# Enhancing Detection of Nighttime Fishing Boat Lights Using VIIRS Satellite Data and Deep Neural Networks

Suk Yoon[1], Kwang-Seok Kim[1], Hee-Jeong Han[1], Hyeong-Tak Lee[1], Hyun Yang[2,*]

[1]Korea Ocean Satellite Center, Korea Institute of Ocean Science & Technology, Busan, South Korea

[2]Division of Maritime AI & Cyber Security, Korea Maritime & Ocean University, Busan, South Korea

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## Abstract

Illegal nighttime fishing remains difficult to monitor because vessels often deactivate the Automatic Identification System (AIS). This study presents a supervised deep neural network (DNN) approach for detecting nighttime fishing vessel lights using the Day/Night Band (DNB) data from the Visible Infrared Imaging Radiometer Suite (VIIRS) onboard the Suomi NPP and NOAA-20 satellites. The model integrates DNB radiance features with lunar illumination information to reduce false detections caused by moonlight. The dataset comprises summer-season observations (2020–2021) in waters near Jeju Island, South Korea, with labels derived from temporally matched AIS records. The proposed DNN is evaluated using a stratified train–test split and compared with conventional machine-learning baselines. Experimental results demonstrate improved performance, achieving an F1 score above 0.90, indicating the robust detection capability under low-light maritime conditions. These findings highlight the potential of VIIRS DNB data combined with deep learning for large-scale nighttime maritime monitoring beyond AIS-dependent systems.

**Keywords:** nighttime fishing boat detection, VIIRS DNB, deep neural network, lunar illumination correction, AIS-based validation

## 1. Introduction

Nighttime light observations from space have been widely used to detect artificial illumination associated with human activities, including fishing operations [1-3]. With improved radiometric sensitivity and spatial resolution, the Day/Night Band (DNB) of the Visible Infrared Imaging Radiometer Suite (VIIRS) enables more accurate nighttime vessel detection compared with earlier satellite systems [4-5]. Nighttime fishing vessel detection is critical for maritime surveillance, as illegal fishing vessels often deactivate the Automatic Identification System (AIS) transmitters, making AIS-based monitoring insufficient for identifying non-cooperative targets [6]. VIIRS DNB data provide an alternative observation source by capturing artificial lighting emitted during nighttime fishing operations, particularly for light-intensive fisheries common in Northeast Asia [7-8].

However, previous studies based on threshold-based or traditional machine-learning methods often struggle to handle nonlinear radiance variations caused by lunar illumination and background ocean noise [9]. Although more complex deep learning approaches have been applied to VIIRS DNB imagery, their practical applicability is frequently limited by data availability, model complexity, or insufficient consideration of lunar illumination effects [10]. In this study, AIS data are not used to identify AIS-dark vessels directly but to provide reference information for validating the correspondence between

* Corresponding author. E-mail address: yanghyun@kmou.ac.kr

nighttime light emissions and known fishing vessel activity [8, 11]. The proposed method focuses on detecting fishing vessel lights [12], which may be observed regardless of AIS transmission status. In contrast to existing approaches, this study adopts a practical supervised deep neural network (DNN) framework that balances detection performance and operational feasibility using directly received VIIRS DNB data.

Moreover, deep learning–based approaches for nighttime fishing vessel detection have rarely been evaluated in Korean coastal waters. To address these limitations, this study proposes a DNN-based nighttime fishing vessel detection framework tailored to fisheries operating near the Korean Peninsula. Fig. 1 shows a VIIRS DNB image captured on 17 July 2021 at 16:37, in which bright spots indicate artificial lights emitted from urban areas and fishing vessels at sea.

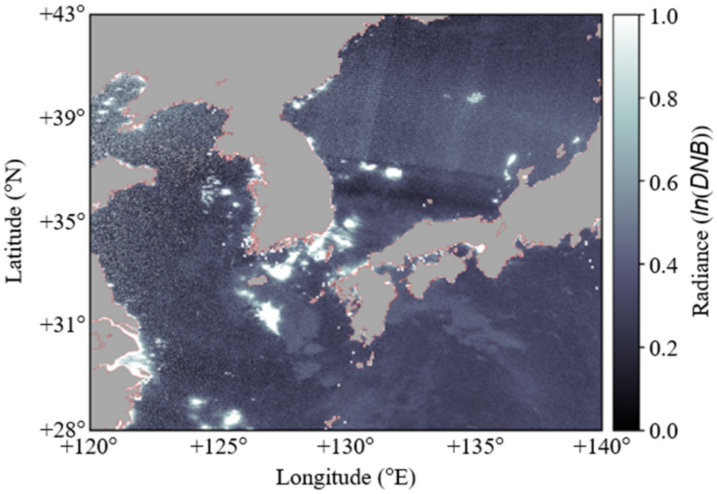



Fig. 1 VIIRS DNB nighttime light image over the Korean Peninsula

## 2. Method

This study presents a supervised DNN framework for detecting nighttime fishing vessel lights using VIIRS DNB data. AIS information is used to construct labeled datasets, and a lightweight DNN incorporating lunar illumination features performs pixel-level classification. The approach aims to provide a computationally efficient and practical solution for nighttime vessel detection.

