UAV Velocity Prediction

Using Audio data

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AGENDA

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Introduction

Member Motivation

Members

Eunyoung Bang

University : Kangwon National

Major : Computer Engineering

Interest field : Machine Learning, Deep Learning

Yeongmin Seo

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Major : Cyber Security

Interest field : Security, Machine Learning

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Interest field : AI, Deep Learning

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University : Institut Polytechnique de Paris

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Interest field : Cybersecurity, Telecommunications, AI

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University : Purdue

Major : Cyber Security

Interest field : Cyber Security

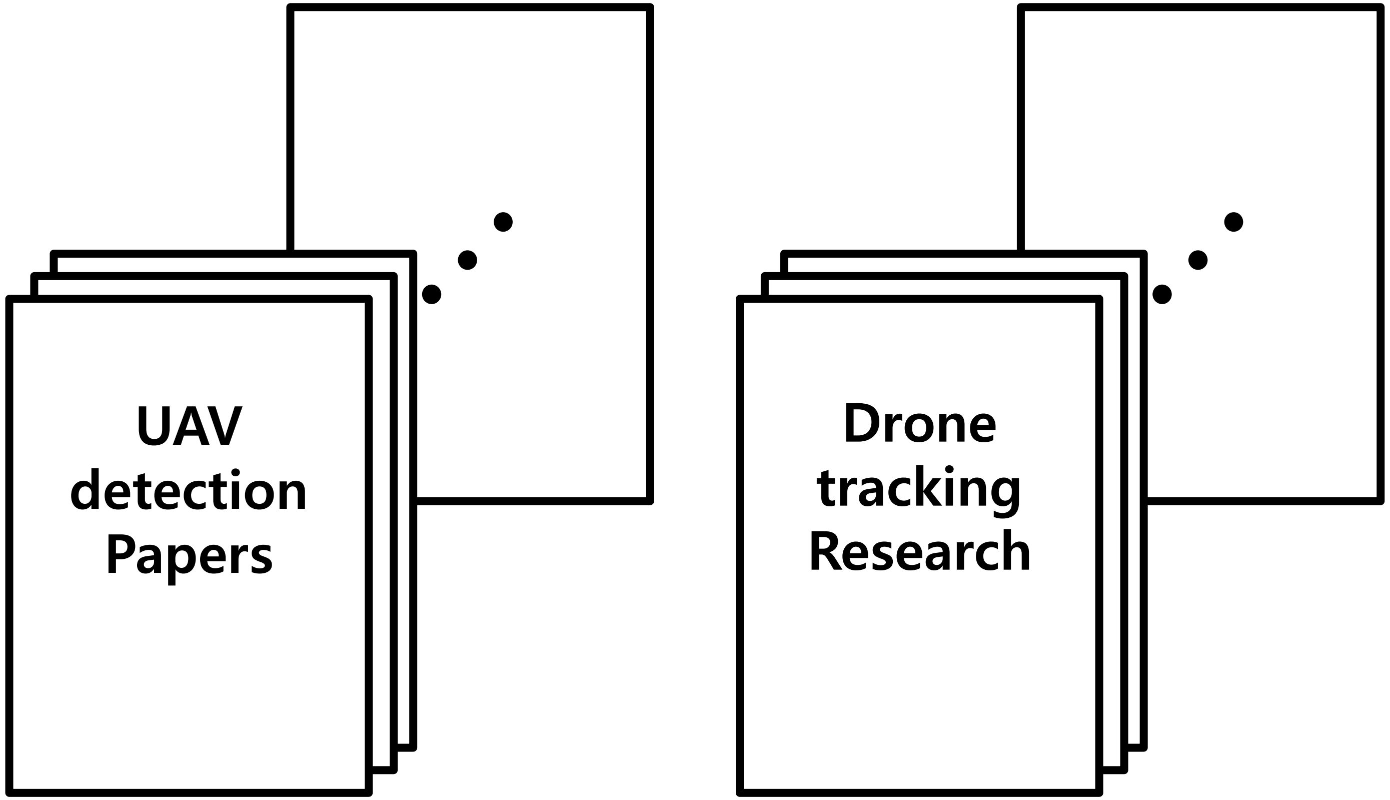
Problem Statement

Drone crashes into Russian oil refinery in possible attack [1]

FBI says PA electricity station likely 'target' of drone incident [2]

Problem Statement

How can we respond to malicious UAVs?



Motivation

Our goal is

Motivation

Our goal is

UAV Velocity Prediction Using Audio data

Motivation

Why Audio Data? [3], [4], [5]

- Even with noise limitations, it provides good results for distinguishing the drone's sound.
- Audio data obtain relatively results at less cost than other methods.

