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PAPER

Hail Intelligent Recognition Algorithm Based on HAM-Unet

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SUMMARY Hail, recognized as a severe convective weather phenomenon, carries significant destructive . Accurate identification is crucial to minimize economic damages and safeguard lives. The primary challenges in detecting hail include the scarcity of valid hail samples and the imbalance of these samples in high-resolution datasets. In response, this paper introduces the HAM Unet model, an hail identification framework that leverages multisource data and environmental factors.The model combines the FEM-Unet semantic segmentation architecture data fusion techniques. By integrating radar reflectivity, FY-4B satellite imagery, ERA5 climatic parameters, and topographical data, HAM -Unet improves both its precision and resilience. Extensive training and validation have equipped HAM-Unet with good capabilities, achieving remarkable scores in Probability of Detection (POD), False Alarm Rate (FAR), and the Critical Success Index (CSI). The model not only show potential in improving the accuracy and reliability of hail identification but also provides innovative ideas and methods for improvement of hail monitoring and warning Systems.
key words: *Hail Detection, Deep Learning, Multi-source Data Fusion, Severe Convective Weather.*

1. Introduction

Severe convective weather, including hail, thunderstorms, strong winds, tornadoes, and intense short-duration precipitation, is characterized by its small scale and brief duration yet holds a substantial potential for destruction. These events, critical due to their limited spatial extent and sudden onset, pose significant challenges for accurate and timely detection. Among these, hail is especially damaging, threatening agricultural production, urban infrastructure, and public safety.Despite advancements in meteorological radar technology providing high-resolution volumetric data, accurately identifying hail events remains challenging due to the scarcity of valid hail samples and the imbalance in high-resolution data samples. The rapid advancements in computer technology and artificial intelligence, particularly through machine learning and deep learning, have spurred significant research progress in hail detection. Several machine learning techniques have been employed for hail detection, enhancing the Probability of Detection (POD). Zhang etal[1]. developed a hail detection algorithm using fuzzy logic and integrated factors, which outperformed single-factor algorithms. Additionally, methods like decision trees (Fang et al. [2]; Zheng et al. [3]), Bayesian classification (Zhang and Li [4]; Li et al. [5]), random forests (Liu et al.[6]), and Support Vector Machines (SVM) (Shi et al. [7])have offered new perspectives for detecting hail.

However, the limitations of machine learning in detection performance have led to the adoption of deep learning techniques. Convolutional Neural Networks (CNNs), as used by Gurung et al. [8], have shown promise by extracting deep features from radar images. Subsequent improvements include the use of a U-net based deep image segmentation network by Gu et al. [9],although the limited volume of training data has sometimes resulted in high false alarm rates. Further expanding the data sources beyond high-echo intensity radar data, researchers like Czernecki et al. [10] have integrated remote sensing data with environmental variables, and Shi et al. [11] have focused on radar weak echo regions for enhancing current forecasting methods. Building on this foundation, this research proposes a HAM-Unet based hail detection model that integrates multisource data, including radar reflectivity,satellite channel data, ERA5 environmental parameters, and topographic data. This integrated approach moves beyond reliance on single radar parameters, aiming to improve the model's accuracy and robustness by utilizing comprehensive data inputs. The core innovations of this study are:

1) Implementation of a multisource data fusion strategy, integrating radar, satellite, and environmental data to provide a detailed characterization of hail, enhancing the model's generalization capabilities and accuracy.

2) Development of an integrated data fusion module to effectively address data feature redundancy, further improving the model's reliability in hail detection tasks.

3) Utilization of spatiotemporal attributes of radar data alongside continuous weather process characteristics, integrating both time and spatial features to better capture dynamic changes in hail scenarios.

4) Incorporation of topographic data to consider the impact of terrain on hail formation and development, providing auxiliary geographic environmental information to enhance detection accuracy. These enhancements aim to provide a more effective tool for meteorologists and researchers in the ongoing effort to mitigate the impacts of severe convective weather phenomena.