### *2.1. Overview*

This study proposes a supervised DNN framework for detecting nighttime fishing vessel lights using VIIRS DNB satellite data. The overall methodology consists of three main components: (1) collection and preprocessing of directly received VIIRS DNB radiance data, (2) construction of labeled training and validation datasets using temporally matched AIS information, and (3) pixel-level classification of fishing vessel lights using a lightweight DNN model that incorporates lunar illumination features. Section 2.2 describes the study area and target maritime environment near Jeju Island. Section 2.3 explains the acquisition and preprocessing of AIS data used for labeling and validation. Section 2.4 details the reception and processing of VIIRS DNB satellite data and describes the architecture and training procedure of the proposed DNN model. This structured approach is designed to evaluate the feasibility of a practical and computationally efficient DNN-based solution for nighttime fishing vessel detection.

### *2.2. Study area*

As shown in Fig. 2, nighttime lights from fishing boats in the waters near Jeju Island were detected using DNB data. The detection results were validated using AIS data collected simultaneously with the DNB satellite data acquisition. The study period and region were deliberately selected to minimize environmental variability and ensure reliable AIS-based validation.

By focusing on a short summer timeframe and a well-monitored maritime area, the proposed approach aims to evaluate the feasibility of DNN-based nighttime fishing vessel detection under controlled conditions. Focusing on a single season and region allows for a controlled assessment of the proposed method, while not aiming to fully evaluate robustness across diverse environmental conditions.

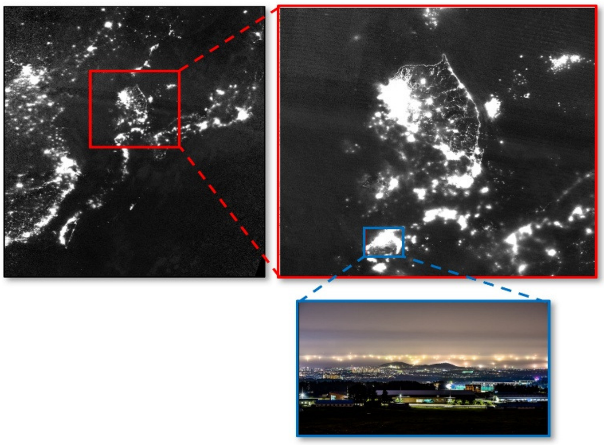


Fig. 2 Study area for nighttime fishing vessel light detection

*2.3. AIS data collection and processing*

To validate the results of the proposed DNN-based nighttime fishing vessel light detection model, AIS data from July 17 to 18, 2021, was obtained from the Korea Coast Guard and processed. This period was chosen because it is less influenced by moonlight. A unified file was created to extract fishing vessel data by combining dynamic and static AIS data and converting the information into a format that allows for comparison and extraction of relevant details. Data corresponding to the exact dates and times at which the satellite data are acquired were selected from this unified dataset for comparative validation. The static AIS data consisted of a single file containing information on approximately 200,000 vessels, while the dynamic AIS data was divided into multiple files over time. Preprocessing was planned to integrate the dynamic and static data to track individual vessel trajectories.

Additionally, labeling was performed to match the latitude and longitude positions from the AIS data with the light intensity values of each pixel in the nighttime light satellite data. Additional factors, such as moonlight variations and cloud distribution, were considered to improve the model's accuracy. Although mandatory installation of AIS transmitters for vessel monitoring has been introduced, most illegal vessels deactivate their AIS transmitters during illegal fishing activities [13], making monitoring and enforcement challenging. While regular on-site inspections using ships and drones are conducted to establish a lawful fishing environment, it remains virtually impossible to monitor and enforce compliance across vast marine areas comprehensively. To address this, the AIS data were processed and validated using the following procedures:

(1) Dynamic data processing: Extract the relevant records corresponding to the study period and region. Ensure their positional and temporal alignment with the DNB satellite data for validation.

(2) Static data processing: Link static vessel information to dynamic data using the Maritime Mobile Service Identity (MMSI) identifier. Integrate vessel-specific details (e.g., type, size, and tonnage) to provide context for validation and analysis.

