Machine Learning based Real Time UAV Detection using Smartphone

Swatter

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Contents

- 1. Introduction
- 2. Related Works
- 3. Methodology
- 4. Progress
- 5. Future Works



Real-time UAV Detection using Smartphones



Team Introduction



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Server Developer



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Acronyms

- ML : Machine Learning
- CNN : Convolutional Neural Networks
- RF : Radio Frequency
- YOLO: You Only Look Once
- MFCC : Mel Frequency Cepstral Coefficient
- NN : Neural Network
- GNB : Gaussian Naïve Bayes algorithm
- KNN : K Nearest Neighbor algorithm
- SVM : Support Vector Machine algorithm
- ReLU : Rectified Linear Unit

- TCP: Transfer Control Protocol
- UAV : Unmanned Aerial Vehicles
- CAGR : Compound Annual Growth Rate



Project Motivation



Drone for delivery

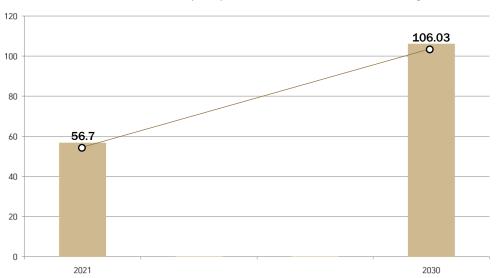


Drone for photography



Project Motivation

Global Unmanned Aerial Vehicle (UAV) market size, 2021 to 2030 [USD BILLION]



[1] B. Aamir, "Unmanned Aerial Vehicle (UAV) market are expected to reach US\$ 106.03 billion by 2030 - astute analytica," GlobeNewswire News Room, 17-Nov-2022. [Online]. Available: https://www.globenewswire.com/en/news-release/2022/11/17/2558200/0/en/Unmanned-Aerial-Vehicle-UAV-Market-to-Reach-US-106-03-Billion-by-2030-Astute-Analytica.



Project Motivation



Drone with bomb



Drone with gun



Project Motivation



Drone assassination attempt on President

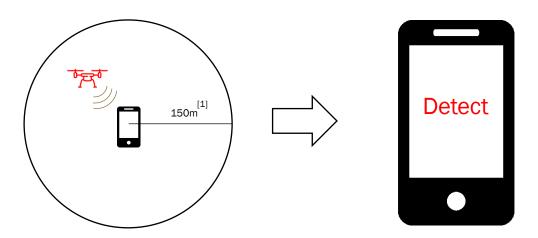


Drone attempts to smuggle out of prison



Project Goal

Real Time UAV Detection with Smartphone



[1] B. Taha and A. Shoufan, "Machine Learning-Based Drone Detection and Classification: State-of-the-Art in Research," in IEEE Access, vol. 7, pp. 138669-138682, 2019, doi: 10.1109/ACCESS.2019.2942944.



Real-time UAV Detection using Smartphones



Relevant literature for detecting Unmanned Aerial Systems

- Vision based UAV detection B.-G. Han el al[1]. YOLO algorithm employs convolutional neural networks (CNN) to detect objects in real-time. This solution requires huge labeled datasets and have problem with visual data's noise.
- Radar based B Torvik et al. [2] proposed 100% accuracy results by simple nearest neighbor approach for binary classification between UAVs and birds. However, this method has Radar Cross-Section and range limitation[3].
- Radio frequency-based UAV detection use RF signals from controller and achieved 80~95% accuracy with ML learning techniques. However, this solution fails when the drone is operated in autonomous mode[2].



^[1] B. -G. Han et al. "Eesign of a Scalable and Fast YOLO for Edge -Computing Devices", Sensors, Bvol. 20, no. 23, 2020.

^[2] B. Torvik, K. E. Olsen and H. Griffiths, "Classification of birds and uavs based on radar polarimetry", IEEE geoscience and remote sensing letters, vol. 13, no. 9, pp. 1305-1309, 2016.

