Deep Learning-Based Drone Classification Using Radar Cross Section Signatures at mmWave Frequencies

RUI FU1, MOHAMMED ABDULHAKIM AL-ABSI2, KI-HWAN KIM3, YOUNG-SIL LEE3, AHMED ABDULHAKIM AL-ABSI4, AND HOON-JAE LEE5

1Blockchain Laboratory of Agriculture and Vegetables, Weifang University of Science and Technology, Weifang, Shandong 262700, China
2Department of Computer Engineering, Graduate School, Dongseo University, Sasaeng-gu, Busan 47011, South Korea
3International College, Dongseo University, Busan 47011, South Korea
4Department of Smart Computing, Kyungdong University, Goseong, Gangwon-do 24764, South Korea
5Division of Information and Communication Engineering, Dongseo University, Sasaeng-gu, Busan 47011, South Korea

Corresponding authors: Ahmed Abdulhakim Al-Absi (absiahmed@kduniv.ac.kr) and Hoon-Jae Lee (hjlee@dongseo.ac.kr)

This work was supported in part by the Ministry of Education, Science and Technology, Basic Science Research Program, through the National Research Foundation of Korea (NRF), under Grant NRF-2016R1D1A1B0101908; and in part by the Ministry of Oceans and Fisheries, South Korea, through the Project titled Marine Digital AtoN Information Management and Service System Development (1/5), under Grant 20210650.

ABSTRACT This paper presents drone classification at millimeter-wave (mmWave) radars using the deep learning (DL) technique. The adoption mmWave technology in radar systems enables better resolution and aid in detecting smaller drones. Using radar cross-section (RCS) signature enables us to detect malicious drones and suitable action can be taken by respective authorities. Existing drone classification converts the RCS signature into images and then performs drone classification using a convolution neural network (CNN). Converting every signature into an image induces additional computation overhead; further CNN model is trained considering fixed learning rate. Thus, when using CNN-based drone classification under a highly dynamic environment exhibit poor classification accuracy. This paper present an improved long short-term memory (LSTM) by introducing a weight optimization model that can reduce computation overhead by not allowing the gradient to not flow through hidden states of the LSTM model. Further, present adaptive learning rate optimizing (ALRO) model for training the LSTM model. Experiment outcome shows LSTM-ALRO achieves much better drone detection accuracies of 99.88% when compared with the existing CNN-based drone classification model.

INDEX TERMS Convolutional neural network, drone detection, micro doppler signature (MDS), unmanned aerial vehicle, UAV, radar cross-section, millimeter-wave.

I. INTRODUCTION

Every new technology invented brings about positive and negative impacts to modern civilization. Recently, unmanned aerial vehicles (UAVs) such as drones have seen a constant rise in adoption in a different domain; this is because the drone has the capability of providing real-time video streaming and image capturing features. The drone has reached a capability of taking autonomous decisions based on different states; thus, it has become the center of attraction employing artificial intelligence techniques in provisioning different applications to military and civilians. Further, with technological growth, drones can be operated using smartphones rather than a traditional remote controller [1]. The drones have been adopted for the prevention of natural disasters [2], [3] search and rescue operations by gaining information [4], [5] and providing essential materials, border surveillance, and providing security to users in the city [6]–[8].

In recent times, there is increased incidents of drone regulation violations and drones have been used in the restricted zone as well [9], [8]; thus, leading to increased risk of disastrous economic and may bring risk to human lives. Currently, drone regulations have been emphasized across the different countries for enforcing a common set of rules. However, with
the advent of technology custom drones might be built which is not registered and these unregistered drones might fly in restricted zones. Thus, it makes drone detection extremely difficult because it is tiny in nature in comparison to moving objects such as busses, cars, etc. Generally, the maximum radar cross-section (RCS) values cars may be the range of 25 dBsm at 76-81 GHz and 18 dBsm at 23 GHz [10]. However, for drones’ radar cross-section value generally ranges from −150−20 dBsm in the X-band [11] and smaller than −20 dBsm at 30−37 GHz [12].

In this perspective, different challenges exist which must improve such as a small robot with radar capability for discovering highly dynamic and uncertain conditions and improving target tracking accuracies with as minimal time as possible [13]. Generally, the above task is performed by fusing data collected from onboard sensors such as inertial sensors, vision-based sensors [14]. However, using these sensors provide a poor result when employed in an indoor environment because of harsher propagation condition and poor visibility conditions. One way of overcoming the above problems is to employ drones with mmWave radars with reduced wavelength; it is tiny in nature and can be easily embedded into on-board of drones, and aid in achieving better detection and tracking of drones [15].