(3) Validation: Compare vessel positions and activities derived from AIS data with the detected light sources from the DNN model to assess accuracy [14-15].

Following validation, additional static information was utilized to classify and analyze the detected vessels [16-19]. Nighttime fishing vessel detection using satellite imagery constitutes an imbalanced classification problem, as the number of background ocean pixels significantly exceeds that of vessel-related pixels. To mitigate this issue, a data-level balancing strategy was adopted in this study. A total of 350 pixels corresponding to fishing vessels were identified based on temporally matched AIS data, and an equal number of non-fishing (dark ocean) pixels were randomly sampled from the same observation scenes. This 1:1 balanced dataset was used for training and evaluation of the DNN model to reduce classification bias toward the dominant background class [7, 19].

### *2.4. Satellite data reception and nighttime light DNB processing*

Fig. 3 illustrates the overall workflow for VIIRS DNB data reception and processing. The Ocean Satellite Center of the Korea Institute of Ocean Science and Technology (KIOST) operates a 2.4 m X-band antenna to receive satellite telemetry signals in the 7.787–8.2375 GHz frequency range. The received signal is first amplified using a low-noise amplifier (LNA) to improve the signal-to-noise ratio and then converted to a lower frequency by a downconverter. The processed signal is subsequently digitized through a modem/baseband (Modem/BB) system.

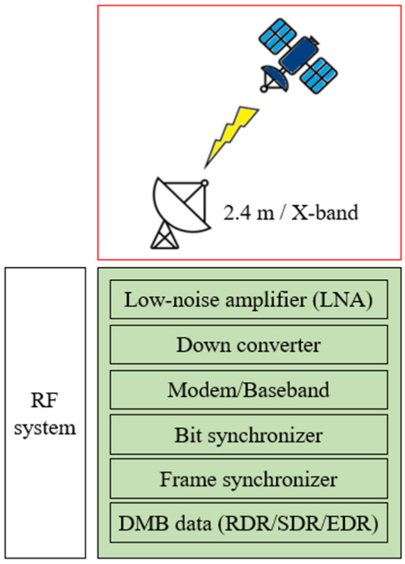



Fig. 3 VIIRS DNB data reception and processing workflow

This section involves the antenna and radio frequency (RF) part for receiving foreign satellite data. In the intermediate frequency (IF) part, the receiver separates the digital data, a process known as modulation. The bit synchronizer regenerates the bit stream to counter noise and, if needed, converts the data into a structured format using a frame synchronizer, which also extracts the clock. The ground operating system uses the frame synchronizer to divide the continuous data stream into meaningful segments.

Additionally, raw data can be stored directly or collected as telemetry data format (TDF) files for image processing and other data applications. A land-based algorithm that does not consider maritime atmospheric corrections [8] was applied, but a new algorithm is required to better analyze ocean-related data. In satellite-based monitoring systems, data processing pipelines are often subject to mission-critical constraints, including limited computational resources, strict reliability requirements, and the need for autonomous error handling.

Recent studies have emphasized the importance of software optimization and efficient processing architectures to support AI-driven applications in satellite systems [1]. These considerations are particularly relevant for VIIRS DNB data processing, where near-real-time analysis must be achieved within constrained operational environments. The reception and collection of VIIRS DNB radiance data, used for nighttime light observations, are conducted through satellites such as Suomi NPP and NOAA-20, which are equipped with VIIRS sensors. As shown in Table 1, the DNB band of the VIIRS sensor is designed as a nighttime visible channel for the panchromatic wavelength range of 0.5–0.9 μm, enabling the detection of low-intensity emitted energy from artificial lighting [4-5].

Table 1 Channel information of VIIRS data

| VIIRS channels (S-NPP, NOAA-20/21) | | |
|---|---|---|
| Band | Wavelength (um) | Spatial resolution (m) |
| M1 | 0.402–0.422 | 750 |
| M2 | 0.436–0.454 | |
| M3 | 0.478–0.498 | |
| M4 | 0.545–0.565 | |
| M5 | 0.662–0.682 | |
| M6 | 0.739–0.754 | |
| M7 | 0.846–0.885 | |
| M8 | 1.230–1.250 | |
| M9 | 1.371–1.386 | |
| M10 | 1.580–1.640 | |
| M11 | 2.230–2.280 | |
| M12 | 3.610–3.790 | |
| M13 | 3.970–4.130 | |
| M14 | 8.4–8.7 | |
| M15 | 10.26–11.26 | |
| M16 | 11.54–12.49 | |
| ***DNB** | 0.5–0.9 | |
| I1 | 0.6–0.68 | 350 |
| I2 | 0.85–0.88 | |
| I3 | 1.58–1.64 | |
| I4 | 3.55–3.93 | |

The data are converted into GeoTIFF format and stored. For data processing and visualization, the GDAL module supported by Python is used to extract map image data from the GeoTIFF format. This information is then utilized to generate input and processed data for further analysis [2, 4].

