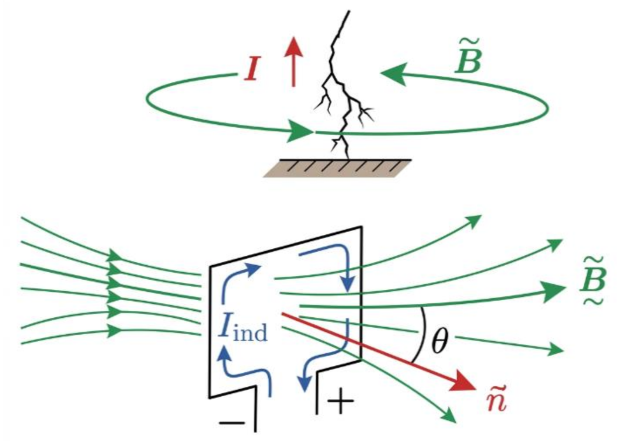


Fig. 7 Illustration of a single loop antenna in an MDF system

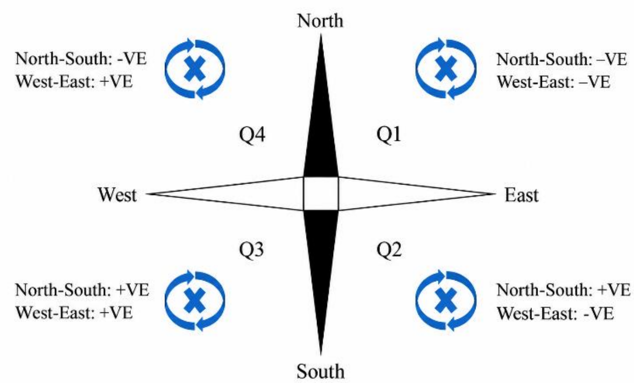


Fig. 8 Example of +CG lightning flash detected by the MDF system using a two-axis loop antenna

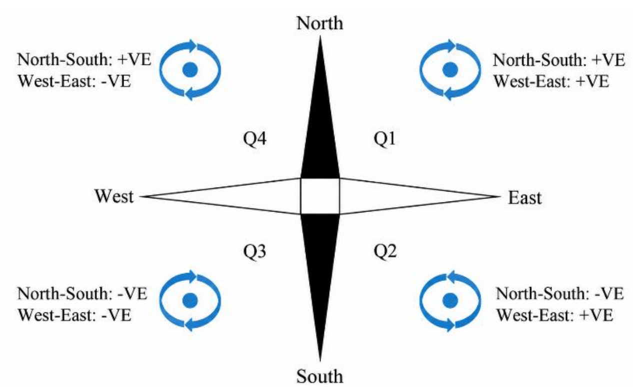


Fig. 9 Example of -CG lightning flash detected by the MDF system using a two-axis loop antenna

3.6. Training Strategy and Evaluation Metrics

Given the well-balanced lightning type and polarity classes, the multimodal waveform, radar and satellite observations datasets with synchronization is split into the training, validation, and testing sets. The class balancing is conducted by equally sampling the classes to minimize bias of learning dominant lightning types and to ensure stable learning of the lightning polarity estimation tasks. All the input images were resized into 224 × 224 pixels and were scaled to be [0, 1] before the learning process. A data augmentation was not employed to maintain the physical meaningful waveform morphology and storm patterns.

The CNN model was trained using categorical cross entropy loss.

$$\mathcal{L}_{\mathrm{CE}} = -\frac{1}{\mathrm{N}} \sum_{\mathrm{i=1}}^{\mathrm{N}} \log(\hat{\mathrm{y}}_{\mathrm{i,y_i}}) \quad (7)$$

Where $\mathrm{y_i}$ is the ground-truth lightning type label and $\hat{\mathrm{y}}_{\mathrm{i,y_i}}$ is the predicted probability for the correct class [36].

Regularised gradient boosting was used to train XGBoost models. Due to the fact that polarity errors can lead to localization errors, accuracy, recall, F1 score, confusion matrices, and quadrant reliability were all included in the evaluation [37].

$$Precision = \frac{TP}{(TP+FP)} \quad (8)$$

$$Recall = \frac{TP}{(TP+FN)} \quad (9)$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision+Recall} \quad (10)$$

The overall accuracy shows how well the classification works while the precision, recall and F1-score show how many false positives and false negatives there were. Confusion matrices show comprehensive errors for each class, and PR curves evaluate the robustness of the classifier. These additional measures provide a thorough assessment of the polarity localization and lightning classification capabilities.