Justice of malicious UAV

The U.S. FAA set
UAV speed limit
100mph.

→

Fast UAV that exceeds
the speed limit

Set a speed limit

Indoor experiment is hard to **accelerate** the speed of **UAV**

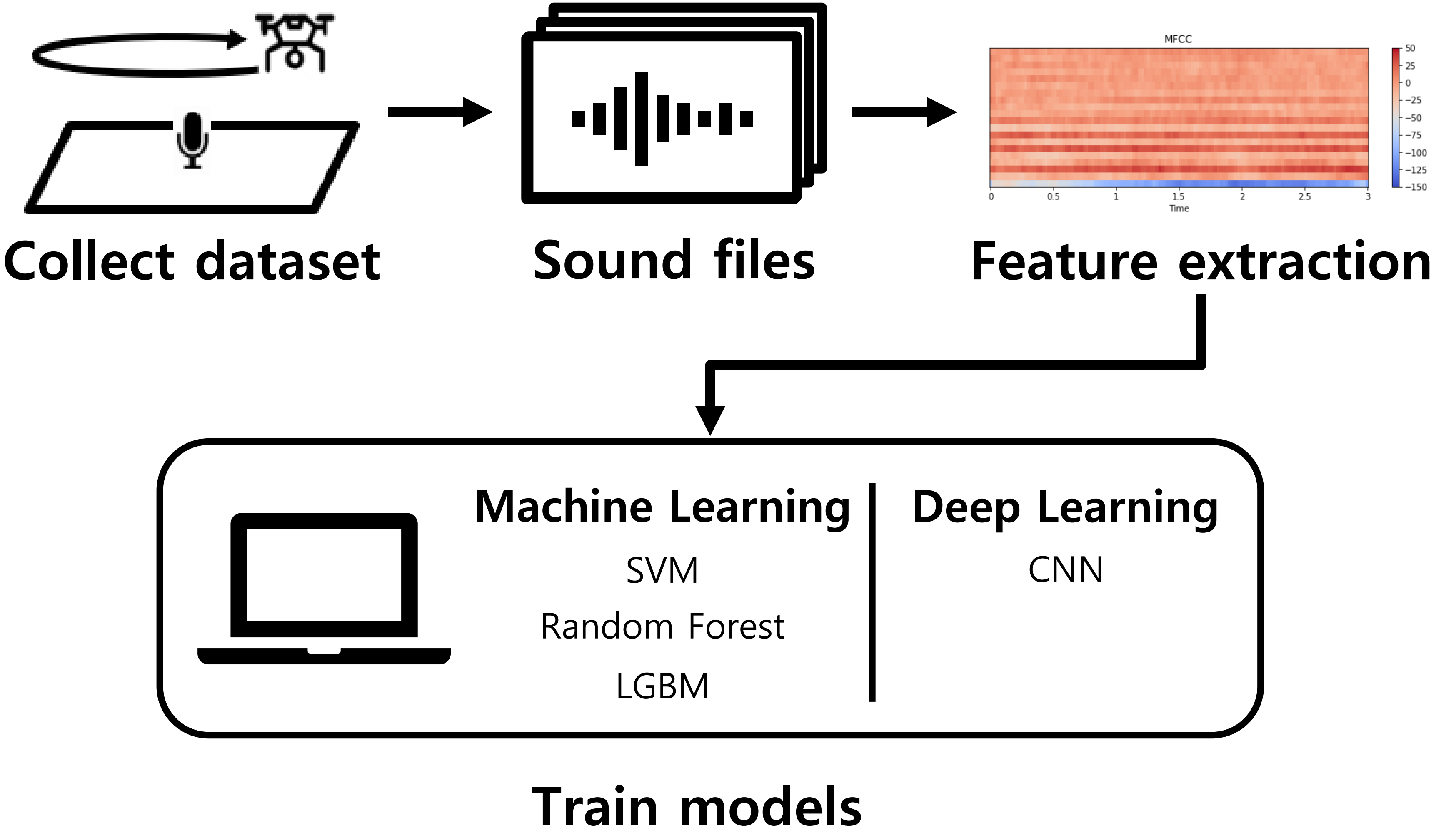
