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Implementation of On-Device AI System for Drone Operated Metal Detection with Magneto-Impedance Sensor

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Abstract

This paper addresses the implementation of an on-device AI-based metal detection system using a Magneto-Impedance Sensor. Performing calculations on the AI device itself is essential, especially for unmanned aerial vehicles such as drones, where communication capabilities may be limited. Consequently, a system capable of analyzing data directly on the device is required. We propose a lightweight gated recurrent unit (GRU) model that can be operated on a drone. Additionally, we have implemented a real-time detection system on a CPU embedded system. The signals obtained from the Magneto-Impedance Sensor are processed in real-time by a Raspberry Pi 4 Model B. During the experiment, the drone flew freely at an altitude ranging from 1 to 10 meters in an open area where metal objects were placed. A total of 20,000,000 sequences of experimental data were acquired, with the data split into training, validation, and test sets in an 8:1:1 ratio. The results of the experiment demonstrated an accuracy of 94.5% and an inference time of 9.8 milliseconds. This study indicates that the proposed system is potentially applicable to unmanned metal detection drones.

Keywords: *Deep Learning, Drone, Magneto-Impedance Sensor, Metal Detection, On-Device AI*

1. Introduction

On-device AI is crucial for autonomous flying drones [1-3]. Drones operate in diverse environments and

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frequently encounter situations where an internet connection is unavailable. On-device AI enables drones to perform tasks independently, even in these challenging conditions. Weight and power consumption are significant considerations for flight; thus, the implementation of a lightweight artificial intelligence model is essential.

Anomaly detection research using unmanned aerial vehicles (UAVs) is gaining widespread attention. Drones, in particular, are equipped with various sensors to perform specific missions. The magnetic impedance (MI) effect [4] refers to the phenomenon where the impedance of a magnetic material changes in response to the strength of an external magnetic field. This electromagnetic phenomenon occurs when pulse current or high-frequency current is applied to a magnetic material. The application of pulse current or high-frequency current varies depending on the strength of the external magnetic field. Pulsed magnetic fields are employed to measure geomagnetism and detect foreign substances based on their intensity. This technology can be utilized as a metal detector for various applications, including landmine detection, metal separation, and airport security inspection.

There have been several studies focusing on metal detection using drones equipped with artificial intelligence. Sungjae Ha et al. [5] conducted a comparative experiment on the detection performance of a convolutional neural network (CNN) and a recurrent neural network (RNN) using data extracted from a magnetic impedance sensor. Hoijun Kim et al. [6] combined long short-term memory (LSTM) and gated recurrent unit (GRU) models to detect and classify metal objects from signals collected from MI sensors. They improved accuracy by managing the sequence length of the input data and performing additional operations during the prediction process. Ahmed Barnawi et al. [7] utilized UAV-based aerial magnetometry to identify magnetic anomalies in the ground magnetic field. By processing data locally on the edge server, they were able to analyze magnetic field data in real time, thereby reducing communication latency and bandwidth requirements. Lee-Sun Yoo et al. [8] proposed a data processing method to detect metal anti-personnel mines (M16) using a Magnetometer System mounted on an unmanned aerial vehicle (UAV or drone). Guoying Wang et al. [9] introduced an improved graph neural network incorporating a transformer, a graph attention mechanism, and a multi-channel fusion mechanism for anomaly detection in unmanned aerial vehicles.

Previous research has presented various studies utilizing artificial intelligence approaches with magnetic impedance sensors. However, for unmanned aerial vehicles (UAVs) such as drones, communication can be limited. Therefore, research into on-device AI-based metal detection and classification is necessary. This paper proposes a lightweight artificial intelligence model to process self-impedance sensor data and aims to implement the system. The structure of this paper is as follows: Chapter 2 explains the proposed on-device AI system and details the artificial intelligence model. Chapter 3 presents the experimental environment and results. Finally, Chapter 5 provides conclusions and considerations.