^[3] B. Taha and A. Shoufan, "Machine learning-based drone detection and classification: State-of-the-art in research", IEEE Access, vol. 7, pp. 138669-138682, 2019.

Acoustic node for detecting Unmanned Aerial Systems

- The rotation of the drone's rotor blades produces a humming sound that can be sensed and recorded, even within the range of human hearing.
- Y Wang et al.[1] Machine learning algorithm and MFCC were applied to detect UAVs.
- Using features for classification provide explanations for understanding how the ML classification was produced.

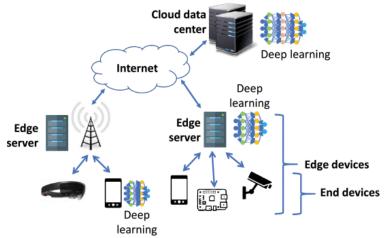
This solution provided 78% accuracy and fewer computational resources than others.

[1] Y. Wang et al. "A Feature Engineering Focused System for Acoustic UAV Detection", 2021 Fifth IEEE International Conference on Robotic Computing (IRC), 2022.



Acoustic UAV detection on Edge device

- 3 Challenges: Latency, Scalability, and Privacy [1]
- TensorFlow Lite was proposed for mobile and embedded devices, with mobile GPU support.
- In contrast to cloud computing, edge computing's latency is significantly lower, as large quantities of data do not have to travel through a backhaul network to the cloud[2].



[Deep learning on edge devices and cloud data centers]

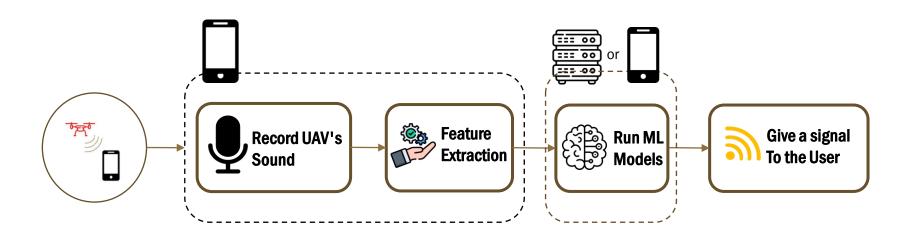
[1, Fig 1] J. Chen and X. Ran, "Deep learning with edge computing: A review", Proc. IEEE, vol. 107, no. 8, pp. 1655-1674, Jul. 2019. [2] P. Joshi et al. "Enabling All In-Edge Deep Learning: A Literature Review" 2023, IEEE Access (Volume: 11)



Real-time UAV Detection using Smartphones



Overview of two methods for drone detection





2.1 Drone Types



Autel Evo 2

• Weight: 1192 g

• Max Speed: 20 m/s



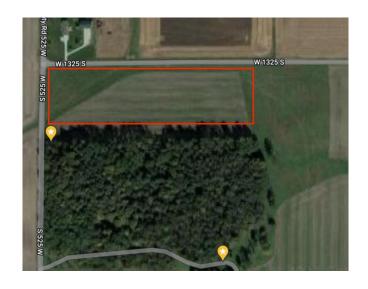
DJI Phantom 4

• Weight: 1380 g

• Max Speed : 20 m/s

Location of data collection

- Location
 - New Richmond, Indiana, (40.2227062, -87.0000169)
- Time
 - February 13, 06:00 A.M





Sound data samples

Audio Type	Number of Samples	Total Time(sec)
UAV	200	500
Noise	200	500
Total	400	1000

5 seconds per each sample



Feature extraction

TABLE II
DRONE ACOUSTIC FEATURE EXTRACTION METHOD

Feature	Shape
chroma_stft	12
chroma_cqt	12
chroma_vqt	12
mel	128
mfcc	40
rms	1
centroid	1
bandwidth	1
contrast	7
flatness	1
bandwidth	1
rolloff	1
poly shape	2
tonnetz	6
zero crossing	1

- Feature extraction methods
- ⇒ Python library, Librosa
- → Models can understand the sound through Feature extraction

Selecting ML Algorithm

- Machine Learning is our main method of UAV detection.
- Using ML algorithms is suitable for audio classification.
- In another paper[1], 4 algorithms were selected.

