LSTM-Transformer Hybrid Network for UAV-Bird Classification Using Radar Track Information

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***Abstract*—With the increasingly widespread application of unmanned aerial vehicles (UAVs), the potential safety hazards caused by "unauthorized flights" have become increasingly prominent. Therefore, accurately distinguishing between UAVs and birds is of great significance. Due to the similarity in their radar static characteristics, traditional recognition algorithms are prone to confusion during the recognition process, resulting in frequent false alarms. To address this issue, this paper proposes an LSTM-Transformer hybrid architecture-based classification framework for UAVs and birds, which is based on the dynamic characteristics of track sequences. This framework can effectively distinguish between UAVs and birds by virtue of a small amount of track information such as target position, speed, and RCS. Specifically, the framework uses an LSTM network as the dynamic memory encoding module, which processes time-series data through its unique gating mechanism and converts the dynamic changes in target motion and radiation information into high-dimensional feature encodings. Subsequently, the Transformer module deeply explores the complex relationships within them through the self-attention mechanism, achieving the integration of spatial feature correlations and temporal global features. The processed data is extracted by the "comprehensive reasoning module" to output the type confidence. Verified on real collected radar track data, the proposed algorithm in this paper outperforms existing algorithms in terms of classification accuracy, MCC, and recall rate under different data lengths, fully demonstrating the effectiveness of the proposed algorithm.**

I. Introduction

In recent years, with the rapid development of UAV technology, the widespread application of UAVs in production and daily life has greatly facilitated our daily activities. However, the increasingly serious issue of "illegal flights" (i.e., flights ignoring no-fly regulations) has posed significant risks, endangering public safety and even national security. As UAV "illegal flight" incidents become more frequent, accurately identifying "low, slow, small" UAV targets has become especially important. Since both birds and "low, slow, small" UAVs have small radar cross sections (RCS) and their radar echo signals exhibit similar amplitude and spectral characteristics, target identification can easily lead to confusion and false alarms. Therefore, the key issue to solve is how to quickly, real-time, and effectively detect and identify targets.

Common monitoring systems typically rely on a combination of radar, infrared, and optical sensors. Optical sensors are known for their high resolution and excellent color reproduction, which aids in precise target identification and tracking, and is widely used in military reconnaissance and environmental monitoring. Currently, most research integrates visible-light images with deep learning frameworks, achieving significant results. For example, Lee et al. successfully inferred and accurately extracted small target features using a hybrid preprocessed image data set, allowing UAV identification within images [1]. Ojdani designed a parallel system based on telescopes for UAV identification and tracking, improving the coordination between detectors and trackers [2]. Liu et al. proposed a target detection algorithm based on DETR, which employs multi-functional fusion to effectively detect UAVs and birds in airport environments, demonstrating excellent detection performance [3].

However, optical sensors are limited in adverse conditions such as night or fog and snow, where their detection capability significantly drops. In these cases, infrared sensors, which rely on the target's inherent infrared characteristics, have certain advantages. Xu et al. proposed an infrared UAV target detection algorithm based on an asymmetric attention fusion mechanism [4]. Ren et al. introduced a shape-prior segmentation and multi-scale feature-based infrared UAV target detection method. Fang et al. used a multi-scale U-Net structure to fuse multi-scale features of targets for infrared UAV detection [5]. Although optical sensors perform well in terms of clarity and detail capture, they are highly susceptible to environmental factors. In low-visibility conditions, the detection ability of optical sensors significantly decreases, affecting subsequent target recognition and judgment.