The processed data are stored, with the annual storage volume exceeding 100 terabytes. DNB data are generated using the channels shown in Table 1. Raw data received from satellites are processed using Tersasan 3.2, which includes the Community Satellite Processing Package (CSPP) 3.2 for preprocessing. The CSPP software processes VIIRS Level 1B data for science data records (SDR) and Level 2 data for environmental data records (EDR) production. To improve the accuracy of DNB data, cloud-covered areas must be removed, which is a process known as cloud masking. For this purpose, cloud removal was performed using JPSS-JRR-CloudMask information, based on NASA's new algorithm [4]. In this study, a cloud mask was used as a reference to qualitatively verify vessel detection results and to aid understanding [19-20].

Cloud mask values are divided into four levels, as summarized in Table 2. Value 0 (Clear) indicates a clear sky condition with little or no cloud cover (cloud probability $\leq 0.1$). Value 1 (Probably clear) represents mostly clear conditions with a cloud probability between 0.1 and 0.5. Value 2 (Probably cloudy) indicates mostly cloudy conditions with intermittent clear patches (cloud probability between 0.5 and 0.9). Value 3 (Cloudy) represents nearly complete cloud cover, with a cloud probability of $\geq 0.9$, indicating a very high likelihood of complete cloud cover [7]. These classifications improve the precision of nighttime light data by ensuring clear observations. Fig. 4 illustrates the DNN model used to detect nighttime fishing vessel lights from DNB data.

Table 2 Cloud mask values and their descriptions

| Cloud mask value | Numerical value | Description |
|---|---|---|
| Clear | 0 | Cloudy probability $\leq 0.1$ |
| Probably clear | 1 | Cloudy probability $\geq 0.1$, but $\leq 0.5$ |
| Probably cloudy | 2 | Cloudy probability $\geq 0.5$, but $\leq 0.9$ |
| Cloudy | 3 | Cloudy probability $\geq 0.9$ |

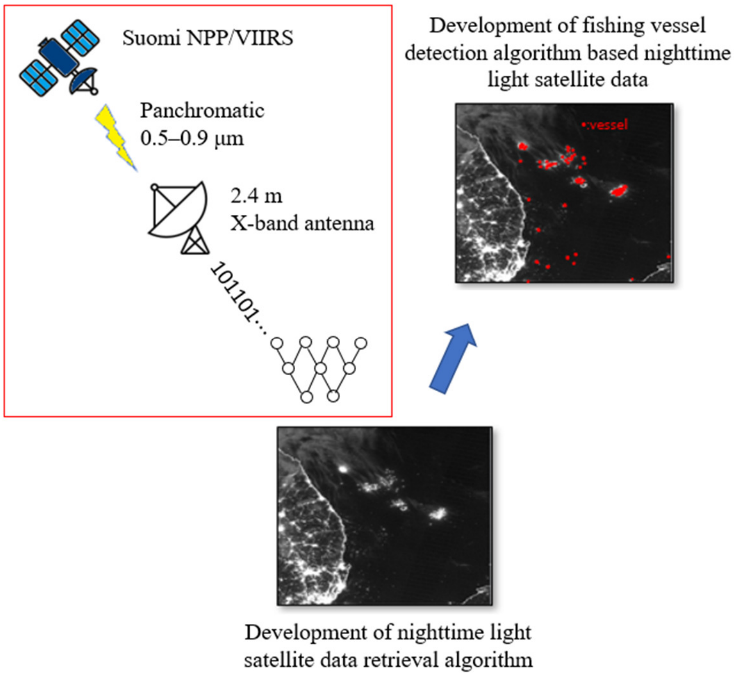



Fig. 4 DNN-based nighttime fishing vessel detection framework

As shown in Fig. 5, this model consists of 4 hidden layers. The triangle markers represent DNB input data, and the rectangle markers represent MOON input data, respectively. The star markers represent fishing vessels, while the diamond markers indicate non-fishing vessels or general sea areas. To introduce nonlinearity in the function output, the Rectified Linear Unit (ReLU) activation function was employed. The cost function used is mean squared error (MSE), and the optimization function selected to minimize the cost function is the Adam optimizer. The Adam optimizer combines the advantages of momentum-based methods, which rapidly approach the global optima, and adaptive learning rate methods, which allow for nearly linear movement toward the Global Optima, even if the speed is slower.