2. Related Works

2.1 Machine Learning Algorithms

Zhen et al. [24] utilized decision tree algorithms to ana- lyze hail-related radar factors in the Tianjin area. Although decision trees are somewhat interpretable, their effectiveness

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is limited by the linear nature of decision boundaries and their vulnerability to over fitting, especially when dealing with small datasets or complex feature correlations. Xiu et al. [25] employed a variety of machine learning techniques to detect severe convective weather. However, their models' generalizability was hampered by limited data samples, resulting in less-than-optimal predictive accuracy. Li et al. [26] improved hail detection in South China using Bayesian methods, but this approach is heavily dependent on prior knowledge and tends to underperform in situations of data scarcity. Shi et al. [27] used a Composite Vector Support Machine (CWSVM) to classify hail, which enhanced model robustness but struggled with feature extraction, particularly at higher dimensions, increasing the risk of dimensionality issues and misclassification.

2.2 Deep Learning Algorithms

Wu et al. [12] applied Back Propagation Neural Networks (BPNN) to determine the maximum hail diameter from FY-4A satellite data. While BPNNs effectively address non-linear challenges, their performance largely depends on the quality and variety of the data; under conditions of weak satellite features, the model's detection capability is compromised. Rong et al. utilized the HailPred[18] model for hail detection. combined ConvLSTM [15] and PredRNN++ [16]to extract temporal features from radar data and used ResNet18 [17] for deep feature recognition.Despite enhancing the spatiotemporal continuity of the features, this approach struggles with high-resolution detection over large areas. Gu et al. [9] introduced deep image segmentation techniques, including U-net, to conventional CNN models for hail detection, thus improving the precision of local feature recognition. Nonetheless, the scarcity of hail data and insufficient training have led to a high false positive rate in practical applications and limited adaptability to new environments. Current research on hail detection primarily utilizes machine learning algorithms, such as SVM and decision trees, or deep learning techniques, such as CNNs [13] and U-net [14], focusing on image classification and object detection. These methods, which rely solely on single radar parameter features, overlook the multifactorial causes of hail formation. Employing algorithms that consider an array of factors could enhance detection performance in complex severe weather scenarios.

3. Proposed Method

3.1 Model Workflow Overview:

This study introduces the HAM-Unet model, which is designed to address the significant challenges in hail detection by leveraging the spatiotemporal characteristics of hail as a continuous weather phenomenon. Unlike traditional models that rely solely on radar data, this model integrates multiple data sources to achieve a more comprehensive capture of hail-related features.Figure1 shows the overall structure of the proposed module.

1) Spatiotemporal Feature Extraction: Utilizing the SimVp technique, the model extracts critical spatiotemporal features from radar data gathered within the last 30 minutes. This technique applies a sophisticated blend of convolutional neural networks and temporal analysis, enabling the model to discern subtle changes and patterns in weather data. This contextual analysis, which integrates both historical and recent weather data, is crucial for the accurate detection of hail.

2) Comprehensive Data Fusion: The IntelliFuseCore module, synthesizes spatiotemporal features derived from radar data, FY4B satellite observations, and ERA5 environmental parameters. This fusion process employs algorithms to enhance the model's ability to delineate hail characteristics and adapt to various climatic conditions. Additionally, this module incorporates topographic data to consider the impact of terrain on convective weather phenomena, thereby ensuring a holistic approach to feature integration.

3) Data Encoding and Decoding: The FEM-Unet module plays a pivotal role in encoding and decoding the integrated data. It utilizes a deep learning frame- work designed to optimize feature extraction and enhance pattern recognition. This module is equipped with multiple layers of neural networks that analyze and reconstruct the encoded data, improving the model's efficiency and enabling it to deliver precise hail detection outcomes with reduced false positives.