→

Set the experimental threshold at 10mph

Methodology

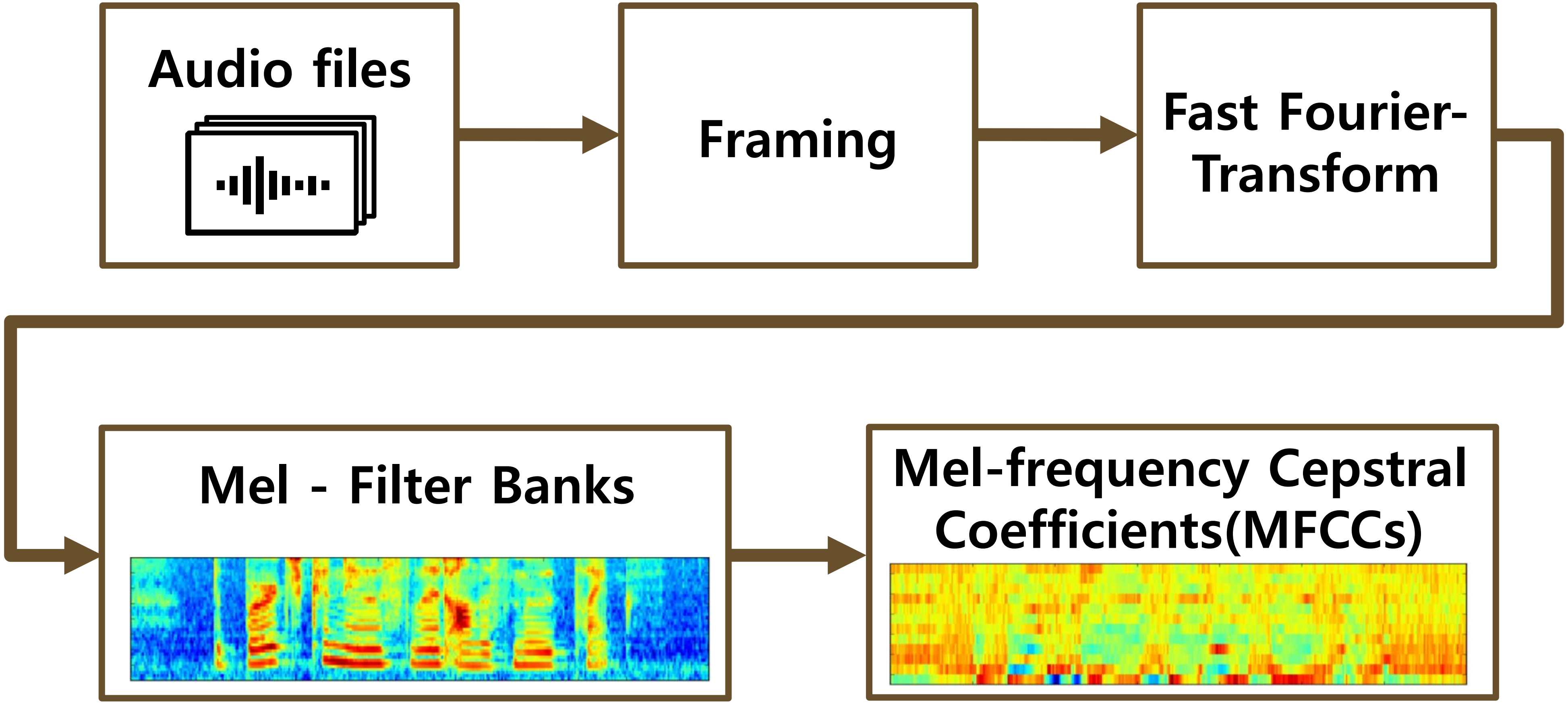
Background
Dataset
CNN Architecture

Background

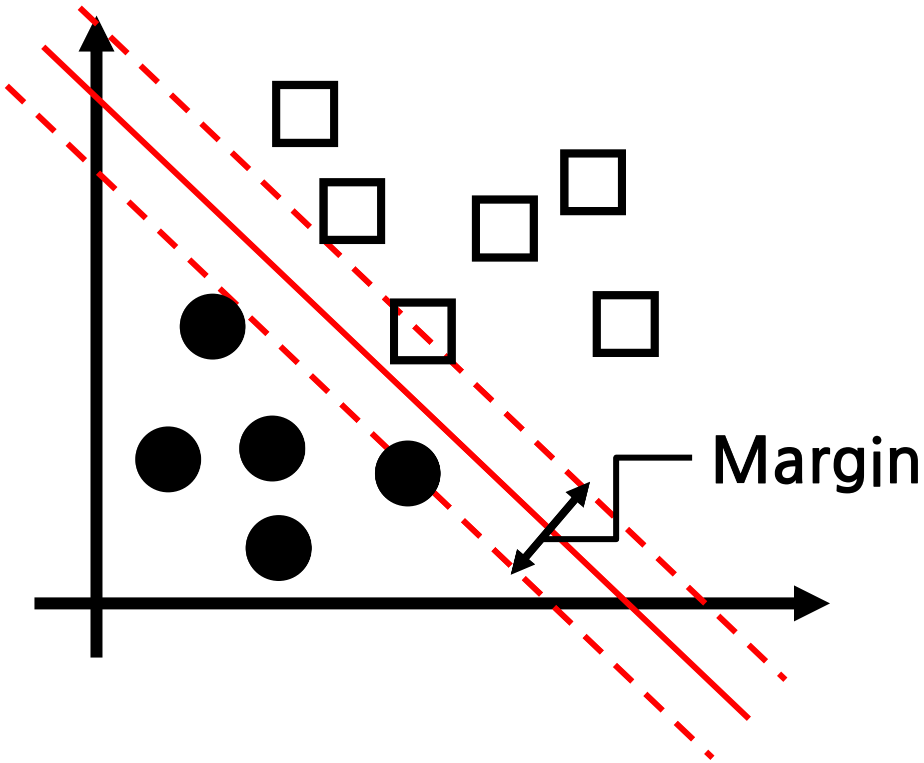

Collect dataset
Sound files
MFCC