In contrast, radar offers advantages such as a larger detection range and less susceptibility to weather conditions, allowing it to operate stably in all weather and at any time of day. This makes radar particularly important for monitoring airport airspace. Currently, micro-motion features, as a common method for fine radar signal description, are widely used in UAV radar detection. Molchanov et al. used short-time Fourier transform to extract micro-motion features and trained three classifiers based on these features, successfully classifying 10 types of rotorcraft UAVs and birds. These classifiers included a linear SVM, a nonlinear SVM, and a naive Bayes classifier [6]. Ren et al. adopted a two-dimensional regularized complex logarithmic Fourier transform and subspace reliability analysis for

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micro-motion feature extraction, distinguishing between UAV and bird targets [7]. Hoffmann et al. combined micro-motion features with a Constant false alarm rate detector, improving UAV detection and tracking performance [8]. However, in real-world environments, micro-Doppler analysis may experience signal blind spots in detection range's edge areas or at specific angles, leading to target omissions.

In addition to micro-Doppler features, radar-acquired target motion parameters and RCS radiation characteristics play a crucial role in distinguishing between birds and UAVs. Chen et al. proposed a UAV and bird classification method based on motion model conversion frequency estimation, using mechanical scan surveillance radar data [9]. Messina and Pinelli used surveillance radar data to classify UAVs and bird targets, creating a feature set based on RCS, signal-to-noise ratio, tracking trajectories, and speed, and employed a support vector machine (SVM) classifier for classification [10]. Samaras et al. used X-band surveillance radar's real measurement data, using micro-motion, RCS, signal-to-noise ratio, and radial velocity as CNN inputs to classify UAVs [11]. Mohajerin et al. combined motion trajectories, speed, and target RCS with a multi-layer perceptron (MLP) classifier, successfully distinguishing UAVs from birds, achieving high classification accuracy [12].

However, the above algorithms still face two challenges in radar target classification:

- Feature Overlap Leading to Confusion: Birds and "low, slow, small" UAVs exhibit similar characteristics in radar detection, especially in terms of RCS, position, and speed. This overlap in features increases the likelihood of confusion during classification, leading to misjudgments and false alarms, which negatively affect the overall classification accuracy.
- Limitations of UAV Track Data and Need for Feature Mining: Although deep learning algorithms can capture the dynamic dependencies and potential patterns of time series, and mine complex feature correlations in time series data through multi-layer nonlinear transformations, UAV track data has problems of small data volume and limited feature dimensions (only including position, speed, RCS, etc.). The small amount of data stems from the narrow collection range caused by flight control, and the difficulty in exhaustively sampling various flight patterns; limited features make it difficult for the model to obtain unique distinguishing information.

Therefore, it is necessary to explore the potential correlations and dynamic laws of features, and map low-dimensional features to high-dimensional space to enrich expressions, supporting the algorithm to learn stable classification rules.

In this paper, we propose a UAV and bird classification algorithm based on an LSTM-Transformer hybrid architecture, which integrates the dynamic evolution relationship between target motion information and radiation information. This algorithm uses the LSTM network as a dynamic memory encoding module, leveraging its unique gating mechanism to process time-series data, effectively capturing and encoding the dynamic characteristics of targets. Meanwhile, the Transformer module is introduced to enhance global information modeling using a self-attention mechanism, better capturing complex relationships between features. After processing by LSTM and Transformer, the dynamic characteristics of the data are fully reflected, and then analyzed by the "comprehensive reasoning module" to output classification confidence through operations like convolution pooling. This algorithm combines dynamic memory encoding, global information modeling, and comprehensive reasoning, enabling real-time inference and achieving real-time, precise classification of UAVs and birds.