2. On-Device AI System for Drone-Operated Metal Detection

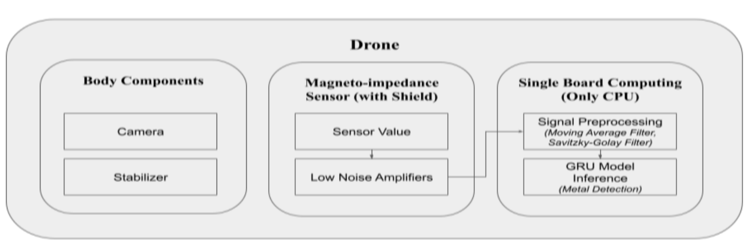


Figure 1. Proposed system for drone-operated metal detection with magneto-impedance sensor

An on-device artificial intelligence system for metal detection in drones is proposed. To ensure the stability of the sensor's collection direction, a stabilizer was installed. Additionally, a downward-facing camera was configured to verify performance. To avoid interference with other signals, a shield was placed around the sensor. Low Noise Amplifiers were applied to the sensor values to transmit single-board signal values. After pre-processing these values, artificial intelligence inference is performed.

The magnetic impedance sensor mounted on the drone collects magnetic field data necessary for landmine detection. The data is stored as integers ranging from 0 to 65,535 and is collected at a frequency of 100Hz. During the preprocessing stage, the rate of change is calculated by considering 50 sensor values as one sequence. The rate of change, $\Delta S = [\Delta s_1, \Delta s_2, \cdots, \Delta s_{49}]$, is calculated for each sequence $S = [s_1, s_2, \cdots, s_{50}]$, where the rate of changeΔs_i is defined as $\Delta s_i = s_{i+1} - s_i$ for $i = 1.2.\cdots, 49$. Based on the rate of change, the data is labeled as 1 if a landmine is present and 0 if it is not. To remove noise, a moving average filter and a Savitzky-Golay filter were used [10, 11].

The Gated Recurrent Unit (GRU) [12] is a model designed to process sequential data. Its simple structure makes it well-suited for lightweight applications. Figure 2 illustrates the structure of the proposed GRU model. The proposed lightweight GRU model receives input sequences and processes information over time. GRU layers effectively learn temporal patterns in the data, while dropout layers are employed to prevent overfitting. Finally, a fully connected layer and a softmax output layer perform the classification task.

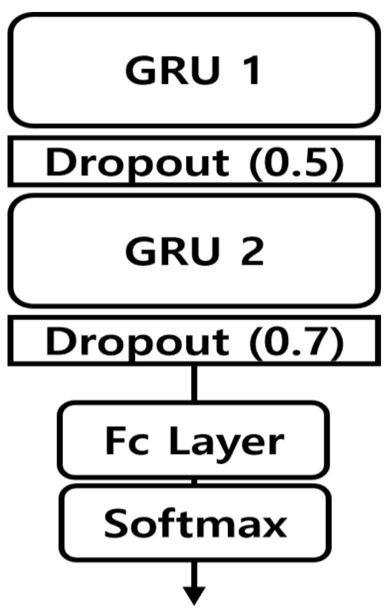


Figure 2. Representation of the proposed lightweight GRU model. This diagram shows the structure of the model, including two GRU layers with dropout, a fully connected layer, and a SoftMax output layer

3. Experimental Environment and Result

3.1 Experimental Environment

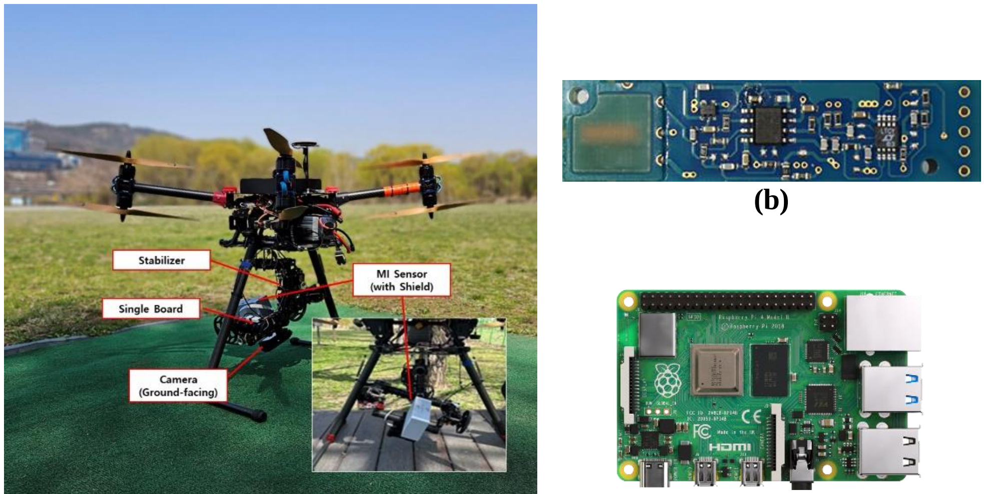


Figure 3. Drone and sensor images used in the experiment (a) drone (b) MI sensor (c) single-board computer