There are some advantages of using mmWave frequencies [16] in the radar systems such as it is conceivable to detect smaller drones and provide good resolution. Using RCS measurement, drone which is flying in a restricted zone can be intercepted and suitable action can be taken by the respective authority. Cellular network providers have already begun installing fifth-generation network radio (5G NR) [17], and at the earliest is expected to provide fifth-generation mobile edge computing (MEC) [18] server operating at mmWave frequencies to the dense user for city environment [19]. Using this infrastructure for UAV interception will significantly aid in reducing overall cost. [20] proved that the existing cellular base station could operate as a radar with small modification. [21] presented RCS measurement collection through mmWave frequency considering both small and large drones. [21] collected RCS measurement considering different measurement angles through mmWave frequency. Similar to [21] in [22] collected signature through polarimetry Ku-band frequency modulated continuous wave (FMCW) radar system. [22] converted the entire signal information into the image and then these images were trained using a convolution neural network and then the classification of the drone is performed. However, this model induce huge computation overhead as it collects a large amount of RCS data and that convert it into an image and then performs classification using GoogLeNet and CNN deep learning models. Using GoogLeNet the drone classification accuracies is 89.96% and using CNN they achieved accuracies of 96.61%.

In addressing drone classification problem, this paper, presents deep learning based drone classification model namely long short-term memory- adaptive learning rate optimizing (LSTM-ALRO). Here the improved weight optimization and adaptive ALRO model incorporated into the standard LSTM model for achieving better drone classification accuracy. The significance of drone classification using the LSTM-ALRO model is described in section III. The LSTM-ALRO based drone classification model reduces computation overhead for drone classification by introducing a weight optimization model. The modeling of the adaptive learning rate optimization model further aid in achieving better drone detection accuracies considering both smaller and larger drones. The LSTM-ALRO model achieves better accuracies, precision, recall, and F1-measure outcomes for performing drone classification for both small and large drones.

This paper is organized as follows. Section II, discussed related work for solving done classification problems and identifies the limitation of the existing drone classification model. In section III, preset the proposed deep learning-based drone classification at mmwave frequency. Section IV simulation result and analysis is discussed. The concluding remarks and future work are discussed in the last section.

II. RELATED WORK

This section discusses various recent drone classification models through machine learning and deep learning models. Number of recent work such as [12], [23], and [24] have discussed RCS signatures of a different drone with different frequency levels. In [23] used DJI Phantom drone for measuring the RCS signature at 94 GHz radar system. In [25] used two commercial drone models and RCS measurement with frequency range of 5.8 to 8.2 GHz. [12] used non-metallic drones and wideband RCS measurement were collected at 30 to 37 GHz. In [22], [26], [27] the RCS measurement were collected by employing Ku band radar. Most of the above related work have focused on collecting RCS measurements considering limited number of drones and frequency levels. [21] discussed drone material factors affecting RCS measurement considering certain 5G spectrum and overcomes presented comprehensive 3D measurements of RCS features of nine diverse drones and RCS measurement with Li-Po batteries. [21] presented quasi-3D RCS signatures of a diverse drone model with frequency ranging from 26 to 40 GHz for construction of a drone dataset.

[28] utilized convolution neural network (CNN) for drone classification using micro-Doppler signatures, a number of researchers [29]–[31] have presented different models using CNN for drone classification. However, these model requires effective preprocessing techniques in improving drone classification accuracy [27]. In [22] modeled an effective preprocessing technique using GoogleNet and CNN to eliminate useless data from micro-Doppler signatures. However, the major limitation of [22], is the entire signal information must be converted into an image and later these images are trained using GoogleNet and CNN [32], as results induce high computation overhead.

In addressing the aforementioned problems of the existing model is in the next section this work design the LSTM
This section presents deep learning-based drone classification at mmWave frequency. First, the system model used for performing drone classification is presented. Second, present the deep learning models for classifying drones. Finally, an adaptive learning model for enhancing drone classification accuracies is performed. The model notations and parameters are described in Table 1.

### A. SYSTEM MODEL

Here different kind of drone moves through a monitoring area and drone classification is done using RCS measurement collected using mmWave. The RCS is measured considering the different frequencies and these measurement values are trained using LSTM-ALRO (Long short-term memory-Adaptive learning rate optimization) model in order to carry out drone classification tasks.

