

ON THE FEASIBILITY OF MACHINE LEARNING-BASED DETECTION OF AIRCRAFT LIGHTNING STRIKE RISK AREAS

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Abstract

As aircraft approach electrified clouds, they may trigger lightning discharges. Although aircraft lightning strikes rarely cause serious accidents, they can damage airframes and onboard instruments, leading to aircraft downtime for inspection and repair and, consequently, flight delays and cancellations. The Japan Aerospace Exploration Agency (JAXA) has analyzed meteorological observation data in the spatial and temporal vicinity of aircraft lightning strikes and identified significant trends, based on which a method for detecting areas with a high risk of aircraft lightning strikes was previously proposed. In this study, we incorporate a machine learning approach—specifically, a support vector machine (SVM)—to further improve the performance of lightning strike risk detection. Experimental results show that the proposed SVM-based model achieves enhanced detection performance, with a probability of detection of 86% and a false alarm rate of 39%. These results demonstrate the feasibility and effectiveness of incorporating machine learning techniques into operational aircraft lightning strike risk detection systems.

Keywords: Aircraft lightning, flight operation safety, machine learning, weather radar

1. Introduction

As aircraft approach electrified clouds, they may trigger lightning discharges. Although aircraft lightning strikes rarely cause serious accidents, they can damage airframes and onboard instruments, resulting in aircraft downtime and flight delays. Moreover, carbon-composite components generally require more time and labor to repair than conventional metallic structures, making lightning strikes an increasingly important operational issue as their use becomes widespread.

To reduce the occurrence of aircraft lightning strikes and improve the safety and efficiency of flight operations, the Japan Aerospace Exploration Agency (JAXA) has analyzed meteorological observation data in the spatial and temporal vicinity of lightning events and identified significant trends. Based on these findings, we previously proposed a method for detecting areas with a high risk of aircraft lightning strikes [1, 2]. This method has since been adopted by Japanese companies providing meteorological information for flight operations and is currently used in operational airline support systems.

The previous method relies on thresholding several weather radar products and combining them logically. Owing to its simplicity and interpretability, the approach has been well accepted in operational use. Its successful deployment provides a basis for introducing more advanced techniques, and it is reasonable to expect that detection performance can be further improved by incorporating a larger number of input variables through machine-learning-based methods.

In this study, we investigate the use of a support vector machine (SVM) for aircraft lightning risk detection. The SVM allows the incorporation of multiple feature parameters while retaining a degree of interpretability and requires tuning only two hyperparameters, in contrast to the multiple thresholds required by the conventional method.

2. Machine Learning–Based Detection Approach

2.1 Feature Parameter Definition

Feature parameters were derived from the spatial relationship between aircraft positions and meteorological conditions observed by weather radar and radiosonde measurements. We generated horizontal maps of vertically integrated reflectivity (VIR), reflectivity at the $-10\,^{\circ}\mathrm{C}$ altitude level (MTR), echo-top temperature (ETT), and echo-top height (ETH). Echo-top parameters were defined using a reflectivity threshold of $20\,\mathrm{dBZ}$.

VIR, ETT, and ETH characterize the vertical structure of convective systems, whereas MTR is closely related to storm electrification processes [3]. Details of the generation of these fields are provided in [1]. Based on these maps, we derived the following feature parameters—1) Maximum VIR within a $5\,\mathrm{km}$ radius of the aircraft, 2) Maximum MTR within a $5\,\mathrm{km}$ radius of the aircraft, 3) Minimum ETT within a $5\,\mathrm{km}$ radius of the aircraft, and 4) Maximum ETH within a $5\,\mathrm{km}$ radius of the aircraft.

2.2 Preconditioning

Before inputting the feature parameters into the SVM, we applied a standard preconditioning procedure consisting of centering and scaling. Each feature parameter was normalized as $\tilde{x} = (x-\mu)/\sigma$, where μ and σ denote the mean and standard deviation of the feature parameter x, respectively. The means and standard deviations were computed after excluding outliers.

The SVM includes two hyperparameters—the regularization parameter and the kernel coefficient—and this normalization enables the use of identical hyperparameter values across all feature parameters.

2.3 Support Vector Machine (SVM)

We employed the support vector machine (SVM) implementation provided by the Python machine learning library `scikit-learn`, using the `SVC` classifier. The specifications of the SVC are summarized in Table 1. We adopted the radial basis function (RBF) kernel and examined several candidate values for the regularization parameter C and the kernel coefficient γ. These two hyperparameters were selected through a grid search during the training process.

In addition, we set the `class_weight` option to `balanced` in order to address class imbalance in the training data. As in many severe weather datasets, positive samples corresponding to lightning strikes are scarce, whereas negative samples are dominant. This weighting scheme compensates for the imbalance by assigning larger penalties to misclassified positive samples.