Name of Algorithm	Hyperparameters
NN (Neural Network)	Learning rate = 0.001, epochs = 15
GNB (Gaussian Naïve Bayes)	Default
KNN (K-Nearest Neighbor)	N_neighbors = 6, others are default
SVM (Support Vector Machine)	C = 10, kernel as linear

[1] Y. Wang et al, "A Feature Engineering Focused System for Acoustic UAV Detection," 2021 Fifth IEEE International Conference on Robotic Computing (IRC), Taichung, Taiwan, 2021, pp. 125-130



Server Development



CentOS 7



C++ 17



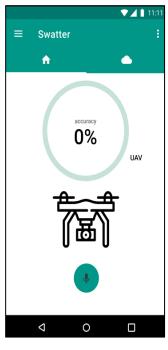
Python/C API

- 1. Install CentOS 7 on VMWare 17
- 2. Implement server program
- 3. Embed Python inside a C++ program
- 4. Use Transmission Control Protocol (TCP)

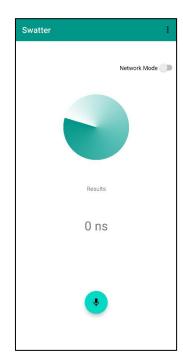


Application Development

- Model converted using TensorFlow lite
- Program specifications
 - Kotlin (java), Android API 27
- Three main functions
 - Record sound
 - Draw result of UAV Inference
 - Transmit sound data to cloud server



[UI before Develop]



[UI after Develop]



Real-time UAV Detection using Smartphones



Verifying Feature Extraction

- Feature extraction using sample data
 - Librosa built-in data is used
- Verified that shapes are matched with previous paper[1]

```
df = pd.DataFrame(index = ['MFCC', 'mel', 'chroma_stft', 'contrast', 'tonnetz']
                  ,columns = ['Shape'])
#df.index.name = 'Features'
## sample data
y, sr = librosa.load(librosa.ex('trumpet'))
print(y)
mfcc = librosa.feature.mfcc(y, sr=sr)
mfcc = np.mean(mfcc.T,axis=0)
# print(mfcc)
df.iloc[0] = mfcc.shape[0]
mel = librosa.feature.melspectrogram(v.sr=sr)
mel = np.mean(mel.T, axis=0)
df.iloc[1] = mel.shape[0]
## chroma stft
chroma_stft = librosa.feature.chroma_stft(y,sr)
chroma_stft = np.mean(chroma_stft.T, axis=0)
df.iloc[2] = chroma_stft.shape[0]
## contrast
stft = np.abs(librosa.stft(y))
contrast = librosa.feature.spectral_contrast(S=stft,sr=sr)
contrast = np.mean(contrast.T, axis=0)
df.iloc[3] = contrast.shape[0]
tonnetz = librosa.feature.tonnetz(y=librosa.effects.harmonic(y),sr=sr)
tonnetz = np.mean(tonnetz.T, axis=0)
df.iloc[4] = tonnetz.shape[0]
```

[Program for verifying feature extraction]

[Results of program]