### B. LSTM MODEL FOR DRONE CLASSIFICATION

Here we present a new LSTM model that can efficiently address the gradient descent problems. The LSTM for enhancing the structure of gradients with respect to time is described using the following equations

\[
d_u = g_u \odot d_{u-1} + j_u \odot h_u \tag{1}
\]

\[
i_u = p_u \odot \tanh(d_u) \tag{2}
\]

where \(d_u\) defines the cell state and \(i_u\) represent the hidden state, \(\odot\) signify point-wise product and \(g_u, j_u, p_u\) and \(h_u\) represent gates. The gate \(h_u\) is obtained through the following equations

\[
h_u = \tanh(X_{hi}i_{u-1} + X_{hy}y_u + c_h) \tag{3}
\]

Then, the gate \(g_u\) is defined using the following equation

\[
g_u = \sigma(X_{gi}i_{u-1} + X_{gy}y_u + c_g) \tag{4}
\]

Similarly, the gate \(j_u\) is obtained using the following equation

\[
j_u = \sigma(X_{ji}i_{u-1} + X_{jy}y_u + c_j) \tag{5}
\]

Then, the gate \(p_u\) is defined using the following equation

\[
p_u = \sigma(X_{pi}i_{u-1} + X_{py}y_u + c_p) \tag{6}
\]

Generally, an optimization \(\alpha(i_U)\) are utilized as the outcome at instance \(u\) with respect to that the loss \(\ell_u\) is computed and is mathematically defined as

\[
\ell_u := \ell(\alpha(i_U)) \tag{7}
\]

A notable characteristic of the LSTM model is the use of recursive association among cell states \(d_u\) that is linear in nature. This linear association aids the gradients to flow for the longer period. However, the weight matrices \(X_{hi}, X_{gi}, X_{ji}, X_{pi}\) in the LSTM model computational graph is polynomial in nature which grows with respect to time; thus, different paths induce magnitude of gradient imbalance, thus affecting the computation overhead by not allowing the gradient to not flow through hidden states of the LSTM model. Existing deep learning-based drone classification models [22], [33] are learned using Adam optimization model with fixed learning rate; as a result, impacts drone classification accuracies when introduced in a highly dynamic and uncertain environment [7].

### TABLE 1. Notation and description.

| Parameter | Description |
|-----------|-------------|
| \(d_u\)   | Cell state |
| \(g_u, j_u, p_u\) and \(h_u\) | Gates |
| \(i_u\)   | Loss |
| \(y_u\)   | Hidden state |
| \(\ell_u\) | Element of parameters full gradient that comes because of temporal paths |
| \(c_n, c_g, c_j, c_p\) | Element of full gradient that comes because of residual paths |
| \(X_{hi}, X_{gi}, X_{ji}, X_{pi}\) | Weight matrices |
| \(X_{hy}, X_{gy}, X_{jy}, X_{py}\) | Sigmoid activation function |
| \(\alpha\) | Output used at time instance \(u\) |
| \(a_u\)   | Parameter combining \(P_u\) and \(Q_u\) for different iteration |
| \(\hat{a}_u\) | After applying probability |
| \(G_u\)   | Define function representing the diagonal matrix |
| \(Q_u\)   | Composed of full gradients which ascend due to residual paths |
| \(P_u\)   | Composed of full gradient ascend due to temporal paths |
| \(d_0\)   | Determined value |
| \(P\)     | Probability for optimizing hyper-parameter |
| \(\beta_u\) | Identically and independently distributed variable |
| \(\omega_j\) | Sequence |
| \(\tilde{R}_j\) | Momentum parameter |
| \(\tilde{\theta}_j\) | Squares of gradient |
| \(\delta'\) | Defines value closer to 1 |
| \(D\)     | Optimization function |
| \(\gamma\) | the learning rate of constant |
| \(\mu_1\) and \(\mu_2\) | Constant |
for higher weight matrices it affects the gradients from linear paths. As a result, affecting drone classification performance. In addressing the aforementioned problems here we introduce the backpropagation mathematical operation of the LSTM model. First, let $x$ be an element of the weight matrix $X_{hi}, X_{gi}, X_{ji}, X_{pi}, X_{hy}, X_{gy}, X_{iy}, X_{ipy}$. Define,

$$
P_u = \begin{bmatrix}
G_u & 0_o & \text{diag}(i_u)
\
\tilde{G}_u & 0_o & \text{diag}(\tilde{i}_u)
\end{bmatrix} \quad (8)
$$