3.2 Radar Spatiotemporal Feature Extraction Module

The SimVp model is engineered to dissect and analyze radar data through a sophisticated three-part architecture consisting of the Encoder, the Translator, and the Decoder. Each component is designed to perform distinct tasks that collectively enhance the model's ability to effectively extract and interpret spatiotemporal features.The Simvp structure is shown in Figure2. Encoder: Serving as the foundational component of the model, the Encoder employs a series of convolutional layers arranged sequentially. This arrangement is crucial for the initial extraction of spatial features from the radar data inputs. Each convolutional layer is designed to incrementally capture more refined spatial details, setting the stage for complex subsequent processing. Translator: At the core of the model, the Translator incorporates an Inception architecture.This component begins the temporal analysis with a 1×1 convolutional kernel, which simplifies the incoming features while preserving essential information. The Translator then applies a series of convolutional operations using various kernel sizes (3x3, 5x5, 7x7, and 11x11). This multi-scale strategy enables the model to capture diverse temporal patterns effectively. The outputs from these operations are concatenated to create a comprehensive feature map that robustly represents dynamic, time-dependent changes. Decoder: The Decoder component reconstructs the temporal sequence into actual frames that embody the dynamics captured by the Translator. It employs multiple deconvolution operations to reassemble the

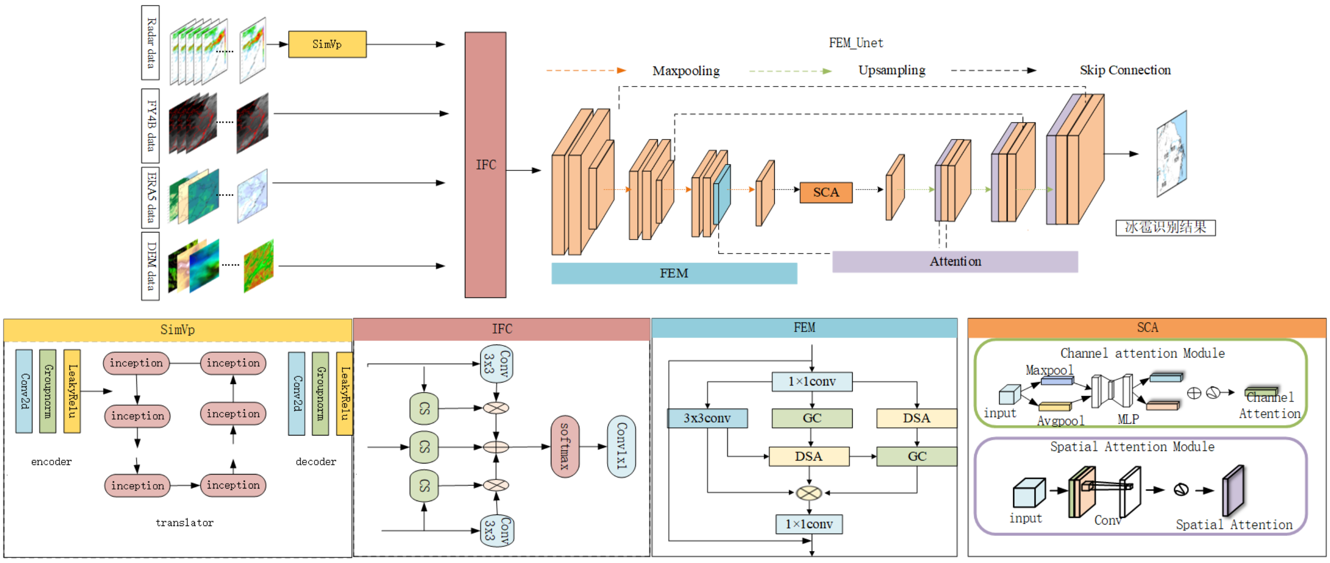

Fig. 1 HAM-Unet Model

frame structure, translating the processed data into spatial dimensions of height, width, and depth across various channels. This crucial final step synthesizes all the previously extracted and processed information, culminating in a detailed representation of the radar data's spatiotemporal features. The cohesive integration of the Encoder, Translator, and Decoder within the SimVp model forms a robust eight-layer Encoder-Decoder structure equipped with Inception units. This architecture not only facilitates efficient extraction of temporal features but also captures the intricate temporal evolution within the radar data. The comprehensive design ensures that the model not only identifies static features but also interprets dynamic changes over time, thereby providing a powerful tool for radar spatiotemporal feature extraction.