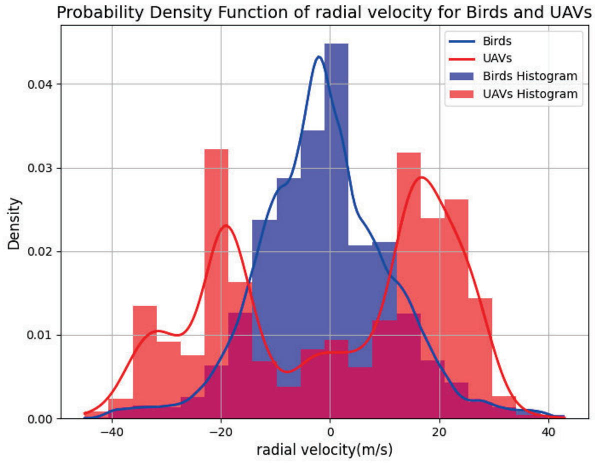
II. Problem Description

The real-time radar target trajectory feature sequence collected for target i is denoted as $X_T^i = \{\varphi_1^i, \varphi_2^i, ..., \varphi_t^i\} \in \mathbb{R}^{t \times 6}$, where t represents the sampling time, and $\varphi_t^i \in \mathbb{R}^{1 \times 6}$ is the feature vector of the i-th target at time t, which includes the position information, velocity information and scattering information RCS σ_t^i. The position information x consists of the i-th target's azimuth $\theta_t^i, [^\circ]$, radial distance r_t^i, [m], and height h_t^i, [m], while the velocity information represents the radial velocity $v_{r,t}^i, [\mathrm{m/s}]$ and the tangential velocity $v_{\theta,t}^i$. Implementing real-time classification based on trajectory information faces two major challenges:

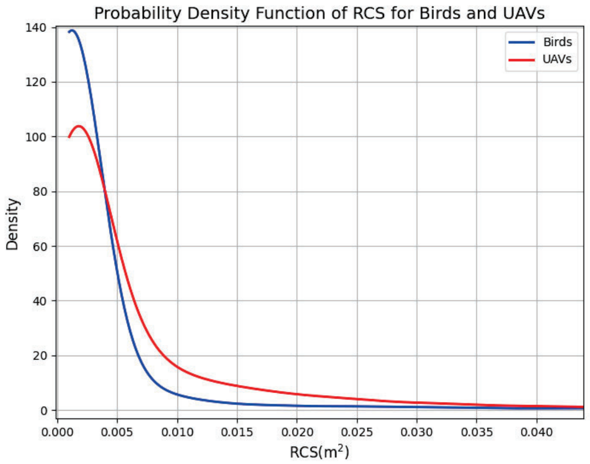
Problem 1: Similar signatures between UAVs and birds. The radial velocity, flight altitude, and RCS characteristics of low, slow, small UAVs and birds are highly similar in radar detection. This similarity makes it extremely difficult to distinguish between birds and UAVs based solely on the target's position, velocity, and RCS information. As shown in Fig. 1(a) is the statistical distribution and probability density function of the radial velocity of birds and UAVs, while Fig. 1(b) is the probability density curve of the RCS for birds and UAVs. In particular, specially designed small UAVs intentionally adjust their flight and radiation characteristics to mimic those of birds. As a result, their behavior in radar monitoring data is almost indistinguishable from birds in terms of numerical range and variation trend.

Problem 2: Neglect of temporal dynamics. Most trajectory classification methods primarily focus on the static feature analysis of a target at a specific moment, neglecting the rich temporal sequence information embedded in the target's trajectory data. The flight process of birds and UAVs is a continuous and dynamic process, with differences in their dynamic motion characteristics. UAVs typically exhibit stable and regular movement patterns during tasks, such as diving, circling, climbing, and level flight. On the other hand, birds, as biological entities, demonstrate highly diverse and agile movement states. Additionally, the radar cross-section fluctuates with the target's attitude angle, and the changes in the RCS sequence reflect the target's posture and motion.

In summary, this paper proposes a deep learning-based feature integration and time series classification method. By learning the implicit dynamic evolution patterns in the target's trajectory, including motion patterns, mobility features, and



(a) Radial velocity distributions for birds and UAVs



(b) Radar cross section distributions for birds and UAVs

Fig. 1: Statistical characterization of radar signatures: Comparison of birds and UAVs

the correlation between target posture and RCS signal characteristics, the method enables real-time and precise dynamic identification of targets.