Table 1 – Specifications of SVC

Item	Specification
C	[1, 10, 50, 100, 500, 1000, 10000]
kernel	`rbf`
γ	[0.01, 0.05, 0.1, 0.5, 1, 10]
class_weight	`balanced`

3. Experimental Results

The dataset was divided into training, validation, and testing subsets with proportions of 80%, 10%, and 10%, respectively. Through training and validation, the regularization parameter C and kernel coefficient γ were selected as 1 and 0.1, respectively. Based on the validation data, the probability of detection (POD) and false alarm rate (FAR) were 77% and 38%, respectively (see [] for definitions). For comparison, the conventional threshold-based method achieved a POD of 79% and an FAR of 55% for the moderate risk level defined in [1]. Thus, the proposed SVM substantially reduces the FAR while maintaining comparable detection performance. On the independent testing data, the SVM achieved a POD of 86% and an FAR of 39%, demonstrating robust generalization performance. Figure 1 shows an example of detection results obtained by the SVM model. The detected risk areas are indicated by red filled circles and are overlaid on a radar reflectivity factor field at an altitude of $2\,\mathrm{km}$.

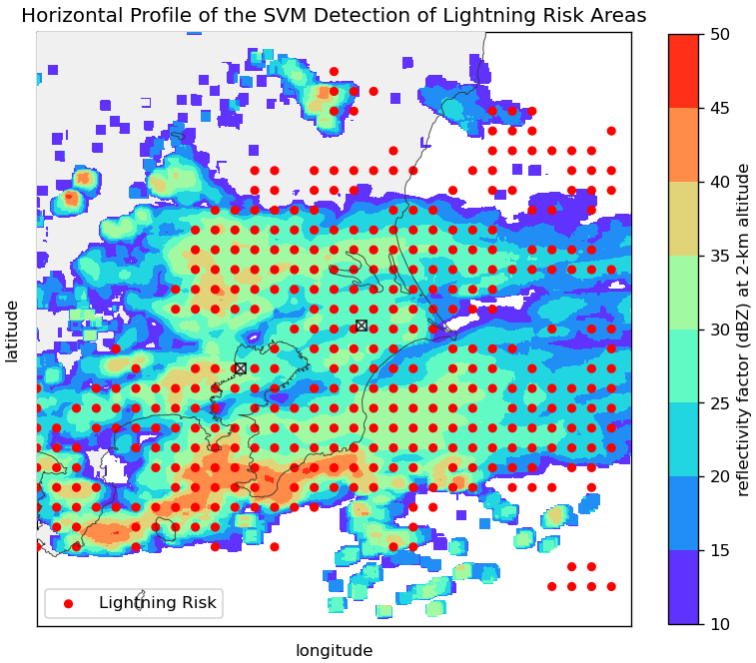


Figure 1 – An example of aircraft lightning strike risk areas detected by the SVM model. The risk areas are indicated by red filled circles and are overlaid on a radar reflectivity factor field at the $2\,\mathrm{km}$ altitude level.

4. Conclusion

Lightning is a major environmental hazard affecting aircraft operations with significant economic and operational impacts. To mitigate aircraft lightning strikes, JAXA previously proposed a method for detecting lightning strike risk areas based on ground-based meteorological observations. The method has been adopted by Japanese information technology companies and is currently used to provide real-time risk information to airlines.

In this study, we incorporated a machine learning approach into the detection framework by employing a support vector machine (SVM). Feature normalization and class weighting were introduced to handle heterogeneous parameters and severe class imbalance. The trained SVM achieved a POD of 77% and an FAR of 38% on validation data, and a POD of 86% and an FAR of 39% on independent testing data, representing a significant improvement over the conventional threshold-based method, particularly in terms of false alarm reduction.

Future work will include additional experiments with multiple data partitions to assess the stability of the learned hyperparameters and detection performance. In parallel, advances in phased array weather radars [4, 5, 6, 7, 8, 9, 10, 11, 12], signal processing techniques [13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29], and data processing techniques [30, 31, 32, 33, 34, 35] are expected to improve the quality of meteorological features and further enhance aircraft lightning strike risk detection.

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References

[1] Yoshikawa E and Ushio T. Tactical Decision-Making Support Information for Aircraft Lightning Avoidance: Feasibility Study in Area of Winter Lightning. *Bulletin of the American Meteorological Society*, 100, pp 1443-1452, 2019.

[2] Yoshikawa E, Horishita S and Ushio T. Aircraft Lightning Potential Area Detection Enhanced by Echo Top Height and its Evaluation with Winter Lightning Cases. *Journal of Atmospheric Electricity*, Vol. 39, No. 2, pp 70-78, 2021.