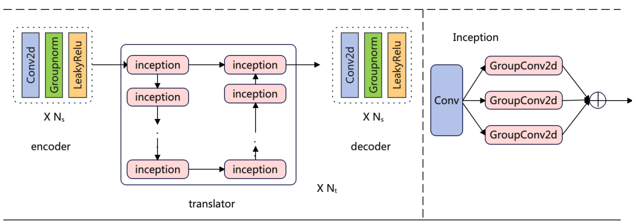

Fig. 2 SimVp Structure Diagram

3.3 Data Fusion Module

To enhance feature integration from multiple data sources, we developed an data fusion module, as illustrated in Figure 2. This module initially processes radar spatiotemporal features and FY4B satellite data separately through respective Channel Selection (CS) modules equipped with 3x3 convolutional layers. These data sets are preliminarily integrated using matrix multiplication, ensuring initial fusion of spatial and temporal features. Subsequently, ERA5 environmental data, processed by another dedicated CS module, is integrated with the radar and satellite data. The integration culminates in a fusion, facilitated by a softmax function and a 1×1 convolution, to produce the final output. The computational workflow within the CS module is described by the following equations:

$$P_c = \frac{1}{h\times w}\sum_{i=1}^{h}\sum_{j=1}^{w}\max(F_c(i,j)) \tag{1}$$
$$A_w = \mathrm{ReLU}(U\cdot P), U \in \mathbb{R}^{c\times c} \tag{2}$$
$$A_s = \mathrm{sigmoid}(V\cdot P), V \in \mathbb{R}^{(h\times w)\times(h\times w)} \tag{3}$$
$$\tilde{F} = A_w \cdot A_s \cdot F \tag{4}$$

Among them F is a feature set with c channels, and each channel has the dimension of " h x w". The max operator is used to calculate Pc on dimension. Pc only represents the value of a certain dimension, and ultimately the values of all dimensions P need to be calculated. For each channel feature Fc in feature set F, a weight matrix U is introduced to carry out a nonlinear transformation, and then the task-relevance weight Aw is calculated. Additionally, the spatial attetion weight As is calculated through the weight matrix V and the signoid function, which is used to asssign the importance of each position in the feature map. Finally, by performing a weighted fusion of the original feature F with these two attention weights, the fused feature F and in the process of model training, continuously adjust the parameters of the weight matrix to enhance the model's attention to key information and improv the fusion efficiency.

3.4 FEM-Unet Module

The structure of the FEM-Unet model is detailed in Figure 4. This model consists of three main components: an Encoder, a Decoder, and a Semantic Feature Enhancement

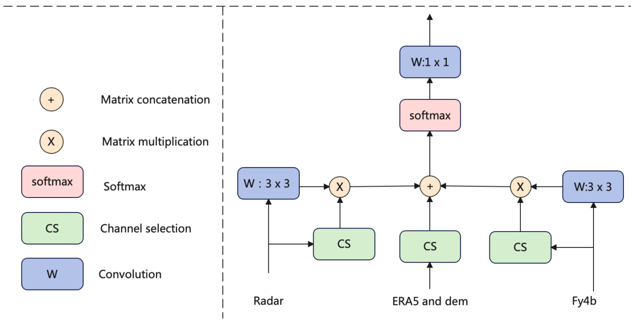

Fig. 3 Data Fusion Module Structure Diagram

Module (FEM). It utilizes the R2Attention-Unet architecture for both encoding and decoding processes, integrating the Feature Enhancement Module (FEM) during the third down sampling stage of encoding. To enhance the model's capability in expressing detailed features, a Spatial Channel Attention (SCA) module is placed at the junctions between the encoding and decoding stages to optimize feature transmission and integration. The decoding process aligns with the R2Attention-Unet[20] architecture, progressively refining the hail detection results. Detailed structures of the FEM and SCA modules are shown in Figures 5 and 6, respectively. These innovations are designed to improve the model's performance and accuracy in detecting hail.