III. Construction of Network Models

This paper employs a deep learning-based feature integration and time series classification method, which leverages extensive target trajectory information to extract motion patterns, mobility capabilities, and the correlation between target posture and RCS signal characteristics. This approach enables real-time, rapid, and precise dynamic target identification. As shown in Fig. 2, the multi-feature dynamic classification network framework is structured as follows:

A. Dynamic Memory Position Encoding Module

In the analysis of target motion trajectories, which are a type of sequence data, the LSTM layer is used to encode the

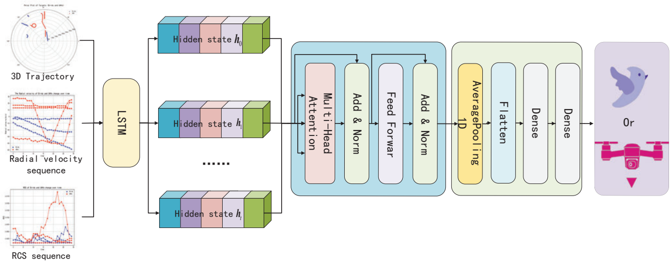


Fig. 2: The structure of the LSTM-Transformer hybrid identification network

position of a target precisely at each timestep, based on the state of the target at the previous timestep. This allows the model not only to be aware of the current position but also to understand the significance of that position in the overall dynamic evolution of the trajectory. By encoding the position information in this way, the model provides rich, logically informed features that are essential for subsequent prediction or classification tasks, thus greatly improving the accuracy and effectiveness of utilizing positional information in sequence data processing.

The calculations for each gate are as follows:

$$\boldsymbol{H}_T, (\boldsymbol{h}_t, c_t) = \mathrm{LSTM}(\boldsymbol{X}_T) \tag{1}$$

where $\boldsymbol{H}_T \in \mathrm{R}^{t \times d_{\text{out}}}$ is the output sequence for all timesteps, $\boldsymbol{h}_t \in \mathrm{R}^{d_{\text{out}}}$ is the final hidden state, $\boldsymbol{c}_t \in \mathrm{R}^{d_{\text{out}}}$ is the final memory state, and d_{out} is the hidden units.

This dynamic adjustment of memory information based on the sequence position indirectly encodes the positional information. Different elements at different positions undergo different memory updates due to their distinct locations in the sequence, making the model aware of both the current position and its significance in the overall sequence, ultimately improving the precision and effectiveness of utilizing position-based features for target classification.

B. Transformer Encoder Module

The trajectory characteristics at different scales do indeed reflect the behavioral patterns of flying objects in different spatial and temporal dimensions, which is crucial for distinguishing between birds and drones. In the target time-series data, there are long-range dependencies, such as the trend of position and velocity over an extended period, which can significantly influence the classification of the target. The multi-head attention mechanism in the Transformer encoder allows the model to attend to long-range dependencies across multiple time steps, capturing the relationships between distant time points. This enhances the model's ability to understand the target's overall characteristics. Furthermore, the feedforward neural network performs non-linear transformations on the features processed by the attention mechanism, increasing the expressiveness of the features and helping the model learn more complex and abstract target representations, which aids in distinguishing between different target categories.

$$\boldsymbol{T}_{out} = \text{Transformer-Encoder}(\boldsymbol{H}_T) \tag{2}$$
$$= \text{FFN}\Big(\text{MultiHead}(\boldsymbol{H}_T)\Big) \tag{3}$$

where $\boldsymbol{T}_{out} \in \mathrm{R}^{t\times d_{\text{out}}}$ is the output sequence of Transformer-Encoder module.