$$
Q_u = \begin{bmatrix}
0_o & \beta_o & 0_o
\end{bmatrix}
$$

Then, $a_u$ can be defined as follows

$$
a_u = (P_u + Q_u) a_{u-1} \quad (11)
$$

By iterating the above equation, we can rewrite it as follows

$$
a_u = (P_u + Q_u) (P_{u-1} + Q_{u-1}) \ldots (P_2 + Q_2) a_1 \quad (12)
$$

The matrix $P_u$ defines a function of long-short term model gates, hidden and cell states; this is because $P_u$ is composed of full gradient ascend due to temporal path mentioned in Eq. (1). A noticeable feature is the entire gates and hidden state $i_u$ are constraint with respect to outcome obtained through tan hot sigmoid activation functions. However, on the other side, the cell state $d_u$ progress elementwise with Eq. (1) and are constraint by session instance $u$; thus, with determinate $d_0$, the values $P_u$ are constrained. Similarly, the matrix $Q_u$ is composed of full gradients which ascend due to residual paths. The element of the matrix $Q_u$ are set of weight in a linear function $X_{hi}, X_{gi}, X_{ji}, X_{pi}$. If the weights are set very large element in $Q_u$ can become extremely large and it becomes even worse when we multiply $Q_u$ in Eq. (12), because product operation will result in polynomial, and it is difficult to bound them with respect to time. Thus, $P_u$ get inhibited in comparison with $Q_u$ because of the existence of gradient component magnitudes imbalance; thus, it is problematic of suppressing the gradient components of $P_u$.

In order to address the above problems here, we optimize the gradient value in such a way that $P_u$ is not intimidated when $Q_u$ is extremely high. Thus, aid in multiplying $Q_u$ between above zero to one to reduce the magnitude. The proposed weight optimization model is shown in Algorithm 1. The proposed weight optimization model doesn’t allow the gradient to flow through different $i_u$ states in an independent manner considering probability $1 - \mathcal{P}$, where $\mathcal{P}$, $\in [0, 1]$ as hyper-parameter used for the optimization process.

Now we show that gradient component obtained through $Q_u$ get reduced using gradient loss function outcome from Algorithm 1.

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### Algorithm 1 Weight Optimization Model

| Step | Description |
|------|-------------|
| 1.   | Start       |
| 2.   | Input: $(y_u^{1, U}, i_0, d_0, \mathcal{P})$ |
| 3.   | $\ell = 0$ |
| 4.   | $\forall u \leq U$ do |
| 5.   | If Bernoulli $(\mathcal{P}) = 1$ then |
| 6.   | $\tilde{i}_{u-1} \leftarrow \text{stop-gradient (}i_{u-1}\text{)}$ |
| 7.   | Else |
| 8.   | $\tilde{i}_{u-1} \leftarrow i_{u-1}$ |
| 9.   | $i_u, d_u \leftarrow \text{LSTM} (y_u, \tilde{i}_{u-1}, d_{u-1})$ |
| 10.  | $\ell \leftarrow \text{loss (}a(i_u)\text{)}$ |
| 11.  | $\ell \leftarrow \ell + \ell_u$ |
| 12.  | Obtain $\ell$ |
| 13.  | Stop |

Let $a_u = \left[ \frac{dd_u}{dx}, \frac{d_i}{dx} U \right]^T$ and $\tilde{a}_u$ are equivalent with respect to $a_u$ when weight optimization model with probability $1 - \mathcal{P}$ is applied during backpropagation; thus, the $\tilde{a}_u$ becomes

$$
\tilde{a}_u = (P_u + \beta_u Q_u) + (P_{u-1} + \beta_{u-1} Q_{u-1}) \ldots (P_2 + \beta_2 Q_2) \tilde{a}_u \quad (13)
$$

where $\beta_u, \beta_{u-1}, \ldots, \beta_2$ are identically and independently distributed and other variables are similar to Eq. (12).

The Eq. (13) doesn’t allow the gradient to pass-through $i_u$ states of LSTM model with probabilities of $1 - \mathcal{P}$ in a stochastic manner as described below

$$
\mathcal{F}_{\beta_2, \ldots, \beta_u} [\tilde{a}_u] = (P_u + \mathcal{P} Q_u) + (P_{u-1} + \mathcal{P} Q_{u-1}) \ldots (P_2 + \mathcal{P} Q_2) \tilde{a}_1 \quad (14)
$$

In this work the $Q_u$ is dropped in a stochastic manner in the gradient component. Thus, aid in reducing the $Q_u$ in comparison with the standard LSTM model and aid in reducing computation overhead by not allowing the gradient to not flow through hidden states $i_u$ of LSTM model. Further, the existing model has shown using Adam optimizer for batch-based learning achieves good learning efficiency; However, the existing model is trained using constant learning rate; thus, when adopted to classify drone achieves very poor results. For addresses in the next subsection, we introduce an adaptive learning rate optimization model for achieving better drone classification accuracies.