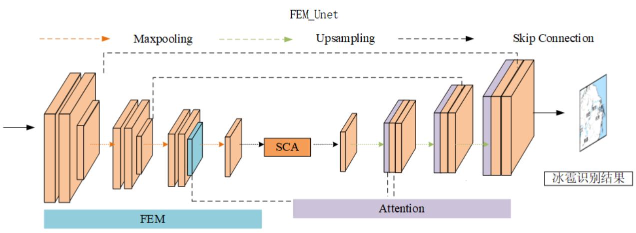

Fig. 4 FEM-Unet Structure Diagram

3.4.1 FEM

The Feature Enhancement Module (FEM) integrates two primary technologies: Dilated Self-Attention Convolution (DSA)[21] and Gated Convolution (GC). The processing sequence begins with a 1×1 convolution block, which forwards the data to a 3×3 convolution layer. Subsequently, the data undergo processing by a DSA module and a GC module. The dilation rates of the two sequential DSA modules are set at 2 and 3, respectively, facilitating multi-scale feature extraction. Outputs from the 3×3 convolution and the initial GC module are combined with the output from the second DSA module. This amalgamated output is then processed through the second GC module. The final integrated output features are produced by concatenating these three outputs and processing them through another 1×1 convolution block.

1) Dilated Self-Attention Convolution (DSA): This component employs a Transformer-based multi-head self-attention mechanism, enabling the model to assimilate global information across different representational subspaces. By replacing traditional linear embeddings with convolutional embeddings, DSA not only captures extensive contextual information but also retains intricate local spatial details. Adjusting the dilation rate allows DSA to enhance the model's perceptual range across various scales, which is critical for accurately and efficiently detecting hail-related features.

2) Gated Convolution (GC): GC utilizes gated mappings to regulate information flow, processing input features from diverse receptive fields. This gating mechanism not only directs the model towards extracting more discriminative features but also concentrates on features pertinent to hail detection, while minimizing interference from irrelevant or noisy data. GC's distinctive gating method bolsters the model's accuracy, particularly under complex weather conditions. The computation formula for GC is as follows:

$$Gate = W_g \cdot F_{high} \tag{5}$$

$$F = W_f \cdot F_{low} \tag{6}$$

$$G = \emptyset(F) * \sigma(Gate) \tag{7}$$

In the framework, Wg and Wf represent weight matrices with different weights, while Fhigh and Flow denote the two inputs. The Gate is an attention matrix, and represents the softmax function. Finally, F is the feature embedding, and denotes the sigmoid activation function.

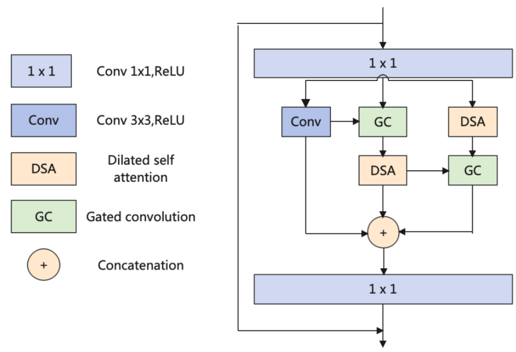

Fig. 5 FEM Structure Diagram

3.4.2 SCA

Inspired by the Convolutional Block Attention Module (CBAM)[22], this study introduces a Spatial-Channel Attention (SCA) mechanism, integrating channel and spatial self-attention processes through Multi-Head Self-Attention (MHSA), as depicted in Figure 6. The SCA module employs self-attention to precisely compute global dependencies between channel and spatial features, enhancing the representation of information across these dimensions. This process draws on the self-correlation features of transformers, particularly using absolute position embeddings in spatial MHSA within the SCA module to delineate feature space associations. In contrast, channel MHSA avoids position embeddings, which strengthens the inter-channel associations.

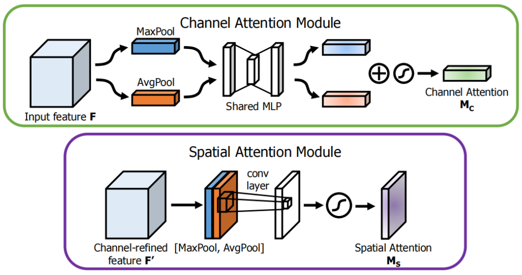

Fig. 6 SCA Structure Diagram

In hail detection applications, the SCA module has proven highly effective. It merges channel and spatial attentions to accurately capture essential features and the global context of the input data, boosting the Probability of Detection (POD) and hail detection efficiency. Channel Attention (CA): Within hail detection tasks, the channel attention mechanism emphasizes channels that are directly relevant to hail, while diminishing interference from irrelevant information. This focused approach significantly enhances the model's precision and effectiveness inanalyzing complex meteorological data. Spatial Attention (SA): By utilizing absolute position encoding, spatial attention augments the model's capacity to understand spatial relationships and the distribution of hail features within the data. This capability is crucial for accurately identifying the spatial structure of hail, thereby improving the detection outcomes.