The testing dataset was then used to assess the trained CNN and XGBoost models. The results of the experiment are shown and examined in the section that follows.

4. Results and Discussion

This section evaluates the proposed multimodal framework. The performance of the CNN and XGBoost models for the classification of lightning and determination of polarity is assessed from four aspects, including (i) overall classification performance, (ii) the effect of multimodal fusion, (iii) confusion matrix analysis, and (iv) Precision-Recall (PR) curve evaluation. Experimental results demonstrate the effectiveness of the proposed multimodal framework in accurate lightning classification and localization prediction.

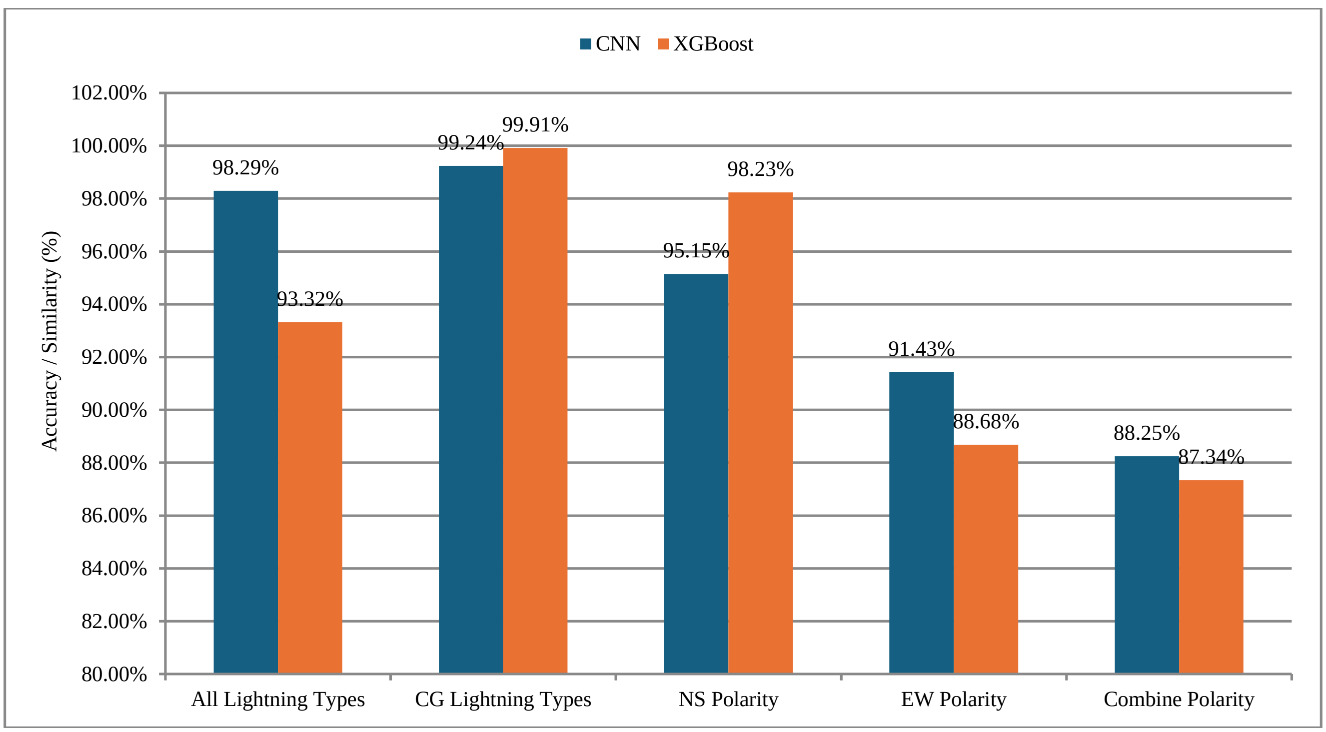


Fig. 10 Classification performance of the multimodal framework for CNN and XGBoost models

The fusion of PicoScope waveforms of the electric field, the radar reflectivity CAPPI images, and Himawari CTH data were fruitful, as illustrated in Figure 10. XGBoost outperformed slightly over CNN for CG lightning categorization with 99.91% and 99.24% accuracies, respectively. When compared with the previous studies, Zhu et al. [4] achieved about 97% lightning classification accuracy with convolutional encoding features and a machine-learning lightning classification method, and Sun et al. [16] obtained about 98.9% lightning classification accuracy using a deep-learning method on VLF/LF lightning waveforms. In the proposed work, the higher lightning classification accuracy might be due to additional radar reflectivity and Himawari CTH that complement electrical lightning waveforms. Nevertheless, their numerical comparison should be made with caution, since the dataset and lightning classification task are not the same.