50
25
0
−25
−50
−75
−100
−125
−150
0
0.5
1
1.5
2
2.5
3
Time
Feature extraction
Machine Learning
SVM
Random Forest
LGBM
Deep Learning
CNN
Train models

Background

MFCC [6]



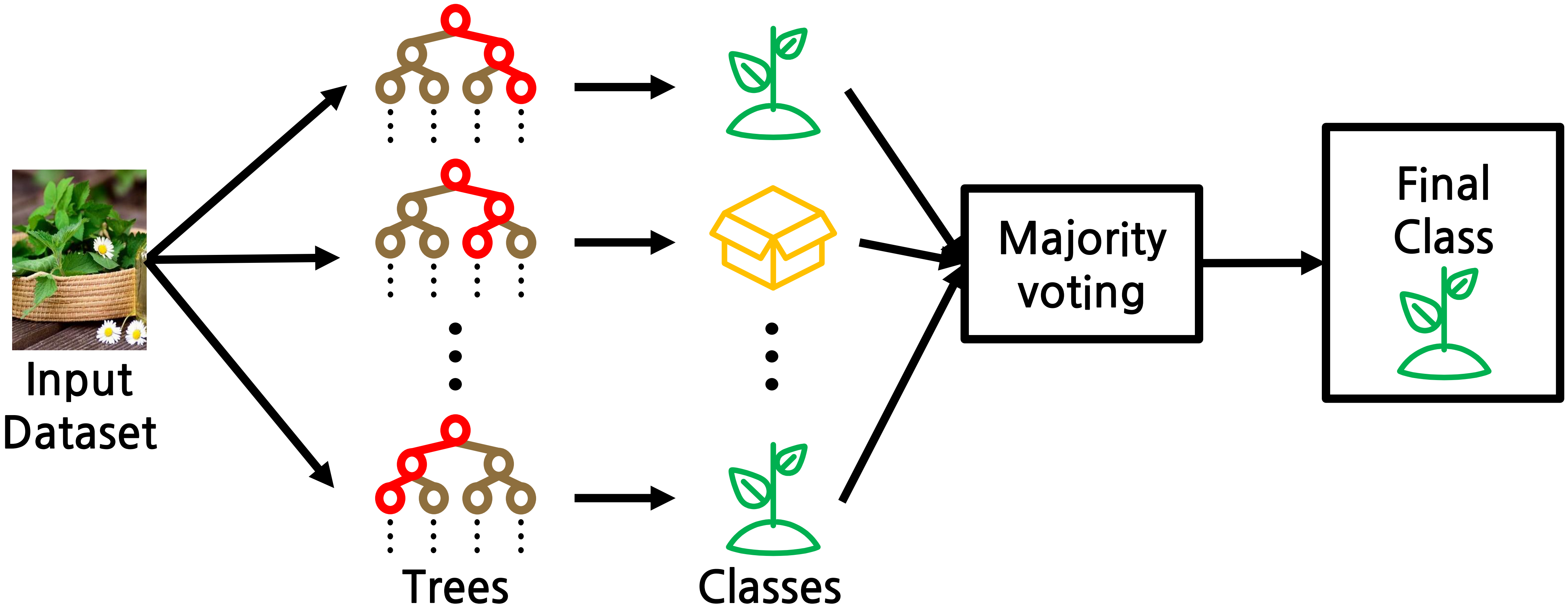
SVM [7]