The drone used in this experiment is a rotary-wing ultra-light aircraft, specifically an X8 type multirotor equipped with 8 motors. To ensure the camera mounted on the drone remains level despite any tilt and shaking during movement, a camera gimbal was installed. The experimental sensor was mounted on this camera gimbal, ensuring constant horizontal measurements during flight. For metal detection using on-device AI, a Magneto-Impedance (MI) sensor and a single-board computer were installed on the drone. The MI sensor used was the MI-CB-1DJ from AICHI STEEL (Japan). For artificial intelligence model inference, a Raspberry Pi 4 Model B, a single-board computer, was employed. Table 1 provides the detailed specifications of the proposed system.

Table 1. Drone and sensor specifications

Product	Parameters	Specifications
Drone	Type	Multyrotor X8-type (Octo)
	Size (L×W×H)	80×80×65
	Prop.	16×7
	Weight	9.8 kg
	Max Speed	60 km/h
	Battery Type	LiPo 6S
MI Sensor	Detection range	2.0 µTpp
	Sensitivity	5V/ µT
	Noise	100pT/1σ
	Power supply voltage	15.0 V
Single-board Computer (Raspberry Pi 4 Model B)	Processor	Broadcom BCM2711, quad-core Cortex-A72 (ARM v8) 64-bit SoC @ 1.5GHz
	Memory	8GB LPDDR4
	Input power	5V DC via USB-C connector

Figure 4(a) shows the environment where data was collected. The area around the metal object to be detected is an open space free of other metals. The drone collected data by moving left and right at altitudes between 1 and 10 meters within the designated experimental area. Approximately 20,000,000 sequences of data were obtained over a total of 6 flights, each lasting 1 hour. The acquired dataset was divided into 80% for the training set, 10% for the test set, and 10% for the validation set, and used for model learning.

The evaluation of the experiment utilized four indicators to assess the performance of the learned model: accuracy, mean square error (MSE), root mean square error (RMSE), and mean absolute error (MAE). Accuracy is calculated by dividing the number of correct predictions by the total number of predictions. The mean squared error is the average of the squared differences between the predicted and actual values; a smaller MSE indicates that the model's predictions are closer to the actual values. The root mean square error is the square root of the average of the squared differences between the predicted and actual values; a smaller RMSE indicates more accurate predictions. The mean absolute error is the average of the absolute differences between the predicted and actual values; a smaller MAE indicates that the model's predictions are closer to the actual values. Additionally, inference time was measured.

Figure 4(b) shows the custom-built labeling tool used for data collection. This tool, constructed using PyQt5, features a GUI and collects sensor data via socket communication. The collected data is visualized in real-time, displaying the probability of the presence or absence of landmines in a tabular format. Furthermore, the tool analyzes the frequency component of the data through FFT analysis and supports accurate detection by labeling mines based on the rate of change.

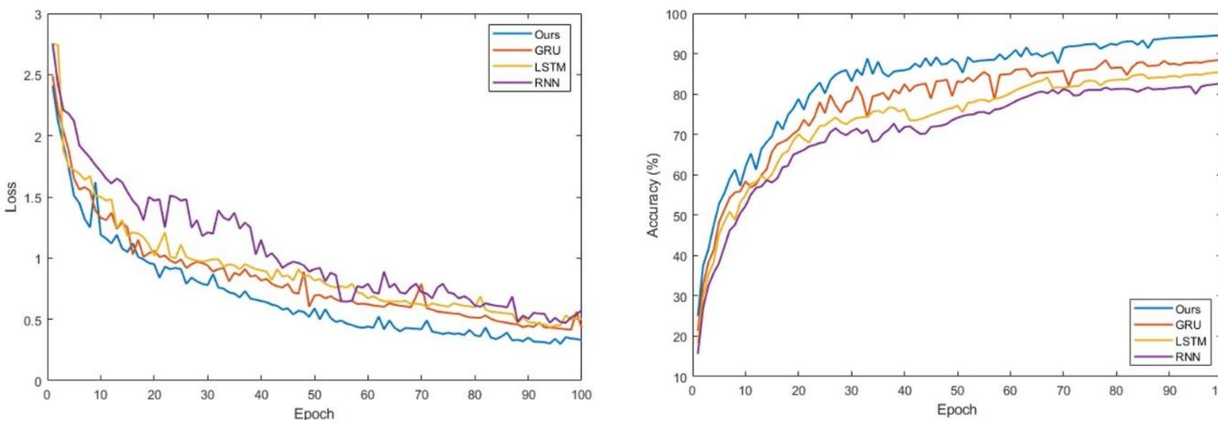
(a) (b)