However, for all lightning type classification, CNN obtained 98.29%, and XGBoost obtained 92.32% of accuracy, indicating the convolutional architecture is more effective to learn generalized feature representations across multiple lightning categories through its hierarchical feature extraction capability. The results of polarity localization reveal a different trend of performance. XGBoost achieved the best accuracy of 98.23% for North-South (NS) polarity classification, outperforming CNN with 92.15%. The results show that the ensemble learning mechanism of XGBoost can well capture the nonlinear relation in the multimodal feature space, thus allowing a more reliable discrimination of the NS magnetic field polarity. However, CNN achieved a 91.43% accuracy for the East-West (EW) polarity, and XGBoost achieved 88.68%. Both models performed well, but the lower accuracy compared to NS polarity suggests that EW polarity classification is inherently more challenging. This behaviour could be related to the increased variability of the east-west component of the magnetic field, which is affected by the orientation of the storm, the direction of propagation and the propagation of electromagnetic waves in tropical thunderstorms. The superior performance of CNN shows that the convolutional feature extraction is more effective to capture the subtle spatial characteristics pertaining to EW polarity.

The combined polarity shows the overall localization performance when both polarities of NS and EW have to be predicted accurately simultaneously. Results showed a decline of accuracy for both models. The CNN model achieved an overall accuracy of 88.25%, and XGBoost achieved an accuracy of 87.34%. This decrease is expected to be due to the final localization decision relying on the correct classification of two orthogonal components of the magnetic field. An error in the NS or EW polarity will directly impact the combined forecast. Hence, the observed drop of approximately 10-12% with respect to the single polarity accuracies indicates a cumulative propagation of classification errors and not a limitation of the proposed multimodal framework.

The methods employed in lightning location estimation in the past primarily have been based on the Time-of-Arrival (TOA), Time-Difference-of-Arrival (TDOA), Direction-of-Arrival (DOA), and spatial information. For instance, Han et al. [3] employed a DOA-based lightning localization method, and [10, 11] respectively used signal arrival-time and magnetic direction-finding techniques for lightning location estimation. Lu et al. [8] also proposed applying multisource spatial information with deep learning for lightning location monitoring. Compared with these methods, the lightning localization framework presented in this study first employs multimodal information from waveforms, radar, and satellite to predict both NS and EW magnetic-field polarity and then implements MDF for discharging location quadrant determination. The advantage of this strategy is that it can utilize electric-field waveforms, CAPPI radar reflectivity, and Himawari CTH for lightning polarization analysis. Thus, the lightning location decision not only takes into account the lightning signal characteristics, but also the surrounding thunderstorm environment. The overall lightning polarizations accessed a high degree of accuracy, indicating the viability of applying multimodal lightning data for polarity-based lightning location.

The contribution of multimodal feature fusion in comparison to the corresponding unimodal models for both CNN and XGBoost is further illustrated in Table 1. Multi-modal learning, on average, produced task dependent. The addition of CAPPI radar reflectivity and Himawari CTH with the PicoScope electric field waveform did not significantly affect the performance of CNN. The marginal decrease in all lightning classification and the CG lightning classification indicates that the electric field waveform already contains highly discriminative information, and the addition of CAPPI radar reflectivity and Himawari CTH improves the model robustness, not the classification accuracy. The small improvements for NS polarity, EW polarity and combined polarity further show that CNN is able to extract informative representations from the waveform independently, and the extra modalities provide limited complementary information.