### C. ADAPTIVE LEARNING RATE OPTIMIZATION MODEL FOR DRONE CLASSIFICATION

This section introduces an adaptive learning rate optimization model for the drone classification model. The Adam optimizer model is a gradient-based method by combining both RMSprop and Adagrad which is widely used to train various classification and regression models. The update rule of Adam methodology is obtained using the following equation

$$
\omega_{j+1} = \omega_j - \gamma \frac{\hat{m}_j}{\sqrt{\hat{v}_j + \delta}} \quad (15)
$$
where

\[ m_j = \mu_1 m_{j-1} + (1 - \mu_1) \frac{\partial D (w_j)}{\partial w}, \quad (16) \]

\[ \nu_j = \mu_2 \nu_{j-1} + (1 - \mu_2) \left( \frac{\partial D (w_j)}{\partial w} \right)^2, \quad (17) \]

where \( \hat{m}_j = \frac{m_j}{\mu_1^j} \), and \( \hat{\nu}_j = \frac{\nu_j}{\mu_2^j} \). The Adam optimizer model computes exponential moving average for every gradient. Similarly, computes the squares of the gradient; then optimize the learning rate by taking ratios of both gradients. The standard Adam optimizer model generally decreases the learning rate or keeps it unchanged and can’t be neglected when it reaches local minima. Thus, an adaptive learning rate mechanism using optimization functions is introduced which is described in Algorithm 2.

**Algorithm Adaptive Learning Rate Optimization Model**

| Step | Description |
|------|-------------|
| 1.   | Start       |
| 2.   | \( \gamma_0 \) Configure learning rate |
| 3.   | \( D (\omega) \), Optimization function with parameter \( \omega \) |
| 4.   | \( j \leftarrow 0 \) (Initialize instance) |
| 5.   | While       |
| 6.   | \( \gamma_{j+1} \leftarrow \gamma_0 D (\omega_j) \) |
| 7.   | \( j \leftarrow j + 1 \) |
| 8.   | End while   |
| 9.   | Obtain \( \gamma_j \) |
| 10.  | Stop        |

The adaptive learning rate optimization model achieves better convergence when employed with the Adam optimization model of Eq. (16) as described below

\[ \omega_{j+1} = \omega_j - \gamma \frac{\hat{m}_j}{\sqrt{\hat{\nu}_j + \delta}} \]  
\[ = \omega_j - \gamma \frac{m_j}{\sqrt{\nu_j + \delta}} \]  
\[ = \omega_j - \gamma \frac{1 - \mu_2}{1 - \mu_1} \frac{m_j}{\sqrt{\nu_j + \delta}}. \]

(20)

where \( \mu_1 \) and \( \mu_2 \) are some constant; if \( j \) is significantly large, then \( \sqrt{1 - \mu_2} / \sqrt{1 - \mu_1} \) is considered to equal to one. Therefore, the adaptive learning rate optimization model can be obtained as follows

\[ \omega_{j+1} = \omega_j - \gamma_j \frac{\omega_j}{\sqrt{\nu_j + \delta}}, \]

(21)

where

\[ \gamma_j = \gamma_0 D (\omega_j) \]

(22)

where (\( \gamma_0 \) is a constant),

\[ m_j = (1 - \mu_1) \sum_{k=1}^{j} \mu_1^{j-k} \frac{\partial D (w_{j-k+1})}{\partial w}, \]

(23)

and

\[ \nu_j = \frac{1 - \mu_2}{1 - \mu_1} \sum_{k=1}^{j} \mu_2^{j-k} \left( \frac{\partial D (w_{j-k+1})}{\partial w} \right)^2. \]

(24)

In this work, the learning rate of constant \( \gamma \) is changed to function \( \gamma_j = \gamma_0 D (\omega_j) \) to make sure the learning rate is optimized in an adaptive manner. Using Eq. (21), the sequence \( \{ \omega_j \} \) can be obtained and \( m_j \) and \( \nu_j \) are obtained using Eq. (23) and (24), respectively. The \( \{ \omega_j \} \) converges and satisfies the minimal value of optimization function; this, aid in achieving better drone detection classification accuracies.

**IV. SIMULATION RESULT AND ANALYSIS**

Here experiment is conducted for performing automatic drone classifying using the proposed LSTM-ALRO model. Here receiver operating curve (ROC) performance metric such as accuracy, precision, recall, and F1-Score is used for validating LSTM-ALRO based drone classification model. Here the resulting outcome obtained is compared with existing GoogLeNet and CNN-based drone classification models [22] in terms of accuracies.