[3] Takahashi T. Riming electrification as a charge generation mechanism in thunderstorms. *Journal of the Atmospheric Sciences*, 35, pp 1536–1548, 1978.

[4] T. Ushio et al. Development and observation of the phased array radar at X band. *2014 XXXIth URSI General Assembly and Scientific Symposium (URSI GASS)*, Beijing, China, pp. 1-4, 2014.

[5] Yoshida S, Adachi T, Kusunoki K, Hayashi S, Wu T, Ushio T, and Yoshikawa E. Relationship between thunderstorm electrification and storm kinetics revealed by phased array weather radar. *Journal of Geophysical Research Atmospheres*, 122, pp 3821–3836, 2017.

[6] Mizutani F, Ushio T, Yoshikawa E, Shimamura S, Kikuchi H, and Wada M. Fast-Scanning Phased-Array Weather Radar With Angular Imaging Technique. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 56, No. 5, pp. 2664–2673, 2018.

[7] Ushio T, Yoshikawa E, Kikuchi H, and Wada M. Development and Observations of the Phased Array Radar for Weather Application. *2020 IEEE Radar Conference (RadarConf20)*, Florence, Italy, pp. 1–3, 2020.

[8] Yoshikawa E, Ushio T, and Kikuchi H. A Study of Comb Beam Transmission on Phased Array Weather Radars. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 59, No. 8, pp. 6346–6356, 2021.

[9] Yoshikawa E, Ushio T, and Kikuchi H. Application of Comb Beam Transmission to C-band Phased Array Weather Radar. *2022 IEEE Radar Conference (RadarConf22)*, New York City, NY, USA, pp. 1–5, 2022.

[10] Ushio T, Kim D, Baron P, Wada Y, Mega T, Mizutani F, Wada M, Yoshikawa E, Satoh S, and Hanado H. Recent Progress on the Phased Array Weather Radar at X Band. *2022 IEEE Radar Conference (RadarConf22)*, New York City, NY, USA, pp. 1–4, 2022

[11] Chandrasekar V, Yoshikawa E, Dwarakanth V, Loew E, Blake W, and Pierce M. Considerations for Dual-Polarization Measurements from an Airborne Phased Array Doppler Weather Radar. *2024 IEEE International Symposium on Phased Array Systems and Technology (ARRAY)*, Boston, MA, USA, pp. 1–6, 2024

[12] Chandrasekar V and Yoshikawa E, Assessment of Dual-Polarization Measurements by Phased Array Weather Radar for Airborne Applications. *2025 22nd European Radar Conference (EuRAD)*, Utrecht, Netherlands, pp. 161-164, 2025.

[13] Yoshikawa E, Ushio T, Kawasaki Z, Yoshida S, Morimoto T, and Mizutani F, and Wada M. MMSE Beam Forming on Fast-Scanning Phased Array Weather Radar. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 51, No. 5, pp. 3077–3088, 2013.

[14] Kikuchi H, Wu T, Yoshikawa E, Ushio T, Goto H, Mizutani F, Wada M, and Chandrasekar V. Performance of Minimum Mean-Square Error Beam Forming for Polarimetric Phased Array Weather Radar. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 55, No. 5, pp. 2757–2770, 2017.

[15] Kikuchi H, Yoshikawa E, Ushio T, Mizutani F, and Wada M. Application of Adaptive Digital Beamforming to Osaka University Phased Array Weather Radar. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 55, No. 7, pp. 3875–3884, 2017.

[16] Kikuchi H, Yoshikawa E, Ushio T, Mizutani F, and Wada M. Adaptive Pulse Compression Technique for X-Band Phased Array Weather Radar. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 14, No. 10, pp. 1810–1814, 2017.

[17] Kitahara D, Nakahara M, Hirabayashi A, Yoshikawa E, Kikuchi H, and Ushio T. Nonlinear Beamforming via Convex Optimization for Phased Array Weather Radar. *2018 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC)*, Honolulu, HI, USA, pp. 1831–1835, 2018.

[18] Kikuchi H, Yoshikawa E, Ushio T, and Hobara Y. Clutter Reduction for Phased-Array Weather Radar Using Diagonal Capon Beamforming With Neural Networks. *IEEE Geoscience and Remote Sensing Letters*, Vol. 17, No. 12, pp. 2065–2069, 2020.

[19] Yoshikawa E, Takizawa N, Kikuchi H, Mega T, and Ushio T. An Estimator for Weather Radar Doppler Power Spectrum via Minimum Mean Square Error. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 60, pp. 1–16, 2022.