Figure 4. Data construction environment and construction software through drone flight (a) drone flight experiment environment (b) labeling tool

3.2 Experimental Result

Figure 5 presents the learning convergence graphs for the proposed model compared to existing GRU, LSTM, and RNN models over 100 epochs. Figure 5(a) depicts the loss convergence graph, while Figure 5(b) illustrates the accuracy convergence graph. For all models, loss decreased rapidly during the initial epochs and then gradually stabilized. The proposed model reduced loss the most rapidly, ultimately recording a final loss of 0.33. The GRU model achieved a final loss value of 0.427, the LSTM model recorded a final loss of 0.499, and the RNN model had a final loss value of 0.575.

In Figure 5(b), the accuracy of the proposed model steadily increased over the 100 epochs, reaching 94.5%. The GRU model showed a final accuracy of 88.38%, the LSTM model achieved a final accuracy of 85.38%, and the RNN model attained a final accuracy of 82.48%. Compared to the other models, the proposed model exhibited a faster increase in accuracy during the initial epochs and maintained a higher final accuracy.



(a) **(b)**

Figure 5. Learning convergence graph for each model type over 100 epochs (a) loss convergence graph (b) accuracy convergence graph

Table 2 presents the performance indicators, including mean square error (MSE), root mean square error (RMSE), and mean absolute error (MAE), for each model. The proposed model demonstrated excellent performance in terms of prediction accuracy, exhibiting the lowest error values across all indicators.

Table 2. Comparison of Model Performance Metrics for Different Architecture

Model	MSE	RMSE	MAE
GRU	0.00385	0.06328	0.04372
LSTM	0.00318	0.06039	0.03994
RNN	0.01164	0.06874	0.04513
Ours	0.00310	0.05829	0.03584

Table 3 presents the inference time for each model on a single-board computer. The proposed model demonstrated the fastest performance, recording an inference time of 9.8 ms, followed by the GRU model at 12.8 ms, the RNN model at 14.6 ms, and the LSTM model at 17.2 ms. This indicates that the proposed model is more suitable for real-time applications.

Table 3. Inference Time Comparison on a Single-Board Computer

Model	GRU	LSTM	RNN	Ours
Inference Time (ms)	12.8	17.2	23.1	9.8

4. Discussion and Conclusions

For unmanned aerial vehicles (UAVs) such as drones, communication may be limited, necessitating a system capable of performing analysis on the device itself. On-device AI performs the necessary calculations for the AI model directly on the device, enabling missions to be carried out regardless of the communication environment. This study utilized MI sensors in drones to implement a system for detecting metal through on-device AI. To achieve this, a lightweight GRU model was proposed and implemented on a CPU-based single board.

The limitations of this experiment are as follows. First, there is a lack of generalization due to limitations in obtaining diverse environmental data. The terrain of the real world is complex and variable, influenced by factors such as varying terrain, environmental conditions, and weather. Second, sensor values may vary depending on the drone's altitude, speed, direction, and the shape of the metal. Therefore, to ensure scalability, it is necessary to acquire a large amount of data across various environments and operating conditions.

Further research is required on sensor data augmentation that accounts for different environments and driving conditions. There is an urgent need to supplement sparse datasets by utilizing data augmentation techniques, particularly generative adversarial networks (GANs) and diffusion models. The single board-based metal detection technology proposed in this study shows potential for detecting metals, such as mines, in hazardous areas.

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