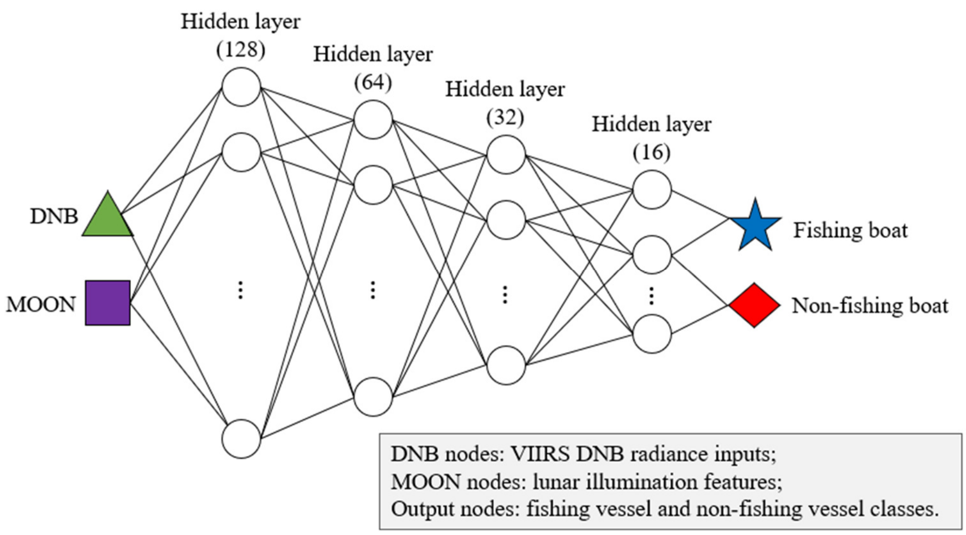



Fig. 5 Architecture of the proposed DNN model

As shown in Fig. 5, the proposed DNN model integrates VIIRS DNB radiance and lunar illumination features to distinguish fishing vessel lights from background ocean noise. All figures were designed to be self-explanatory, with consistent labeling and detailed captions to improve readability and interpretation. Although the detection task ultimately involves binary labeling of fishing and non-fishing pixels, the proposed DNN is formulated to learn nonlinear radiance-based separations between vessel lights and background ocean signals. Accordingly, MSE is adopted as the loss function, and the final classification is performed through threshold-based interpretation of the model output [9, 11, 17]. The design of the proposed

DNN architecture, including feature selection and network configuration, was conducted manually based on domain knowledge and practical operational considerations. While this approach ensures interpretability and computational efficiency, human-led design decisions may limit optimal model configuration, especially as data volume and environmental variability increase.

Recent studies have demonstrated that automated machine learning (AutoML) frameworks can effectively automate feature selection and hyperparameter tuning, thereby improving model performance and scalability in data-driven applications [20]. Incorporating AutoML-based optimization strategies into satellite-based maritime monitoring systems represents a promising direction for future research.

The proposed model adopts a lightweight fully connected DNN rather than more complex architectures such as convolutional neural networks (CNNs). This design choice is motivated by the characteristics of the detection task and the operational constraints of satellite-based maritime monitoring. In this study, nighttime fishing vessel detection is formulated as a pixel-level classification problem using DNB radiance values and lunar illumination information, without explicitly relying on spatial texture or neighborhood patterns. Therefore, a fully connected DNN is sufficient to capture the nonlinear relationship between input features and vessel-light presence. Moreover, the labeled dataset constructed from temporally matched AIS data is relatively limited in size. A lightweight network architecture helps mitigate overfitting, reduces computational complexity, and enables stable training and fast inference, which are essential for near-real-time applications using directly received VIIRS data.

Although the satellite data reception and preprocessing pipeline introduces inherent delays due to satellite overpass scheduling, data downlink, and standard correction procedures, the proposed detection framework is intended for near-real-time operation rather than strict real-time processing. Once VIIRS DNB radiance data become available, the lightweight DNN model enables rapid inference with minimal additional latency. From an operational perspective, the lightweight architecture of the proposed DNN minimizes computational overhead during inference, making the approach suitable for near-real-time maritime surveillance systems when integrated with existing VIIRS data reception and processing workflows.

## 3. Results

To evaluate the performance of the proposed DNN-based nighttime fishing vessel light detection model, the detection results derived from DNB satellite imagery in the summer seasons of 2020–2021 were compared with AIS data. For quantitative evaluation, metrics such as the confusion matrix and F1 score were used. The confusion matrix, categorized as TP, TN, FP, and FN, is shown in Fig. 6, where: T = True, F = False, P = Positive, N = Negative.

| | | Observed value | |
|---|---|---|---|
| | | Positive | Negative |
| Estimated value | Positive | TP | FP |
| | Negative | FN | TN |

Fig. 6 Confusion matrix for nighttime fishing vessel detection

TP (true positive): The model correctly identifies a pixel as nighttime fishing vessel light, and AIS data confirm the presence of a vessel.