[20] Kikuchi H, Yoshikawa E, Ushio T, and Hobara Y. Adaptive Beamforming Using Steering Vector Correction

for Phased-Array Weather Radar. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, Vol. 14, pp. 8419–8426, 2021.

[21] Kitahara D, Kuroda H, Hirabayashi A, Yoshikawa E, Kikuchi H, and Ushio T. Nonlinear Beamforming Based on Group-Sparsities of Periodograms for Phased Array Weather Radar. *IEEE Transactions on Geoscience and Remote Sensing*, Vol. 60, pp. 1–19, 2022.

[22] Kuroda H, Kitahara D, Yoshikawa E, Kikuchi H and Ushio T. Convex Estimation of Sparse-Smooth Power Spectral Densities From Mixtures of Realizations With Application to Weather Radar. *IEEE Access*, vol. 11, pp. 128859-128874, 2023.

[23] Kuroda H, Kitahara D, Yoshikawa E, Kikuchi K and Ushio T. Sparsity-Smoothness-Aware Power Spectral Density Estimation with Application to Phased Array Weather Radar. *ICASSP 2023 - 2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Rhodes Island, Greece, pp. 1-5, 2023.

[24] Wada Y et al. Mitigation of Ground-Clutter Effects by Digital Beamforming With Precomputed Weighting Matrix for Phased Array Weather Radar. *IEEE Transactions on Geoscience and Remote Sensing*, vol. 62, pp. 1-14, 2024, Art no. 5102414.

[25] Wada Y, Kikuchi H, Yoshikawa E, Kitahara D and Ushio T. Phase and Amplitude Correction for Adaptive Beamforming of Phased Array Weather Radar. *IEEE Transactions on Geoscience and Remote Sensing*, vol. 62, pp. 1-11, 2024, Art no. 5111011.

[26] Yoshikawa E, Chandrasekar V, Nishimura K, Kitahara D, Wada Y, and Ushio T. Angular Profile Estimation on Phased Array Weather Radar by Maximizing Marginal Likelihood. *2025 IEEE International Radar Conference (RADAR)*, Atlanta, GA, USA, pp. 1–6, 2025.

[27] Yoshikawa E and Chandrasekar V. Demystifying Pulse Compression in Weather Radar. *IEEE Sensors Reviews*, Vol. 2, pp. 573–588, 2025.

[28] Yoshikawa E, Chandrasekar V, Kitahara D, Nishimura K, Wada Y and Ushio T. Comparison of Re-Iterative Adaptive Beamformers for Phased Array Radars. *2025 22nd European Radar Conference (EuRAD)*, Utrecht, Netherlands, pp. 39-42, 2025.

[29] Yoshikawa E and Chandrasekar, V. Principles of Coherent Doppler Wind Lidar and Doppler Weather Radar: Similarities and Differences in Waveforms and Signal Processing. *Radar Meteorology and its Applications*, Springer Atmospheric Sciences. Springer, Singapore.

[30] Yoshikawa E, Ushio T, Kawasaki Z and Chandrasekar V. Dual-Directional Radar Observation for Preliminary Assessment of the Ku-Band Broadband Radar Network. *J. Atmos. Oceanic Technol.*, 29, pp. 1757–1768, 2012.

[31] Shimamura S, Chandrasekar V, Ushio T, Kim G, Yoshikawa E and Chen H. Probabilistic Attenuation Correction in a Networked Radar Environment. *IEEE Transactions on Geoscience and Remote Sensing*, vol. 54, no. 12, pp. 6930-6939, 2016.

[32] Yoshikawa E, Chandrasekar V, Ushio T and Matsuda T. A Bayesian Approach for Integrated Raindrop Size Distribution (DSD) Retrieval on an X-Band Dual-Polarization Radar Network. *J. Atmos. Oceanic Technol.*, vol. 33, pp. 377–389, 2016.

[33] Kim D-K, Suezawa T, Mega T, Kikuchi H, Yoshikawa E, Baron P and Ushio T. Improving precipitation nowcasting using a three-dimensional convolutional neural network model from Multi Parameter Phased Array Weather Radar observations. *Atmospheric Research*, Vol 262, 2021.

[34] Baron P, Kim D-K, Kawashima K, et al. Comparative study of deep neural networks for very short-term prediction of torrential rains using polarimetric Phased-Array Weather Radar (MP-PAWR). *Proc. SPIE* 11914, SPIE Future Sensing Technologies 2021.

[35] Kitahara D, Wada Y, Mega T, Yoshikawa E, Kikuchi H and Ushio T. Ideas for Radar Data Denoising and Fusion Based on Image Processing Techniques. *2023 XXXVth General Assembly and Scientific Symposium of the International Union of Radio Science (URSI GASS)*, Sapporo, Japan, pp. 1-4, 2023.