4. Experiments and Results

4.1 Datasets

For this study, the period from April to August of 2021-2022, covering the geographical area from 115°E to 123°E and 23°N to 35°N as depicted in Figure 7, was chosen for testing the hail detection algorithm. The selection of this region was based on its dense network of radar and satellite observations, which offers a substantial dataset of hail events. This extensive data availability helps reduce the risk of model overfitting. The data collected during this period formed the basis for our experiments, with the test dataset consisting of 674 samples, while the training set comprised 4,437 samples, as detailed in Table 1.

4.1.1 Radar Data

The radar data used in this study is the operational product

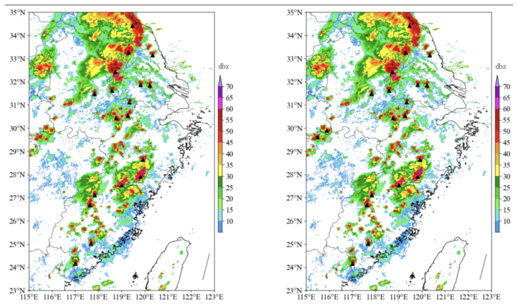

Fig. 7 On the left is the actual hail scene image, on the right is the model output image, and black triangles indicate the presence of hail

V3.0 of the Meteorological Observation Center of the China Meteorological Administration, including the composite reflectivity. The spatial resolution of the data is 0.01°×0.01°, and the temporal resolution is 6 minutes. For the specific characteristic elements used, please refer to Table 1.

4.1.2 FY4B Satellite Data

The FY4B satellite data adopted in this study is the operational product of the National Satellite Center of the China Meteorological Administration. It contains data from the visible light channel, the near-infrared channel, and the infrared channel. The spatial resolution of this observational data is 0.04°×0.04°, and the update time interval is regularized to 5 minutes through the nearest neighbor technique. According to the observational physical characteristics of each channel, the channels related to convective development have been selected, as detailed in Table 1.

4.1.3 ERA5 Data

ERA5 is the fifth-generation atmospheric reanalysis dataset of the global climate from January 1950 to the present by the European Centre for Medium-Range Weather Forecasts (ECMWF). ERA5 provides hourly estimates of a large number of atmospheric, terrestrial, and oceanic climate variables. The data covers the Earth on a 30-kilometer grid and uses 137 levels from the surface to an altitude of 80 kilometers to analyze the atmosphere, including the uncertainty information of all variables when the spatial and temporal resolutions are reduced. The variables that can directly reflect the evolution of convective generation and dissipation have been selected, as shown in Table 1.

4.1.4 Topographic Data

Considering that topographic obstacles such as mountains can force air currents to rise and also enhance convective activities, providing the initial conditions for the formation of hail. In addition, the significant differences in the thermal properties of different terrains can affect air currents through heating differences and also influence the atmospheric stability. Therefore, the topographic height data has been added to the input data part.

4.1.5 Feature Selection

Feature selection is an important step in data mining. Its purpose is to select the most representative and discriminative features from the original data to improve the performance and generalization ability of the model. In this study, the Pearson correlation coefficient is used to select the feature factors with a relatively high correlation with hail. Table 1 shows the factors with a relatively high correlation with hail events calculated by the Pearson correlation coefficient.

4.1.6 data processing

Both input and output of the model maintain a spatial resolution of 0.01, with a temporal resolution set at every 6 minutes. To achieve this, bilinear interpolation was utilized to adjust the data elements to the desired 0.01resolution. Furthermore, the update intervals were standardized to every 6 minutes using nearest neighbor techniques, and all data underwent normalization as part of the preprocessing steps. The model processes two primary types of input data: radar time-series data, which includes radar grid information collected every 6 minutes over the preceding half-hour, and multi-source meteorological grid data, which encompasses grid information for 16 distinct meteorological variables, each with dimensions of 16×1200×800.For the output, the model is engineered to generate grid classification labels for hail events,0 indicates the presence of hail, and 1 indicates the absence of hail. which are formatted in dimensions of 1×1200×800. In addition, considering that the 1200x800 data graphics card does not have enough video memory to train the model, we will split it into 200x200 sizes for training, and finally obtain the output result, which will be concatenated back to the 1200x800 size.