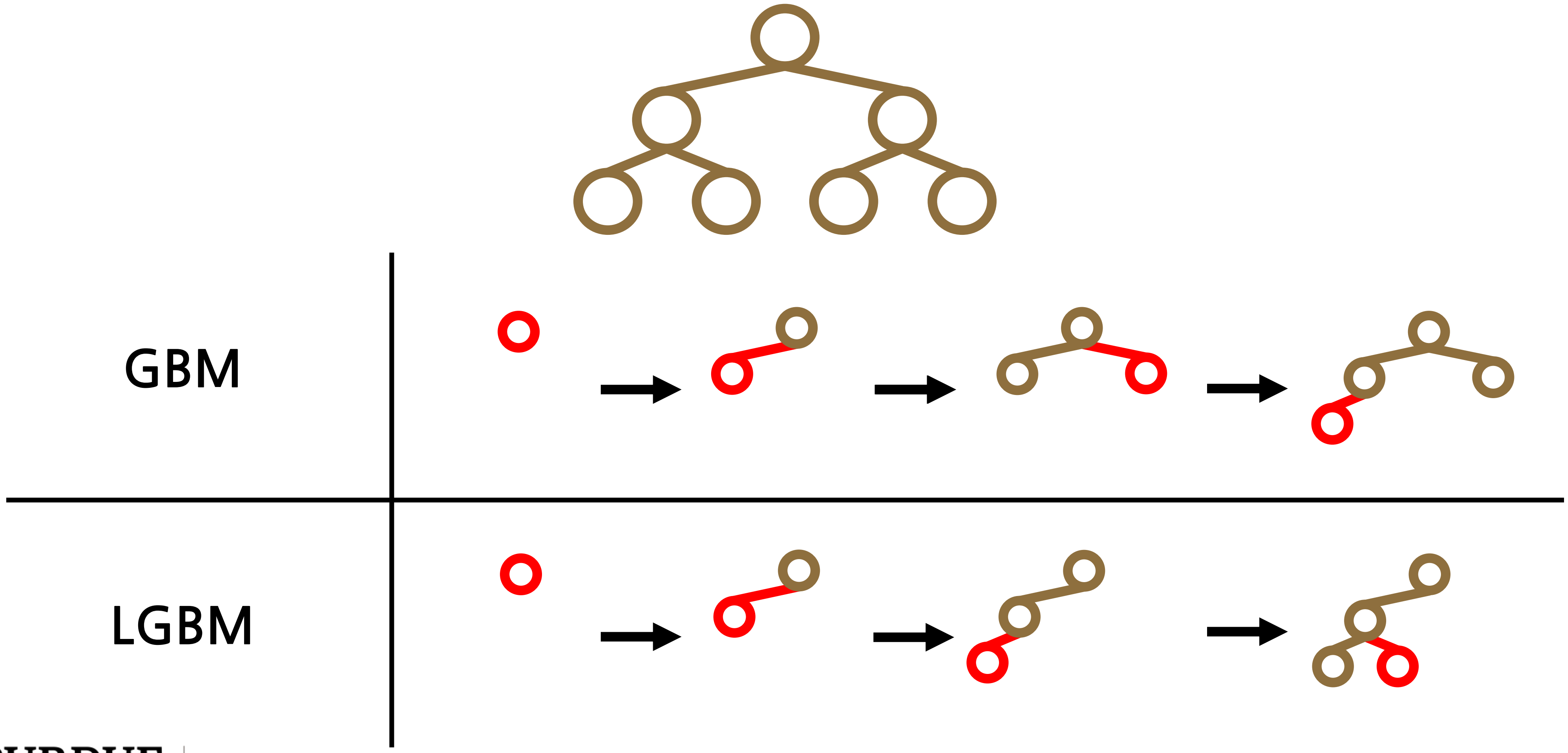
Machine learning
to find the maximum value
of this Margin