TN (true negative): The model correctly identifies a pixel as not containing nighttime fishing vessel light, and AIS data confirm the absence of a vessel.

FP (false positive): The model identifies a pixel as nighttime fishing vessel light, but AIS data indicate that no vessel is present. FN (false negative): The model identifies a pixel as not containing nighttime fishing vessel light, but AIS data confirm the presence of a vessel.

This approach ensures a comprehensive evaluation of the model's performance by validating its predictions against AIS-derived ground truth. The confusion matrix illustrates the performance of the proposed DNN-based nighttime fishing vessel detection model, including TP, TN, FP, and FN cases. To quantitatively evaluate the performance of the proposed model, the true positive rate (TPR), false positive rate (FPR), and accuracy were used. The formulas for TPR and FPR are as follows:

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{1}$$

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{FP} + \mathrm{TN}} \tag{2}$$

$$\mathrm{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \tag{3}$$

These metrics are crucial for evaluating the performance of the proposed model, especially in scenarios where balancing precision and recall is important.

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{4}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{5}$$

$$\mathrm{F1\ score} = 2 \times \frac{\mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \tag{6}$$

Table 3 presents a comparison of the accuracy and F1 score between vessel light detection results inferred from DNB satellite imagery near Jeju Island and the corresponding AIS data for the same period. Additionally, a comparative analysis was performed using a traditional detection method, logistic regression. Logistic regression was selected as a baseline model due to its simplicity and widespread use in traditional vessel light detection studies. The comparison aims to highlight the performance improvements achieved through nonlinear feature learning in a lightweight DNN, rather than to provide an exhaustive benchmark against all modern machine-learning models.

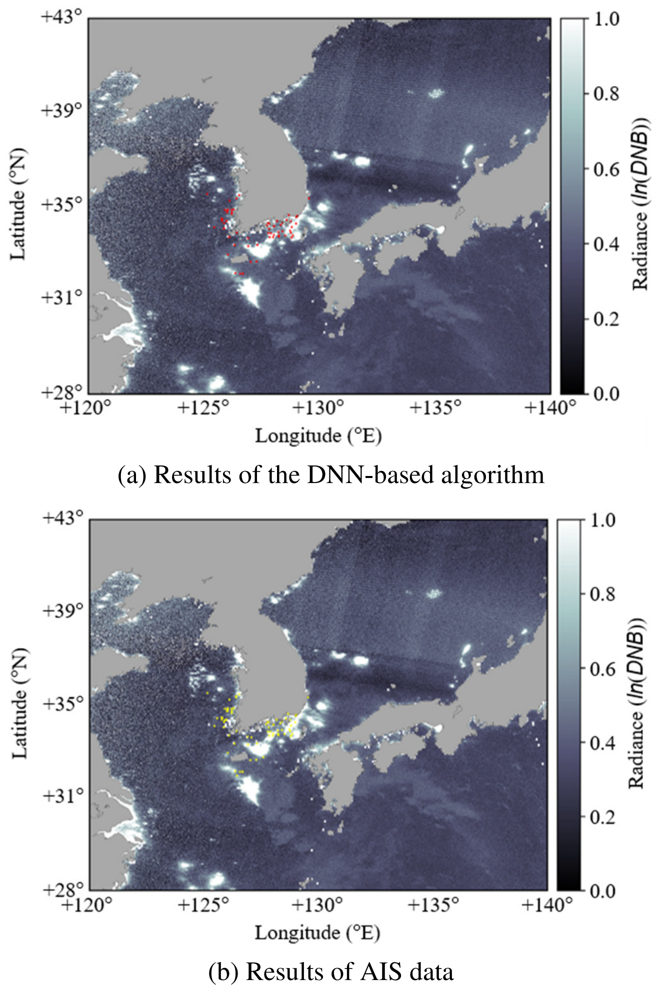
Table 3 Numerical configuration of the proposed DNN model used in this study

| | Parameter | Value |
|---|---|---|
| Input | Input features | DNB radiance, lunar illumination |
| | Input dimension | 2 |
| Network architecture | Number of hidden layers | 4 |
| | Neurons per hidden layer | 128 – 64 – 32 – 16 |
| | Activation function | ReLU |
| Output | Output layer | 1 (binary classification) |
| Training | Loss function | Mean squared error (MSE) |
| | Optimizer | Adam |
| | Initial learning rate | 0.001 |
| | Batch size | 32 |
| | Number of epochs | 500 |
| Validation | Train-test split | 70%/30% |
| Implementation | Framework | Python (Keras) |