4.2 Metrics and Loss Functions

To evaluate the performance of our proposed hail detection model, we utilized several key metrics: Probability of Detection (POD), False Alarm Rate (FAR), Miss Rate, and Critical SuccessIndex (CSI). These metrics help gauge the model's effectiveness by measuring its accuracy and types of classification errors: True Positives (TP): Correctly identified cases of hail. True Negatives (TN): Correctly dismissed non-hail events. False Positives (FP): Incorrectly identified as hail. False Negatives (FN): Hail events that were missed.

$$POD = \frac{TP}{TP+FN} \tag{8}$$

$$FAR = \frac{FP}{TP+FP} \tag{9}$$

$$CSI = \frac{TP}{TP+FP+FN} \tag{10}$$

The comprehensive evaluation using POD, FAR, Miss Rate, and CSI allows us to thoroughly assess our model's ability to classify both hail and non-hail incidents accurately, with CSI providing a combined measure of overall performance. This evaluation framework supports the reliability and utility of our model, setting the stage for further enhancements and comparative analysis. In addition to performance metrics, we employed Bi- nary Cross-Entropy with Logits Loss (BCEWithLogitLoss) for training our model. This loss function is particularly suited for binary classification tasks in models with a logistic regression activation function.

It calculates the cross- entropy between the predicted probabilities (ranging from 0 to 1) and the actual labels to determine the precision of the model. The objective of BCEWithLogitLoss is to closely align the predicted probabilities with the true label distribution, thus improving the model's discriminative ability between hail and no-hail scenarios. The specific formula for calculating BCEWithLogitLoss is as follows:

$$\begin{aligned}\text{BCEWithLogitsLoss} = -\frac{1}{N}\sum_{i=1}^{N} [y_i \cdot \log(\sigma(x_i)) \\ +(1-y_i)\cdot \log(1-\sigma(x_i))\end{aligned} \tag{11}$$

4.3 The results of different data on the HAM-Unet model

To validate the effectiveness of multi-source observational data in detecting hail, Table 2 presents a comparison of the HAM-Unet model's performance, utilizing various data combinations for hail recognition. The comprehensive evaluation metrics in the table above suggest a clear trend: integrating multiple sources of observational data enhances hail detection capabilities.The combination of radar, satellite, ERA5 reanalysis,and Digital Elevation Model (DEM) data in the HAM-Unet model leads to superior performance, with a Probability of Detection (POD) of 95.66 % and a Critical Success Index (CSI) of 91.29%. This configuration not only improves accuracy but also reduces the False Alarm Rate (FAR) to 4.76%, a substantial improvement over the radar-only setup, which has an FAR of 84.6%.Moreover, the addition of terrain data is instrumental in further enhancing both POD and CSI scores. Conversely, relying solely on radar data results in the lowest POD and CSI scores and the highest FAR, highlighting the significant. advantages of a diversified data approach. These findings underscore the critical role of multi-source data integration in boosting the accuracy and reliability of hail detection models, with a notable reduction in false alarms when a comprehensive dataset is utilized. This affirms the importance of diverse data inputs in improving model performance for classifying meteorological phenomena.