**A. MEASUREMENT MODEL**

This work uses RCS measurement data collected from [13]. Here they constructed an anechoic chamber for measuring antenna patterns that guarantee better RCS measurement. The graphical representation of the measurement model is shown in Fig. 1 [21]. The transmitter \( Tx \) and receiver \( Rx \) of dual-polarized Vivaldi horn antenna with quasi-monostatic radar is placed in one end of the shielded anechoic chamber. A VNA is utilized for the generation and recording of the received signal. The frequency is set in the range of 26 – 40 GHz with a bandwidth capacity of 1 kHz, transmit power is set to 20 dBm, and the distance \( R \) among the drone to be tested (DTBT) and test antennas are 5.8m. Herewith step size of 1 the frequency is varied, and measurement is collected. The drone to be tested (DTBT) is placed on the top of the rotating pillar opposite to the chamber than antennas. Tow axes of rotation are done to DTBT using stepped motors. Initially, the drone is rotated in the azimuth plane (i.e., x-axis). Then, it is moved toward the center axis (i.e., y-axis). Positions of Angular are varied from \( \theta \in [-90°, 90°] \) and \( \phi \in [0°, 180°] \) with steps size of 1° as in [21]. For each drone, the bottom hemisphere was measured aiding and reducing measurement time and providing a realistic drone detection mechanism where radar could be placed in the ground.

**B. DRONE USED FOR PERFORMING AUTOMATIC DRONE CLASSIFICATION**

Here we used measurements obtained from one helicopter, one radio-controlled (RC), and eight multi-rotor drones. 

[13] R. Fu et al.: DL-Based Drone Classification Using Radar Cross Section Signatures
The images of drones used are shown in Fig. 2 and the corresponding drone size and material used for designing drones are described in Table 2 [21]. The sample RCS measurement with frequency ranging from 26 GHz-40 GHz of Helicopter Kyosho drone is shown in Fig. 3. A similar study to Fig. 3 with different values and images has been given in [21]. Further, the RCS measurement of different drones for the frequency range of 28 GHz and 38 GHz is shown in Fig. 4 for smaller drones and Fig. 5 for larger drones. A similar study to Fig. 4 and Fig. 5 with different values and images has been given in [21]. Based on the measurement, drones are grouped into two categories: smaller drones are composed of 6 drones categorized under group I, and the remaining 4 drones are under group II.

**TABLE 2.** Types of drones [21].

| Measured object | Dimensions (mm) | Main material | YY (at 1'') | HV (at 1'') | VHHV (at 1'') |
|-----------------|----------------|--------------|-------------|-------------|---------------|
| DJI Matrix Pro  | 135            | Plastic      | -           | -           | -             |
| DJI F450       | 150            | Plastic      | -           | -           | -             |
| Parrot AR Drone| 180            | Syntex       | -           | -           | -             |
| Helicopter Kyosho| 780x139x200 | Plastic      | -           | -           | -             |
| DJI Phantom 4 Pro | 150          | Plastic      | Yes (1)     | Yes (1)     | -             |
| Battery 6S Lipo| 170x25x20      | Lithium ion-poly | -           | -           | -             |
| DJI Matrix 100 | 100            | Carbon fiber | Yes (2)     | Yes (2)     | Yes (2)       |
| Carbon/Full Hex | 100            | Carbon fiber | Yes (1)     | Yes (1)     | -             |
| RMAX 7000      | 80            | Carbon fiber | Yes (2)     | Yes (2)     | -             |
| Walkera Voyager 4| 465x465x352  | Carbon fiber | Yes (2)     | Yes (2)     | -             |

**Case 1.** Here experiment is conducted to perform drone classification using a small drone (i.e., group 1 drones). Here experiment is conducted to classify each drone with respect to other drones; thus, it is a binary classification problem. Receiver operating curve and ROC performance metrics such as accuracies, precision, recall, and F1-score are used for analyzing the drone classification model using LSTM-ALRO. The ROC performance metric at 26 GHz is shown in Table 3 and the ROC performance metric at 40 GHz is shown in Table 4. Comparative analysis considering 26 GHz and 40 GHz is shown in Fig. 6. The ROC attained using LSTM-ALRO varies in range of 0.834 to 1 for 26 GHz and ROC of 1 is achieved for 40 GHz. From result obtained we can see the LSTM-ALRO based drone classification achieve very good detection performance for both smaller and larger frequency level. However, F450 has poor F1-score and recall performance. Similarly, the Heli drones has poor precision and F1-score performance when operating at low frequency. Nonetheless, high detection accuracies is achieved considering larger frequency size.