The proposed DNN-based nighttime fishing vessel light detection model achieved an accuracy of 0.88 and an F1 score of 0.92 in Table 4, both higher than those obtained using traditional logistic regression. Additionally, Fig. 7 compares vessel detection results obtained using the proposed DNN-based method with AIS data. The upper panel shows the DNN-based detection results, while the lower panel presents AIS-reported vessel positions. The comparison was conducted on 17 July 2021 near Jeju Island. Markers in the upper panel indicate vessels detected by the proposed method, whereas markers in the lower panel represent AIS-reported vessel locations. Overall, it is evident that the detected vessel locations align well with the AIS-reported vessel positions, confirming the accuracy and reliability of the proposed approach.

Table 4 Analysis of vessel light detection accuracy in summer seasons in 2020-2021

| | Performance of the fishing boat light detection algorithm | |
|---|---|---|
| | Logistic regression | DNN-based models |
| Accuracy | 0.82 | 0.88 |
| F1 score | 0.90 | 0.92 |




(a) Results of the DNN-based algorithm

(b) Results of AIS data

Fig. 7 Spatial comparison of vessel detection results

## 4. Discussion

This study presented a DNN–based framework for detecting nighttime fishing vessel lights using VIIRS DNB satellite observations. A complete processing workflow for generating DNB radiance products, including RDR, SDR, and EDR, using TeraScan software was described, and a supervised DNN model was developed to identify fishing vessel light signals from nighttime radiance data. To address the strong influence of lunar illumination on DNB measurements, lunar-related features were explicitly incorporated into the model input, resulting in improved detection performance compared to conventional logistic regression.

The experimental results highlight the effectiveness of integrating satellite-based low-light observations with lightweight deep learning techniques for nighttime maritime monitoring, particularly in areas where conventional AIS-based surveillance is limited. AIS-reported fishing vessels provide a practical reference for evaluating light-based vessel detection, while monitoring AIS-dark vessels remains a primary operational objective rather than a directly validated task. The proposed detection framework can also be extended to analyze seasonal variations in fishing activity and spatial patterns of fishing grounds. Although the model demonstrated promising performance under summer conditions near Jeju Island, its robustness and generalizability across different seasons, lunar illumination conditions, geographic regions, and fishing practices remain to be fully assessed.

From a methodological perspective, further comparative evaluations with advanced machine learning algorithms, such as random forest and support vector machine, as well as CNN-based models, are necessary to assess the robustness and generalizability of the proposed approach. While CNN-based models can exploit spatial information effectively, they typically require large labeled datasets and substantial computational resources.

In contrast, the lightweight DNN architecture adopted in this study offers a favorable balance between detection performance and computational efficiency, making it suitable for near-real-time maritime surveillance when integrated with existing VIIRS data processing systems. Future research may also investigate unsupervised or hybrid learning strategies to address the limited availability of labeled data associated with dark-fleet vessels, leveraging autoencoder-based representation learning and sequence-learning techniques to further enhance operational applicability.

## 5. Conclusions

This study developed a DNN-based framework for detecting nighttime fishing vessel lights using VIIRS DNB satellite observations. By incorporating lunar illumination features, the proposed model improved detection performance compared with conventional approaches. The main conclusions are summarized as follows:

(1) The proposed DNN model effectively distinguishes fishing vessel lights from background ocean signals, achieving improved detection performance over conventional logistic regression.

(2) Spatial comparisons with AIS-reported vessel positions demonstrated the reliability and operational applicability of the method for maritime monitoring.

(3) The lightweight network architecture enables near-real-time inference while maintaining robust detection performance.

Future work will focus on multi-seasonal and multi-regional validation to further enhance the robustness and generalization capability of the proposed DNN framework. In addition, unsupervised or hybrid learning strategies will be investigated to address the limited availability of labeled data, particularly for monitoring AIS-dark vessels. Recent advances in autoencoder-based representation learning, combined with optimization or sequence-learning techniques, offer promising solutions for feature extraction and dimensionality reduction in complex detection problems. Incorporating such approaches is expected to further improve the robustness, scalability, and operational applicability of AI-driven satellite maritime monitoring systems across diverse geographic regions, seasonal variations, and environmental conditions.

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## Conflicts of Interest

The authors declare no conflict of interest.

## References

[1] T. A. Croft, "Nighttime Images of the Earth from Space," Scientific American, vol. 239, no. 1, pp. 86-101, 1978.

[2] M. H. Kim, "The Spatio-Temporal Dynamics Estimation of Economic Growth in Border Regions, China, Using DMSP-OLS," Journal of the Korean Cartographic Association, vol. 19, no. 2, pp. 65-77, 2019.