4.4 Results and analysis of different models

In this study, we systematically compare the hail detection capabilities of several models using grid data. The models evaluated include CNN, U-Net, R2U-Net[23], Attention R2U-Net, and our novel HAM-Unet. We assess their performance using key metrics: Probability of Detection

Table 1 The types of data selected, input factors, and the spatiotemporal resolution

data type	Input factors	Timeresolution(min)	Spatial resolution
FY4B satellite observation data	Channel09 Channel10 Channel12 Channel14	15	0.04°×0.04°
Radar data	composite radar reflectivity	6	0.01°×0.01°
ERA5 data	SHR1 SHR3 SHR6 CAPE10-30 PWAT Z0 ZM20C SHIP 500 hPa dewpoint temperature 700 hPa dewpoint temperature	60	0.25°×0.25°
Topographic data	Dem		0.0083°×0.0083°

Table 2 Model results of different data

Data	POD	FAR	CSI
Radar Data + Satellite Data +ERA5 Environmental Parameters + DEM Data	95.66%	4.76%	91.29%
Radar Data +Satellite Data + ERA5 Environmental Parameters	93.67%	4.37%	89.83%
Radar Data + Environmental Parameters	87.63%	8.32%	81.43%
Radar Data + Satellite Data	85.58%	7.06%	81.15%
Radar Data	82.76%	8.46%	80.27%

(POD), False Alarm Rate (FAR), and Critical Success Index (CSI).The input data for each model is the same. In the comparative experiments, the input data of the models was not subjected to data fusion but was simply stacked up by using the cat function in torch.

Our analysis revealed significant performance discrepancies among the models. The U-Net model, for instance, showed a high POD at 84.82%, but suffered from a relatively high FAR of 21.41%, indicating a trade-off between sensitivity and precision. In contrast, the R2U-Net and its variants demonstrated improved balance, with the Attention R2U-Net notably enhancing detection rates while substantially reducing false alarms.The standout performer, HAM-Unet, achieved the highest POD of 95.66% and the lowest FAR of 4.76%, culminating in a CSI of 91.29%. This performance not only highlights the effectiveness of the HAM-Unet in accurately identifying hail events but also illustrates its effi-

Table 3 Hail Detection Results from Different Models

Model	POD	FAR	CSI
CNN	61.13%	11.46%	51.01%
U_Net	84.82%	21.41%	68.90%
R2_Unet	87.37%	14.87%	76.19%
R2Attention_U-Net	89.07%	8.47%	81.34%
FEMU-Net	94.36%	10.74%	83.86%
FEMU-Net +SCA	93.71%	6.19%	87.37%
HAM-Unet(ours)	95.66%	4.76%	91.29%

ciency in minimizing false positives, crucial for reliable meteorological applications. The experimental results underscore the superior performance of the HAM-Unet model in all evaluated metrics, particularly excelling in both POD and FAR. This model's effectiveness suggests significant potential for hail detection technologies in meteorology, Provide effective references for the practical application of meteorology.

5. Conclusion

In this study, we introduce HAM-UNet, a model for hail detection that leverages multi-source data to improve prediction accuracy. A pivotal innovation of HAM- UNet is its integration capability, combining diverse datasets such as radar time-series, satellite imagery, and ERA5 surface observational data. The model utilizes SimVp technology to extract and analyze temporal features of hail events efficiently, offering a dynamic approach to weather monitoring. Furthermore, HAM-UNet features an Internal Feature Combination (IFC) module, which enhances the model's data processing capabilities. This module employs an attention mechanism to optimize the synergy between different data sources, thereby enriching the model's analytical depth and improving its predictive precision.

The architecture of HAM-UNet is based on the FEM-Net framework, which is specifically designed for high- frequency temporal resolution (updated every 6 minutes) and fine spatial resolution (0.01by 0.01). This design al- lows for real-time, accurate classification and monitoring of hail occurrences, which is critical for timely meteorological responses. Validation results have demonstrated that HAM-UNet outperforms existing models in real-time hail classification and recognition. HAM-UNet is adept at filling information gaps,thus enhancing detection accuracy. The integration of multi-source data not only augments the model's interpretability but also substantially elevates its accuracy and reliability.

As we look to the future, we aim to expand our data sources and enrich the model inputs to further bolster HAM-UNet's generalization capabilities and recognition accuracy. Integrating simulations of physical processes with machine learning algorithms will lay a more robust theoretical foundation for the model, thereby enhancing its interpretability and efficacy in handling complex meteorological phenomena. The continuous evolution of observational technologies and data acquisition strategies will also play a crucial role in refining our model. Considering the variability and complexity of hail events, exploring additional deep learning architectures to improve the efficiency and accuracy of spatiotemporal data processing remains a priority.

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