On the other hand, XGBoost benefited more from the multimodal feature fusion, especially for the polarity localization. Lightning classification and CG lightning classification showed only marginal improvements. The addition of radar reflectivity and cloud-top height information dramatically improved the prediction of NS polarity, EW polarity and combined polarity localization. The behaviour suggests that the tree-based learning mechanism of XGBoost relies heavily on complementary information from multiple sensing modalities to discriminate complex relationships associated with magnetic field polarity. The large performance improvements show that the electrical waveform alone is not enough to reliably estimate the polarity in XGBoost. The combination with meteorological observations provides additional discriminative information that highly increases the feature separability. In general, these results confirm that multimodal fusion is most useful for complex polarity localization tasks and is especially helpful for XGBoost, moving its performance from relatively poor in the unimodal setting to highly accurate in the proposed multimodal framework.

Figure 11 illustrates the confusion matrices of the CNN and XGBoost models for CG lightning classification and combined polarity localization, as implemented by the proposed three-modality fusion framework. The diagonal elements of both models are very concentrated, and the off-diagonal predictions for CG lightning classification are negligible. This shows the models can clearly distinguish the CG lightning events and non-CG events. The balanced distribution of true negative and true positive predictions also indicates that the proposed multimodal features do not favour any class, leading to a well calibrated classifier with minimal prediction bias. With just one false positive and one false negative, XGBoost appears to have a clearer decision boundary for binary CG lightning discrimination than CNN. The confusion matrix for XGBoost also shows a strong concentration of values along the diagonal with little misclassification between neighbouring classes. This suggests that the physics-guided descriptors extracted from the waveform, radar and satellite inputs show a clear class separability when used with gradient-boosted decision trees.

The confusion matrices for combined polarity localization show a more even distribution of misclassifications, indicating that the polarity estimation task is much more difficult than the classification of CG lightning. In contrast to the binary CG classification task, the successful localization requires the simultaneous identification of both NS and EW magnetic field polarities based on the MDF principle. As a result, ambiguity in either magnetic component leads directly to localization errors. Both models showed similar distributions of predictions, with no significant bias towards any of the polarity classes. However, CNN had slightly fewer off-diagonal predictions compared to XGBoost, indicating a higher robustness in capturing the complex spatial relationships needed for simultaneous polarity estimation.

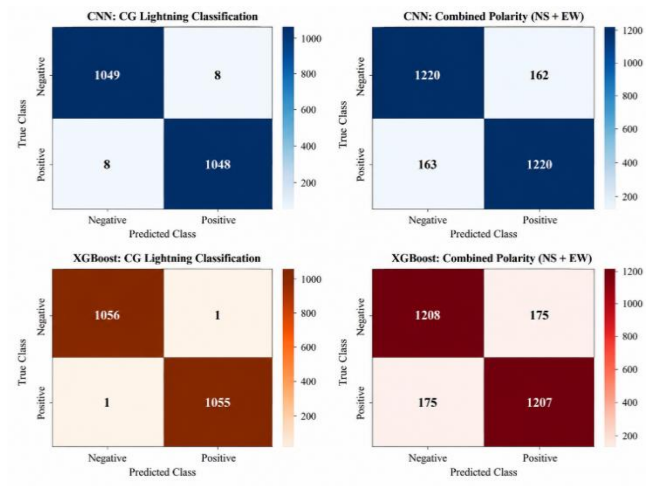


Fig. 11 Confusion matrices of the multimodal CNN and XGBoost models for CG lightning classification and combined polarity localization

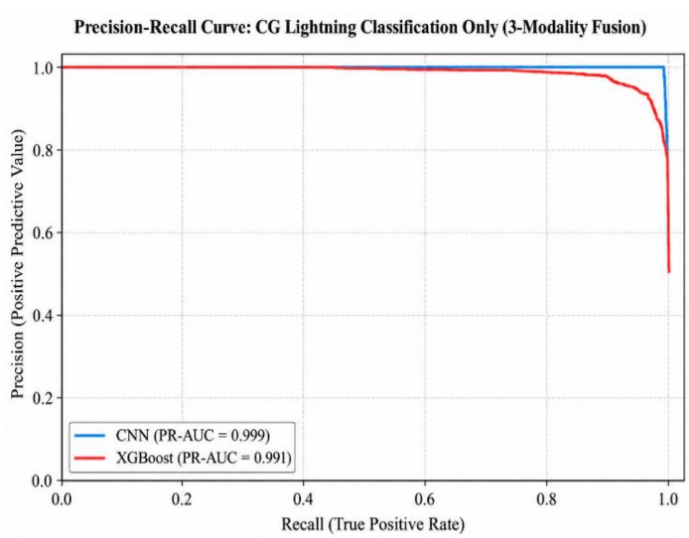
Table 1. Performance comparison between unimodal and multimodal CNN and XGBoost models