[3] C. D. Elvidge, K. Baugh, M. Zhizhin, F. C. Hsu, and T. Ghosh, "VIIRS Night-Time Lights," International Journal of Remote Sensing, vol. 38, no. 21, pp. 5860-5879, 2017

[4] Z. Wang and X. Xiong, "VIIRS On-Orbit Spatial Characterization Using the Moon," IEEE Geoscience and Remote Sensing Letters, vol. 11, no. 6, pp. 1116-1120, 2014.

[5] S. D. Miller, W. Straka III, S. P. Mills, C. D. Elvidge, T. F. Lee, J. Solbrig, et al., "Illuminating the Capabilities of the Suomi National Polar-Orbiting Partnership (NPP) Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band," Remote Sensing, vol. 5, no. 12, pp. 6717-6766, 2013.

[6] S. Yoon, H. T. Lee, M. K. Kim, H. M. Choi, J. S. Lee, H. J. Han, et al., "Night Fishing Boat Light Detection Using DNB Data and Deep Neural Network," Journal of Coastal Research, vol. 116, no., pp. 220-224, 2024.

[7] Z. Gao, J. Zhou, Y. Meng, T. Zhang, and Z. Long, "Night-Time Vessel Detection Based on Enhanced Dense Nested Attention Network," Remote Sensing, vol. 16, no. 6, article no. 1038, 2024.

[8] S. Yoon, H. T. Lee, H. M. Choi, and H Yang, "Verification of Night Light Satellite Data Using AIS Data," Proceedings of the Korean Institute of Navigation and Port Research, pp. 211-212, 2022. (In Korean)

[9] I. Asanuma, T. Yamaguchi, J. G. Park, K. J. Mackin, and J. Mittleman, "Detection Limit of Fishing Boats by the Day Night Band (DNB) on VIIRS," Imaging Spectrometry XXI, vol. 9976, pp. 181-188, 2016.

[10] W. Takeuchi and Y. Huang, "Mapping and Tracking Nighttime Fishing Activities within Japan EEZ Using VIIRS Boat Detection," Asian J Geoinfo, vol. 22, article no. 2209006,-1.

[11] W. Zhou, H. Hu, and T. Cheng, "Multi-Nighttime-Light Data Comparison Analysis Based on Image Quality Values and Lit Fishing Vessel Identification Effect," Frontiers in Environmental Science, vol. 11, article no. 1174894, 2023.

[12] G. Chen, Y. Liu, Y. Tian, and H. Tian, "Use of VIIRS DNB Satellite Images to Detect Nighttime Fishing Vessel Lights in Yellow Sea," Proceedings of the 3rd International Conference on Computer Science and Application Engineering, pp. 1-5, 2019.

[13] GSFC JPSS CMO, Joint Polar Satellite System (JPSS) Algorithm Specification Volume II: Data Dictionary for the Cloud Physical Properties Block 2.0.0, JPSS Ground Project Code 474-00448-02-16-B0200, 2015.

[14] Global Fishing Watch, https://globalfishingwatch.org/data/ais-viirs-reveals-dark-fleet/, 2022

[15] S. Yoon, H.-T. Lee, H.-M. Choi, and J.-S. Lee, "Automatic Extraction and Validation of Nighttime Lights from VIIRS Data Using AIS," KIOST Research Report, pp. 1–12, 2023.

[16] U. Syarifudin, D. Salman, S. A. Ali, and Budimawan, "Application of VIIRS-DNB Satellite Data to Detect Ship Distribution Patterns, Fishing Activity Index and Planning Instrument of Pelagic Capture Fisheries in Bone Bay Waters," International Journal of Science and Research, vol. 6, no. 6, pp. 693-702, 2017.

[17] .Kim, G. H., et al., "Physical Characteristics and Classification of the Ulleung Warm Eddy in the East Sea (Japan Sea)," *The Sea*, vol. 24, no. 3, pp. 121–135, 2019.

[18] M. E. Tsuda, N. A. Miller, R. Saito, J. Park, and Y. Oozeki, "Automated VIIRS Boat Detection Based on Machine Learning and Its Application to Monitoring Fisheries in the East China Sea," Remote Sensing, vol. 15, no. 11, article no. 2911, 2023.

[19] V. S. Devarajulu, "AI-Driven Mission-Critical Software Optimization for Small Satellites: Integrating an Automated Testing Framework," Proceedings of the Small Satellite Conference, article no. 124, 2025.

[20] S. R. Addula and G. S. Sajja, "Automated Machine Learning to Streamline Data-Driven Industrial Application Development," Second International Conference Computational and Characterization Techniques in Engineering & Sciences, pp. 1-4, 2024.