C. Comprehensive Inference Module

The comprehensive inference module is based on the output features of the Transformer encoder. The global average pooling layer integrates and condenses information, the flattening layer transforms the data format, the multi-layer perceptron module deeply analyzes complex relationships and prevents overfitting, and the output layer gives the class probabilities. Each sub-module collaborates and integrates to comprehensively utilize the target data, improving the model's accuracy and generalization ability. It can be expressed by the following formula:

$$\hat{y} = \sigma\left(\boldsymbol{w}_2^{\top}\text{ReLU}\left(\boldsymbol{W}_1\left(\frac{1}{T}\sum_{t=1}^{T}\boldsymbol{T}_t\right) + \boldsymbol{b}_1\right) + b_2\right) \tag{4}$$

where, $\hat{y} \in [0,1]$ is the drone detection probability, $\sigma(\cdot)$ denotes the sigmoid function: $\sigma(z) = \frac{1}{1+e^{-z}}$, $\boldsymbol{T}_t \in \mathbb{R}^d$ is the feature vector at timestep t of $\boldsymbol{T}_{out}$, $\frac{1}{T}\sum_{t=1}^{T}$ represents the 1D global average pooling operation, $\boldsymbol{W}_1 \in \mathbb{R}^{k\times d}$ is the weight matrix of the first dense layer, $\boldsymbol{b}_1 \in \mathbb{R}^k$ is the bias vector of the first dense layer, $\text{ReLU}(\cdot)$ is the rectified linear unit activation function, $\boldsymbol{w}_2 \in \mathbb{R}^k$ is the weight vector of the output layer, $b_2 \in \mathbb{R}$ is the bias of the output layer.

IV. Experimental Verification

A. Experimental Setup

1) Data Analysis and Preprocessing: To verify the performance of the algorithm, a certain search radar is used as the platform to track and identify drone and bird targets in an environment where birds are relatively active. The sampling period is 2 seconds. The collected trajectory data includes a total of 1,122 samples, comprising 904 bird trajectories and 218 UAV trajectories. Each track contains five-dimensional features including azimuth angle, radial distance, height, radial velocity, and RCS. Among the drone track data, there are a large number of tracks with different behavior patterns such as straight lines, circling, and diving.

Each type of sample is divided into training and testing sets with an 8:2 ratio. Since the data lengths of bird and UAV samples are not uniform, and to obtain more data samples, the training set is expanded by using a sliding window approach with a window length of 30 and a step size of 1. This results in trajectory segments consisting of 30 time steps. The testing set is segmented into trajectory fragments of 30 time steps each. Each shorter time sequence is considered a new trajectory sample. The specific dataset division is shown in Table I.

TABLE I: The Specific Dataset Division

Track type	**Bird**	**UAV**
Sample size	[904, x, 5]	[218, x, 5]
Training set	[21838, 30, 5]	[8175, 30, 5]
Test set	[337, 330, 5]	[84, 30, 5]

2) Setting Hyperparameters: The experiments conducted in this paper were implemented on the TensorFlow platform. The CPU configuration used is a processor speed of 2.5 GHz, with a total of 40.0 GB of RAM.

During the model training process, all training data were shuffled, and grid search was used to select the optimal model hyperparameters and the number of layers for both LSTM and Transformer. Finally, the optimal model hyperparameters are shown in Table II.

TABLE II: Optimal Model Hyperparameters

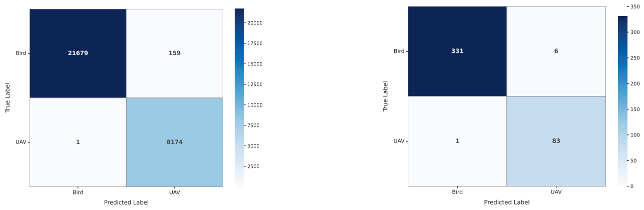
Module	**Hyperparameters**
Memory Encoding Module	• Number of LSTM Layers: 1 • Number of Units per Layer: 128
Transformer Encoder Module	• Number of Attention Heads: 4 • Head Size: 64 • FFN Size: 128 • Number of Encoder Layers: 1
Comprehensive Inference Module	• Number of Dense layer 1 units: 128 • Number of Dense layer w units: 1
Model Training	• Batch Size: 32 • Learning Rate: 1e-4 • Dropout Rate: 0.2

3) Evaluation Metrics and Other Baseline Models: In evaluating the model performance, we use four metrics: Accuracy(ACC), Recall, False Positive Rate(FPR), and Matthews Correlation Coefficient(MCC). The calculations of these metrics can be based on Table III. where ACC refers to the ratio of correctly classified samples to the total number of samples. High recall and low FPR are important for model performance, as they indicate that the model can classify most of the drone samples accurately with low prediction error. MCC is unaffected by class imbalance and comprehensively considers the four scenarios of TP, TN, FP and FN, thus providing an accurate reflection of the model's classification ability.