	CNN			XGBoost		
	Uni- (%)	Multi- (%)	Δ	Uni- (%)	Multi- (%)	Δ
All Lightning Type	98.54	98.29	-0.25	92.21	92.32	+0.11
CG Lightning Type	99.48	99.24	-0.24	99.76	99.91	+0.15
NS Polarity	92.14	92.15	+0.01	48.03	98.23	+50.20
EW Polarity	91.42	91.43	+0.01	56.85	88.68	+31.83
Combine Polarity	88.23	88.25	+0.02	26.29	87.34	+61.05

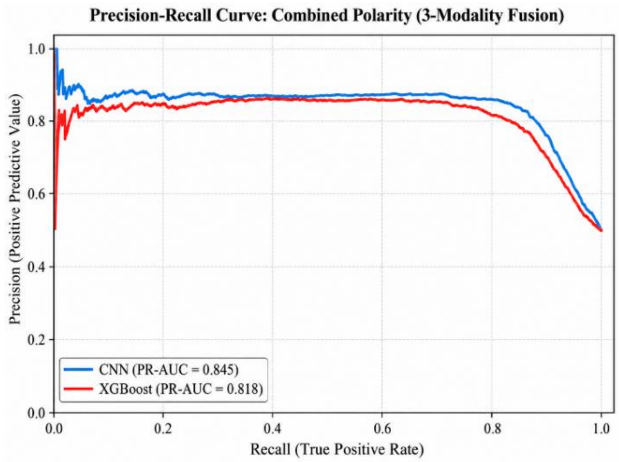
Figure 12 (a) and (b) show the Precision-Recall (PR) curves of the CNN and XGBoost model for CG lightning classification and combined polarity localization. The PR curves of both models for CG lightning classification were close to the upper right corner in almost the whole range of recall, indicating that the change of the decision threshold largely preserved the precision.

The PR-AUC values of 0.999 and 0.991 for the CNN and XGBoost, respectively, indicate that the models are reliable for positive predictions in a wide range of operating conditions.

The multimodal feature fusion produces a stable decision boundary, as evidenced by the nearly overlapping curves. This stability allows the two classifiers to achieve consistent precision without the need for extensive threshold optimization.



(a)



(b)

Fig. 12 PR curves of the multimodal framework: (a) CG lightning classification and (b) combined polarity localization.

The combined polarity localization PR curves show a smoother decrease of precision with increasing recall, which accounts for the extra ambiguity of simultaneous north-south and east-west magnetic field polarity predictions. CNN outperformed XGBoost with a higher PR-AUC of 0.845 vs 0.818 and higher precision at the majority of recall levels, indicating more robustness when operating at more permissive decision thresholds. The gap between two curves for a larger recall value indicates that CNN can find more positive samples while maintaining confidence on predictions. The results show that, along with accuracy and confusion matrices, PR analysis provides additional insight into the behaviour of the classifier at different decision thresholds. This confirms that the proposed multimodal framework is robust under different operating conditions.

5. Conclusion

In this study, a multimodal machine learning framework was proposed for Cloud-to-Ground (CG) lightning classification and polarity localization by integrating PicoScope electric field waveforms, CAPPI radar reflectivity images and Himawari Cloud-Top Height (CTH) information. The findings indicate that lightning characterization is highly precise when electrical and meteorological observations are combined. Both CNN and XGBoost performed well. XGBoost performed better in the classification of CG lightning, while CNN performed better in classification of all lightning and polarity localization. The comparison between unimodal and multimodal learning also further corroborates that multimodal feature fusion improves the classification performance, especially for polarity prediction.

The developed framework shows the potential of integrating heterogeneous sensing modalities to improve lightning monitoring in tropical thunderstorms. The system uses a polarity-oriented localization approach based on the Magnetic Direction Finder (MDF) concept, providing an efficient intermediate method for lightning localization without estimating direct striking coordinates. Future works will focus on validating the framework with more datasets in order to investigate advanced multimodal fusion techniques and extending the approach towards real-time implementation.

Conflicts of Interest

All authors declare no competing interests.

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