MFCC

chroma stft

contrast

tonnetz

 mel

Shape

40

12

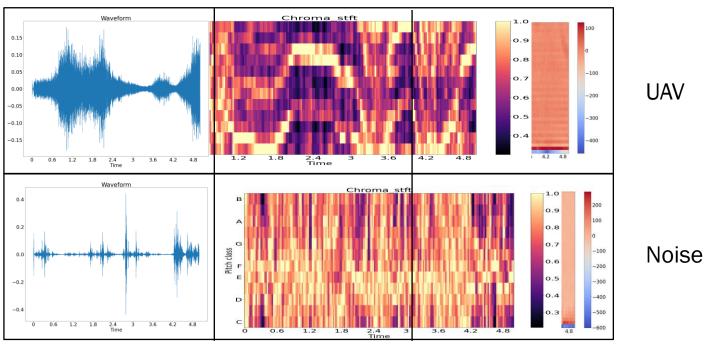
6

128

[1] Y. Wang et al, "A Feature Engineering Focused System for Acoustic UAV Detection," 2021 Fifth IEEE International Conference on Robotic Computing (IRC), Taichung, Taiwan, 2021, pp. 125-130



Feature Visualization





Model training

Models

- NN (Tensorflow)
- SVM, KNN, GNB (scikit-learn)

Data

- X (Predictor Variable): Extracted feature
- Y (Outcome Variable) : Autel Evo2 (0)

DJI Phantom4 (1)

Noise (2)

Train vs Test

- 0.8: 0.2 ratio

Computing Power

- Laptop (Ryzen 5 5625U)



Testing Result

Feature	Accuracy	Recall	Precision	F1 Score
1. chroma_stft	0.81	0.81	0.83	0.80
2. mel	0.89	0.89	0.89	0.88
3. mfcc	0.86	0.86	0.88	0.86
4. contrast	0.76	0.76	0.75	0.75
5. tonnetz	0.78	0.78	0.79	0.76

NN model

[NN model Benchmark]

Feature	Accuracy	Recall	Precision	F1 Score
1. chroma_stft	0.86	0.86	0.86	0.86
2. mel	0.86	0.86	0.87	0.86
3. mfcc	0.96	0.96	0.96	0.96
4. contrast	0.76	0.76	0.77	0.75
5. tonnetz	0.79	0.79	0.81	0.78

SVM model





Testing Result

Feature	Accuracy	Recall	Precision	F1 Score
1. chroma_stft	0.80	0.80	0.81	0.79
2. mel	0.85	0.85	0.85	0.85
3. mfcc	0.93	0.93	0.93	0.92
4. contrast	0.82	0.82	0.84	0.82
5. tonnetz	0.80	0.80	0.80	0.79

KNN model

[KNN model Benchmark]

Feature	Accuracy	Recall	Precision	F1 Score
1. chroma_stft	0.91	0.91	0.91	0.91
2. mel	0.66	0.66	0.77	0.67
3. mfcc	0.88	0.88	0.88	0.87
4. contrast	0.84	0.84	0.86	0.83
5. tonnetz	0.89	0.89	0.89	0.89

GNB model

[GNB model Benchmark]



Model Conversion

■ To implement models into Android



- HDF5 (Hierarchical Data Format 5)
- PB (Protocol Buffer)
- TFLITE (Tensorflow Lite)



Server program

[Multiple threads start in main function]

▶ a ++ EpollCore.cpp
 ▶ a -+ EpollCore.h
 ▶ a ++ EpollEvent.cpp
 ▶ a -- EpollEvent.h

[Classes to control epoll]

- Use Multithreading for smooth service
- Share the jobs to be processed to each thread
- Epoll is used for reducing waste and increasing performance



Packet protocol

- Received byte data is converted to packet
- Two protocols are used for the service

```
int16 packetSize; // Common header
uint16 packetId; // Common header,
uint16 featureOffset; // Address of
uint16 featureCount = 40;
```

[Packet from a client to the server]

```
struct PKT_S_DETECTION_RESULT
{
    uint16 packetSize; // Common header
    uint16 packetId; // Common header
    uint8 result;
};
```

[Packet from the server to the client]



Embedding Python program

[A class for call ML model written in python]