TABLE III: Formulas of Evaluation Metrics for Classification Performance

Evaluation Index	Computational Formula
ACC	$\frac{TP+TN}{TP+FP+TN+FN}$
Recall	$\frac{TP}{TP+FN}$
FPR	$\frac{FP}{TN+FP}$
MCC	$\frac{TP\times TN-FP\times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}$

Additionally, to measure the accuracy of the model's confidence in its predictions, we use the Brier Score (BS). The



(a) Training datasets (b) Test datasets

Fig. 3: The Confusion matrix of the type recognition results for the training and test datasets

lower the Brier score, the smaller the gap between the model's predicted confidence and the actual labels, indicating higher accuracy in the model's confidence assessment. The calculation formula is as follows

$$\mathrm{BS} = \frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - y_i)^2, \tag{5}$$

where: N is the number of targets, y_i and $\hat{y}_i$ are the true label and the model's predicted confidence of the i-th target.

In addition to the method proposed in this study, machine learning models widely used in related fields, which extracts five-dimensional features from the target's original velocity and heading characteristics: average speed, speed standard deviation, heading deviation standard deviation, maneuvering factor, and oscillation factor. These features are used as inputs to a extreme gradient boosting (XGBoost) model for long-duration trajectory recognition of birds and drones. As well as deep learning models such as LSTM networks and Transformer models, are all used as baseline models for comparative analysis.

B. Experimental Results

1) UAV Identification Evaluation Results: Fig. 3 shows the final confusion matrix of the type recognition results for the training and test datasets. In the training dataset, the model can correctly identify 21,679 birds and 8,174 drones. The accuracy (ACC), recall, and false positive rate (FPR) are 99.47%, 99.99%, and 0.73% respectively. In the test dataset, the model correctly classifies 331 birds and 83 drones, achieving similar values of ACC (98.3%), recall (98.81%), and FPR (1.78%).The above results indicate that the proposed LSTM-Transformer model is capable of deeply analyzing the characteristic information contained in the position, velocity, and RCS sequences. At a macroscopic level, it can grasp the overall features such as flight trajectories. At a microscopic level, it can also keenly capture the subtle changes in the individual flight postures and the instantaneous adjustments of velocity and other detailed features. Thus, it can accurately determine whether the target is a bird or a UAV.

2) Model performance comparison: The final model evaluation criteria for the test set are shown in Table IV. The proposed LSTM + Transformer model has the highest accuracy (ACC) of 98.1%, Matthews correlation coefficient (MCC) of 0.950, recall rate of 98.81%, the lowest false positive rate (FPR) of 1.78% and Brier score (BS) of 0.017 at 30 data batches, demonstrating the best model performance. Compared with the LSTM model, at 30 data batches, the ACC and MCC of this model have increased by 1.97% and 4.40% respectively. The false alarm rate (FAR) and BS have decreased by 50.00% and 39.29% respectively.