Background

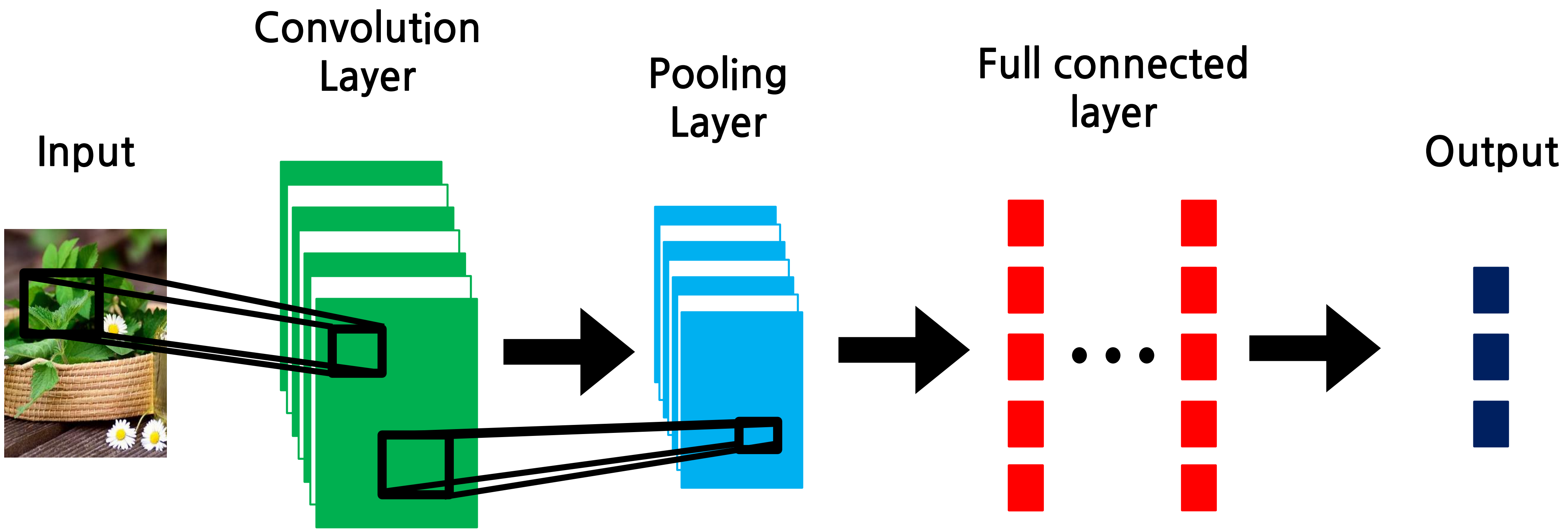
Random Forest [8]



LGBM [9]



CNN [10]

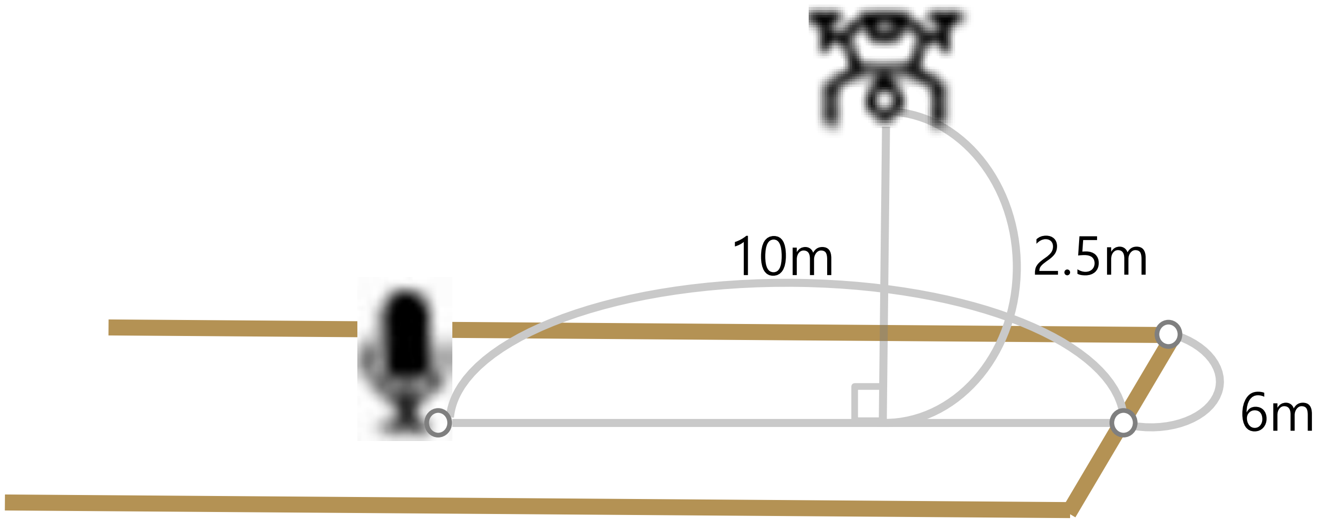

Convolution
Layer
Pooling
Layer
Full connected
layer
Input
Output
• • •

Background

Drone Information (Indoor)