**TABLE 3.** Group I drone classification ROC analysis corresponds to measurement at 28 GHz.

| Type of drones | Accuracy | Precision | Recall | F1-Score   |
|----------------|----------|-----------|--------|------------|
| F450           | 0.972375691 | 1        | 0.834254144 | 0.909638554 |
| Heli           | 0.968692449 | 0.845070423 | 0.994475138 | 0.913705584 |
| Mavic          | 0.998158379 | 0.989071038 | 1      | 0.994505495 |
| P4P            | 0.990791897 | 0.980874317 | 0.991712707 | 0.986263736 |
| Parrot         | 0.992633517 | 1        | 0.955801105 | 0.97740113  |
| Average        | 0.984530387 | 0.963003156 | 0.955246619 | 0.9563029   |
FIGURE 3. Sample RCS measurement of Helicopter Kyosho drone.
FIGURE 3. (Continued.) Sample RCS measurement of Helicopter Kyosho drone.
FIGURE 4. Drones from Group I Monostatic RCS measurement, considering azimuth and elevation angles. The left and center columns indicate RCS measurement at 38 GHz and 28 GHz, respectively of the corresponding drone (right column).
FIGURE 5. Monostatic RCS measurement of drones from Group II, considering azimuth and elevation angles. The left and center columns indicate RCS measurement at 28 GHz and 38 GHz, respectively of the corresponding drone (right column).
TABLE 4. Group I drone classification ROC analysis corresponds to measurement at 40 GHz.

| Type of drones | Accuracy | Precision | Recall | F1-Score |
|----------------|----------|-----------|--------|----------|
| F450           | 1        | 1         | 1      | 1        |
| Heli           | 1        | 1         | 1      | 1        |
| Mavic          | 1        | 1         | 1      | 1        |
| P4P            | 1        | 1         | 1      | 1        |
| Parrot         | 1        | 1         | 1      | 1        |
| Average        | 1        | 1         | 1      | 1        |

FIGURE 6. ROC analysis considering 26 GHz and 40 GHz for Group I drone classification.

TABLE 5. Group II drone classification ROC analysis corresponds to measurement at 28 GHz.

| Type of drones | Accuracy | Precision | Recall | F1-Score |
|----------------|----------|-----------|--------|----------|
| Hexa           | 0.998895028 | 1         | 0.994475138 | 0.997229917 |
| M100           | 0.998895028 | 0.997245179 | 1      | 0.99862069 |
| Walkera        | 0.997237569 | 0.986376022 | 1      | 0.993141289 |
| Y600           | 0.997237569 | 1         | 0.986187845 | 0.993045897 |
| Average        | 0.998066298 | 0.9959053 | 0.995165746 | 0.995509448 |

TABLE 6. Group II drone classification ROC analysis corresponds to measurement at 40 GHz.

| Type of drones | Accuracy | Precision | Recall | F1-Score |
|----------------|----------|-----------|--------|----------|
| Hexa           | 0.999447514 | 1         | 0.997237569 | 0.998616874 |
| M100           | 0.999447514 | 0.99862069 | 1      | 0.999309869 |
| Walkera        | 0.998895028 | 0.997237569 | 0.997237569 | 0.997237569 |
| Y600           | 0.998895028 | 0.997237569 | 0.997237569 | 0.997237569 |
| Average        | 0.999171271 | 0.998273957 | 0.997928177 | 0.99810047 |

TABLE 7. Group II drone classification ROC analysis corresponds to measurement at 26 GHz.

| Type of drones | Accuracy | Precision | Recall | F1-Score |
|----------------|----------|-----------|--------|----------|
| Hexa           | 0.999654696 | 1         | 0.994475138 | 0.997229917 |
| M100           | 0.999654696 | 0.994505495 | 1      | 0.997245179 |
| Walkera        | 0.997237569 | 1         | 0.993141289 | 0.998616874 |
| Y600           | 0.997237569 | 1         | 0.997237569 | 0.998616874 |
| Average        | 0.999769797 | 0.998930151 | 0.998772253 | 0.998848823 |

TABLE 8. Group II drone classification ROC analysis corresponds to measurement at 28 GHz.

Case 2. Here experiment is conducted to perform drone classification using a larger drone (i.e., group 2 drones). Here experiment is conducted to classify each drone with respect to other drones; thus, it is a binary classification problem. Receiver operating curve performance metrics such as accuracies, precision, recall, and F1-score is used for analyzing the drone classification model using LSTM-ALRO. The ROC performance metric at 26 GHz is shown in Table 5 and the ROC performance metric at 40 GHz is shown in Table 6. Comparative analysis considering 26 GHz and 40 GHz is shown in Fig. 7. From the result obtained we can see the LSTM-ALRO based drone classification achieve very good detection performance for both smaller and larger frequency level. However, high detection accuracies are achieved larger frequency size.