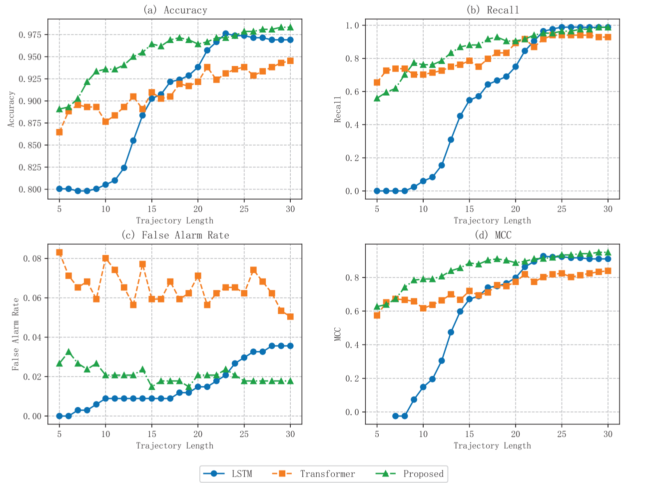


Fig. 4: Performance Comparison of Different Algorithms under Varying Trajectory Lengths

TABLE IV: Performance Comparison of Different Algorithms

L	Model	Evaluation Criteria				
		ACC (%)	MCC	Recall (%)	FPR (%)	BS
5	XGB	-	-	-	-	-
	LSTM	80.1	-	0	**0**	0.186
	Trans.	86.5	0.574	**65.5**	8.31	0.120
	Prop.	**89.1**	**0.627**	56.0	2.67	**0.095**
30	XGB	89.6	0.63	63.8	4.72	0.083
	LSTM	96.9	0.91	**98.8**	3.56	0.028
	Trans.	94.5	0.84	92.9	5.05	0.042
	Prop.	**98.3**	**0.95**	**98.8**	**1.78**	**0.017**
Improved		1.44%	4.40%	0	64.75%	39.29%

Fig. 4 shows the change curves of accuracy, MCC, recall rate, and false alarm rate of each model under different data lengths. In terms of accuracy, the LSTM model has a relatively low accuracy at the beginning, but it gradually rises and tends to stabilize as the data length increases. In contrast, the Transformer and the Proposed method have a relatively high accuracy from the start, and they rise steadily and then stabilize during the data growth process. Regarding the MCC, the MCC value of the LSTM model gradually increases from a relatively low level. The Proposed method eventually reaches the highest value and remains stable, while the Transformer rises in a relatively stable manner. In terms of the recall rate, the LSTM model starts from a relatively low level and gradually increases. The Proposed method and the Transformer have a relatively high recall rate from the beginning, and they rise steadily and then remain at a high level as the data increases. Finally, in terms of the false alarm rate, the LSTM model gradually decreases from a relatively high false alarm rate. The Proposed method always maintains the lowest and stable false alarm rate, and the Transformer decreases steadily. Overall, different models have their own advantages and disadvantages under different data lengths, and the Proposed method performs relatively well in most indicators.The above results indicate:

- The proposed LSTM-Transformer model skillfully integrates the unique advantages of the two models. Whether dealing with short or long data, this algorithm can demonstrate a high degree of stability and accuracy. It can keenly identify the subtle differences in the characteristics of birds and UAVs, thus enabling real-time and effective discrimination of target types.
- Compared with existing models, this LSTM-Transformer model has a stronger feature capture ability. It can accurately obtain multi-dimensional and refined feature information of the target, such as the spatial position distribution, the speed change trend, and the temporal fluctuation of the RCS. It can obtain a more accurate confidence level of the target type, thereby significantly improving the classification performance of birds and UAVs.

V. Conclusions

This paper focuses on the research of realizing the dynamic identification of low-altitude drones and bird targets using radar tracks. Relying on the target track information and attribute information collected by the radar, and combining with the actual application requirements, an innovative dynamic classification framework centered around LSTM-Transformer, is constructed. This framework can stably and accurately identify the dynamic feature differences between low-altitude drones and birds under different data lengths, and thus can accurately distinguish these two types of targets, namely low-altitude drones and birds, in real-time and effectively in practical application scenarios.

In future research, the application of multi-source data fusion technology will be the key consideration. The aim is to effectively reduce the identification errors caused by the influence of external interference on a single sensor in a complex environment. By integrating data from multiple sensors such as radar, optical, and infrared sensors, the system can complement and verify information from multiple dimensions, greatly enhancing the ability to accurately identify targets.

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