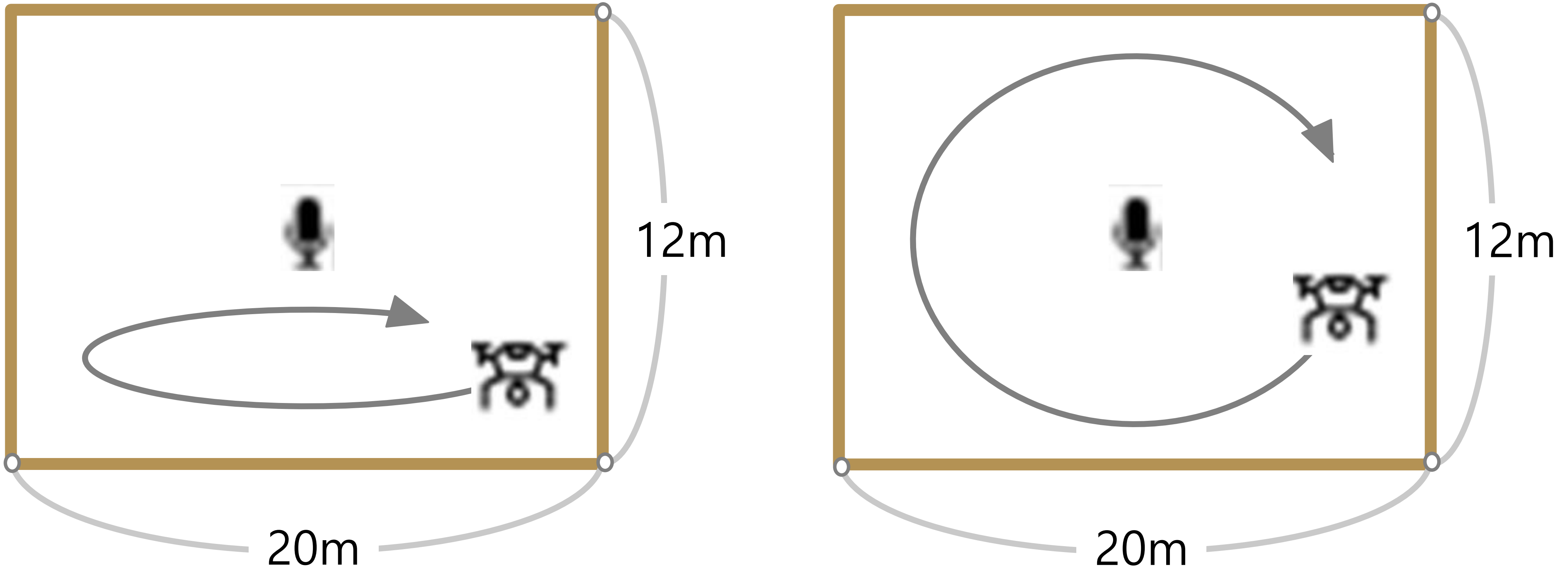
	X8SW
Charging time (min)	About 150
Controlling distance (meter)	About 70
Flying time (min)	About 9
Product Size (mm)	500 X 500 X 190

Background



Microphone	Speed gun	Place
Dell XPS15 9570 SAMSUNG Ion 2020 NT950XCR-G58A	Bushnell Velocity Speed Gun (Accuracy: +/- 1 mph)	K-SW 2nd floor

Methods for Collecting Drone Data



Dataset

Change the length of the dataset

10 sec → 3 sec

Learning time	Memory Usage
High → Low	High → Low

Dataset

Description of dataset

Speed / Type	Fast	Slow	Ratio
Train Data	776	639	80%
Validation Data	261	210	10%
Test Data	261	210	10%

CNN Architecture

Layer Description

	Layer	In Channels	Kernel	Padding	Stride	Activate
Layer1	Conv1D	20	4	2	2	ReLU
Layer2	Conv1D	11	4	2	2	ReLU
Layer3	Conv1D	5	4	2	2	Sigmoid

Result

MFCC Result
Result Graph

MFCC Result

Velocity	Feature 0	Feature 1	Feature 2	Feature 3	Feature 4
Slow	-48.16	-25.84	19.66	0.91	-17.52
Fast	-55.64	-11.42	25.14	-3.21	-23.56
(time: 3sec)	**Feature 5**	**Feature 6**	**Feature 7**	**Feature 8**	**Feature 9**
	21.85	-10.59	20.11	-15.26	9.50
	22.03	-14.79	14.18	-18.04	7.65
	Feature 10	**Feature 11**	**Feature 12**	**Feature 13**	**Feature 14**
	-0.63	-9.87	7.72	-1.24	-1.62
	-3.59	-6.54	1.83	-1.03	-5.80
	Feature 15	**Feature 16**	**Feature 17**	**Feature 18**	**Feature 19**
	0.52	-4.19	-6.14	-3.47	1.66
	-0.25	-5.22	-2.39	-3.67	0.12

MFCC Result

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MFCC Result

Velocity	Feature 0	Feature 1	Feature 2	Feature 4	Feature 7	Feature 12
Slow	-48.16	-25.84	19.66	-17.52	20.11	7.72
Fast	-55.64	-11.42	25.14	-23.56	14.18	1.83
Value difference	7.48	14.42	5.48	6.04	5.93	5.89

Result Graph

Machine Learning and Deep Learning Result

Model	Accuracy	Precision	Recall	F-1 Score
SVM	0.987	0.977	1.000	0.988
Random Forest	0.997	0.996	1.000	0.998
LGBM	0.995	0.992	1.000	0.996
CNN	1.000	1.000	1.000	1.000