Case 3. Here experiment is conducted to perform drone classification using both smaller and larger drones (i.e., both group 1 and group 2 drones). Here experiment is conducted to classify each drone with respect to other drones; thus, it is a binary classification problem. Receiver operating curve performance metrics such as accuracies, precision, recall, and F1-score is used for analyzing the drone classification...
TABLE 9. Comparative study.

| Drone signature data collection | RCS [21], 2020 | Light-CNN [30], 2020 | CNN [22], 2021 | GoogLeNet [22], 2021 | LSTM-ALRO |
|-------------------------------|---------------|----------------------|--------------|----------------------|----------|
| Drone types                   | Yes           | No                   | No           | No                   | No       |
| Total drones considered       | 9             | 3                    | 3            | 3                    | 9        |
| Signature type                | Radar cross section signature | Doppler image signature | Doppler image signature | Radar cross section signature |
| Obstacle considered           | No            | No                   | No           | No                   | No       |
| Drone classification done      | No            | Yes                  | Yes          | Yes                  | Yes      |
| Classification problem considered | No     | Binary               | Binary       | Binary               | Binary and multi-label classification |
| Accuracy                      | -             | 97.14%               | 96.61%       | 89.96%               | 99.88%   |

The comparative study is given in Table 9. From Table we can state that the work in [21] just focused on generating RCS signature rather than Doppler images using mmWave frequency considering diverse range of small and large drones; however, drone classification task is not considered. Recent work such as [22] and [30] have considered drone classification employing deep learning techniques; however, these models are limited to classify small drones only and addresses classification problem as binary classification problem considering Doppler image signature. On the other side, the proposed LSTM-ALRO model is designed to address both binary and multi-class classification problem considering both small and large drones through RCS signature. Thus, LSTM-ALRO can address the limitation of drone classification task of RCS model [21]. However, it is noticed no existing drone classification model including proposed model have considered presence of obstacle in measurement model.

V. CONCLUSION

The drone exhibits dynamic behavior and operates in an uncertain environment; thus, requires an adaptive learning model. However, existing models are trained considering fixed learning rates, thus the result achieved is not
satisfactory. In this paper, we presented an improved Deep learning model namely LSTM-ALRO which can adaptively work well under a highly uncertain and dynamic environment for performing various classes of drone classification (i.e., including both small and large drones). The LSTM-ALRO based drone classification model achieves an accuracy of 99.88% which is significantly higher than that of GoogLeNet and CNN–based drone classification models. The result proves the adaptive nature of the LSTM-ALRO based drone classification model concerning the dynamic characteristic of the drone.

Future work would consider testing the LSTM-ALRO considering a more diverse type of drone and considering multiple measurements considering more diverse angles. Further, the presence of obstacles during RCS measurement construction must be considered in future dataset generation. Our model is expected to perform well under the presence of obstacles which will be considered in the future experimental study.

ACKNOWLEDGMENT
Rui Fu, Mohammed Abdulhakim Al-Abi, and Ahmed Abdulhakim Al-Abi contributed to the main idea and the methodology of the research. Rui Fu and Mohammed Abdulhakim Al-Abi designed the experiment, performed the simulations, and wrote the original manuscript. Rui Fu, Ahmed Abdulhakim Al-Abi, Ki-Hwan Kim, and Young-Sil Lee contributed significantly to improving the technical and grammatical contents of the manuscript. Rui Fu, Ahmed Abdulhakim Al-Abi, and Hoon-Jae Lee reviewed the manuscript and provided valuable suggestions to further refine it. All authors have read and agreed to the published version of the manuscript. Supervision Hoon-Jae Lee.

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RUI FU received the M.S. degree in system theory from Qingdao University, China, in 2015, and the Ph.D. degree from the Department of Information and Communication Engineering, Dongseo University, South Korea. She is currently a Professor with the Institute of Intelligent Manufacturing, Weifang University of Science and Technology, China. Her research interests include artificial intelligence, VANET, UAVs/drone, deep learning, logistics transportation, and mathematics.

MOHAMMED ABDULHAKIM AL-ABSI received the B.S. degree in computer application from Bangalore University, India, and the M.S. degree from Dongseo University, South Korea, in 2018, where he is currently pursuing the Ph.D. degree with the Department of Information and Communication Engineering. His research interests include the IoT, VANET, UAvs/drone, AI, cryptology, network security, side-channel attack, deep learning, cloud computing, computer networks, and digital communications.

KI-HWAN KIM received the B.S., M.S., and Ph.D. degrees in computer networking from Dongseo University, Republic of Korea, in 2020. He is currently an Associate Professor with the International College, Dongseo University. His research interests include cryptography, information security, and side-channel attack (SCA).

HOON-JAE LEE received the B.S., M.S., and Ph.D. degrees in electrical engineering from Kyungpook National University, in 1985, 1987, and 1998, respectively. From 1987 to 1998, he had been engaged in the research on cryptography and network security at the Agency for Defense Development. Since 2002, he has been working as an Associate Professor with the Department of Computer Engineering, Dongseo University, where he is currently a Full Professor. His current research interests include security communication systems, side-channel attack, and USN and RFID security. He is a member of the Korea Institute of Information Security and Cryptology, the IEEE Computer Society, and the IEEE Information Theory Society.

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