Application

Implementation

- Record Audio with Uncompressed Audio File

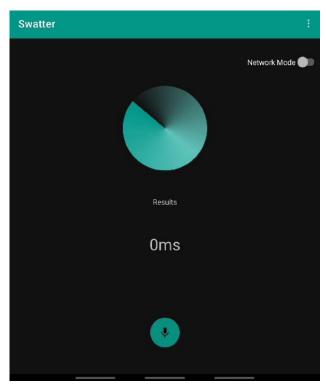


- MFCC feature extraction



- TensorFlow Lite Interpreter

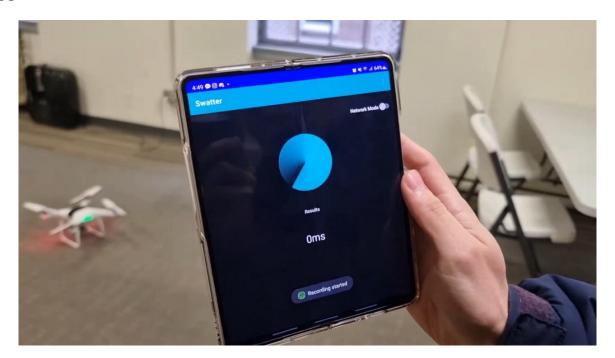








Demo video





Test between smartphones and server

	Smartphone	Server
Average of inference time	0.90525 ms	5270 ms

- Compare inference time.
- Using only smartphones more faster than using Server.



Future work

Real-time UAV Detection using Smartphones

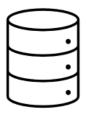


Future Work

Developing various functions on smartphone



- Warning UAV's appearance
 - Save GPS location
 - Share appearance to security



- Collecting UAV's sound
 - Restore audio file
 - Send to database

Reference

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Thank you

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Q&A

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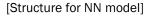
Real-time UAV Detection using Smartphones



Structure of Neural Network Model

- Neural network model structure
- High flexibility, depends on usage.
- 3 Dense layers
 - 128 nodes for 2 layers, 1 node for output
- 2 Activation layers
 - 'ReLU' function
- 2 Dropout layers
 - Dropout rate: 0.1

Layer (type)	Output Shape	Param #
input_2 (InputLayer)	[(None, 128)]	
dense_3 (Dense)	(None, 128)	16512
activation_2 (Activation)	(None, 128)	0
dropout_2 (Dropout)	(None, 128)	0
dense_4 (Dense)	(None, 128)	16512
activation_3 (Activation)	(None, 128)	0
dropout_3 (Dropout)	(None, 128)	0
dense_5 (Dense)	(None, 1)	129
Total params: 33,153 Trainable params: 33,153 Non-trainable params: 0		





Server program

- Epoll can notify to users when monitored file descriptor is ready
- The 3 system calls that let you ask Linux to monitor lots of file descriptors are poll, epoll and select.
- On each call to select() or poll(), the kernel must check all of the specified file descriptors to see if they are ready.
 - -> When monitoring a large number of file descriptors that are in a densely packed range, the timed required for this operation greatly outweights [the rest of the stuff they have to do]

Server program

```
bool ClientPacketHandler::Handle_C_AUDIO_DATA(PacketSessionRef & session, BYTE * buffer, int32 len)
     BufferReader br(buffer, len);
     PKT_C_AUDIO_DATA* pkt = reinterpret_cast<PKT_C_AUDIO_DATA*>(buffer);
     if (pkt->Validate() == false)
          return false;
     float* features = pkt->GetFeatures();
     int8 result = GMLManager.RunModel(features, pkt->featureCount);
     cout << "Handle_C_Audio, Result: " << result << endl;</pre>
     return true;
```

[Handle the packet from and do follow-up]



Server program

- ClientPacketHandler.cpp
- ClientPacketHandler.h
- DetectingSession.cpp
- DetectingSession.h
- DetectingSessionManager.cpp
- DetectingSessionManager.h
- MLManager.cpp
- MLManager.h

- Offer the detection operation
- Call ML model to classify and send results to client