Result Graph

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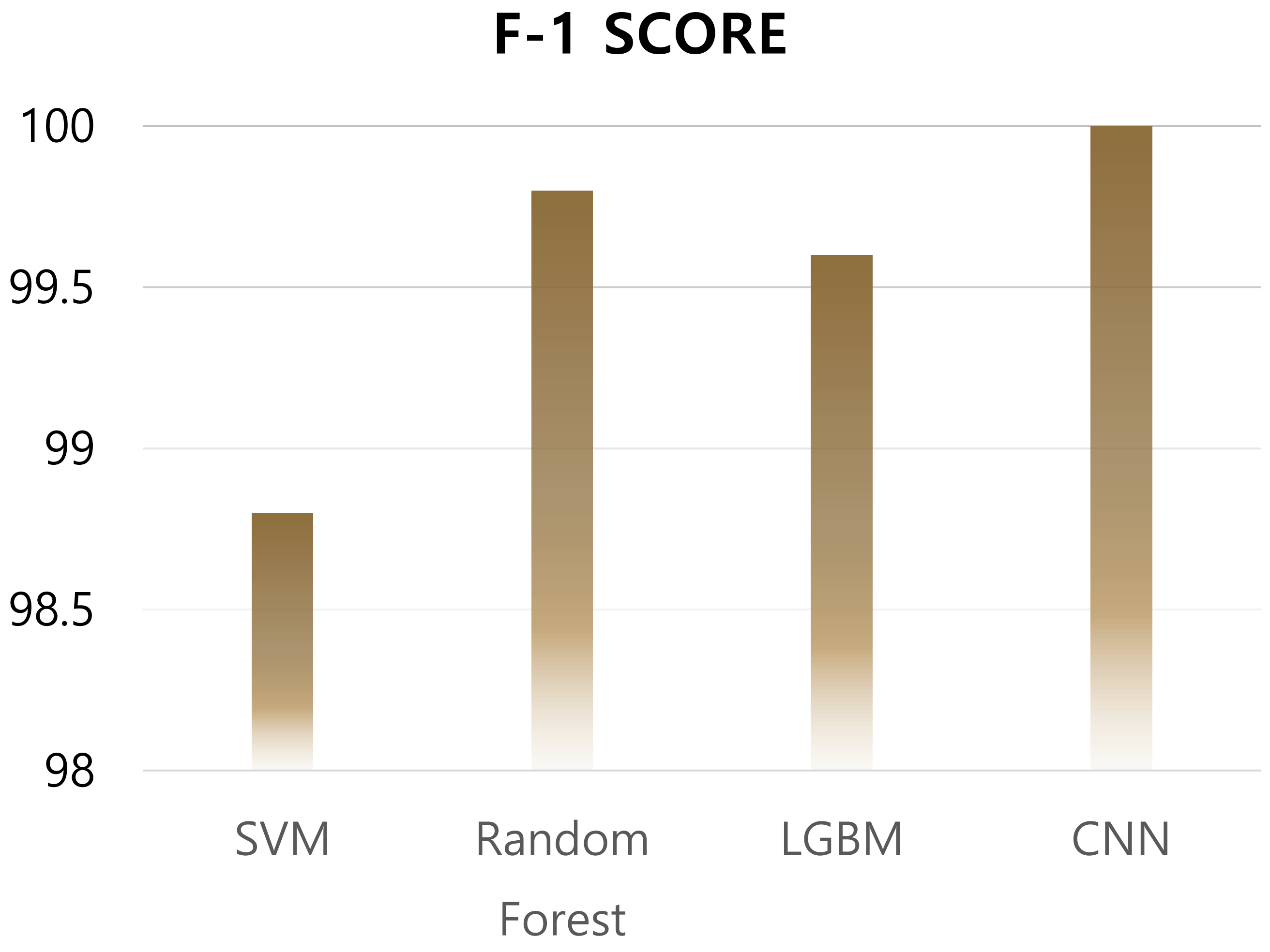
Result Graph

	F-1 Score
SVM	0.988
Random Forest	0.998
LGBM	0.996
CNN	1.000



Conclusion

Summary
Future Work

Summary

- **Why** we decided to do this project?

  - Drone Strike, Kamikaze attack

- How to **solve** the problem?

  - Predicting the velocity of the UAVs

- What does result **means**?

  - Possibility of prediction of UAV velocity

Future Work

- Generalization of the model
  - Outdoor environments of datasets
  - Expanding the range of drone types
- Improved performance of the model
  - Gradually increase the speed limits by 5 mph

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Thank you for listening

Q&A

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