Machine Learning based Real Time UAV Detection using Smartphone

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MIDTERM PRESENTETION

Team Introduction, Project goal & Motivation



Team Introduction



Joonki Rhee
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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

- Use of drones [1]
 - Military drones
 - Drones for delivery
 - Drones for emergency rescue
 - · Drones in medicine
 - Drones for photography
- Global unmanned aerial vehicle (UAV) market was valued at US\$ 56.7 Billion in 2021 and is estimated to reach a valuation of US\$ 106.03 Billion by 2030 at a CAGR of 7.5% from 2022 to 2030 [2].

[1] Drones. BuiltIn. (n.d.). Retrieved January 30, 2023, from https://builtin.com/drones.

[2] B. Aamir, "Unmanned Aerial Vehicle (UAV) market 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.



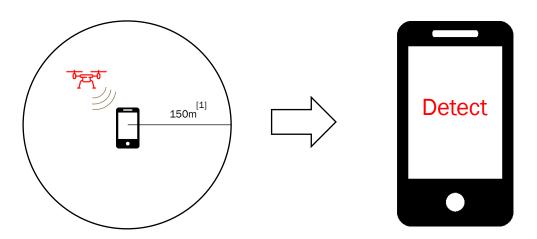
Project Motivation

- As drone technology advances, incidents of careless misuse, military surveillance, and malicious activity of drones have increased[1].
- Drone assassination attempt on Venezuelan President Nicolas Maduro in 2018[2].
- Three people were arrested for carrying cigarettes and phones by drone to a prisoner in 2020[3].
- Drones also allow criminals to plot a heist, hack into your phone or laptop[4].
- ⇒ Drone detection ability is important to prevent accidents, crimes caused.
- [1] R. Schradin, "Malicious drones the UAV threat facing law enforcement and military," The Last Mile, 08-Sep-2022. [Online]. Available: https://thelastmile.gotennapro.com/malicious-drones-the-uav-threat-facing-law-enforcement-and-military/. [Accessed: 29-Jan-2023].
- [2] BBC. (2018, August 5). Venezuela president Maduro survives 'drone assassination attempt'. BBC News. Retrieved January 30, 2023, from https://www.bbc.com/news/world-latin-america-45073385 [3] "Report: Trio planned to use drone to to get tobacco, phones to Inmate," Northwest Georgia News, 13-Apr-2020. [Online]. Available: https://www.northwestgeorgianews.com/report-trio-planned-to-use-drone-to-to-get-tobacco-phones-to-inmate/article_44c25a12-7d96-11ea-8c97-73fe94e065d4.html. [Accessed: 30-Jan-2023].
- [4] R. Tabbara, "15 reasons to install a drone detection system at your company's infrastructure," 911 Security. [Online]. Available: https://www.911security.com/blog/15-reasons-to-install-a-drone-detection-system-at-your-companys-infrastructure. [Accessed: 29-Jan-2023].



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

Implementation of UAV detection using smartphone



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** feature were applied to detect UAV detection.
- Using features for classification provide explanations for understanding how the ML classification was produced.

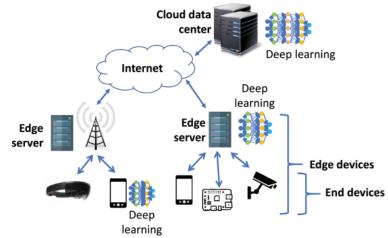
This solution provided 78% accuracy and fewer computational resources than others.

[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 Challenge : Latency, Scalability, 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 less, as numerous of data does not have to travel through a backhaul network to 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)



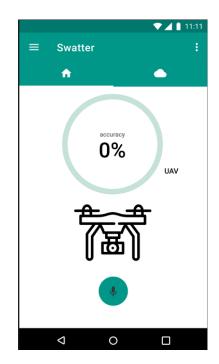
Real-time UAV Detection using Smartphones

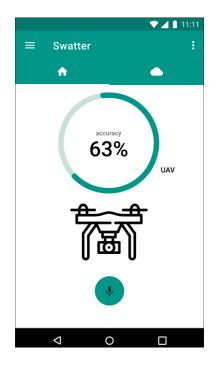
User Flow, System Flow Chart, Machine Learning Algorithm



User Flow

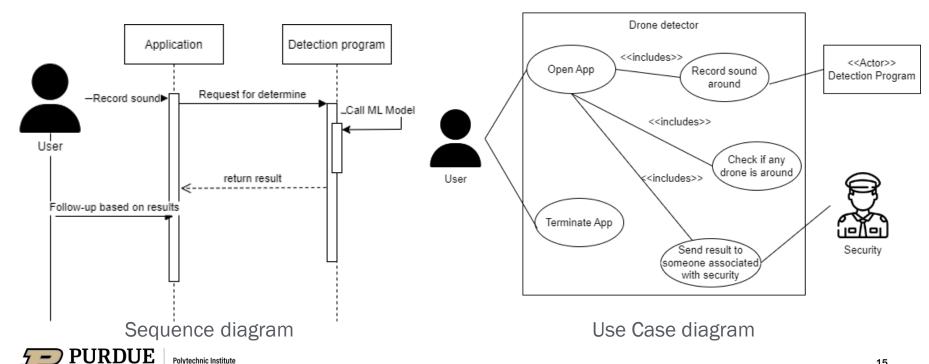
- 1. Open the app and record sound.
- 2. Wait and check a result



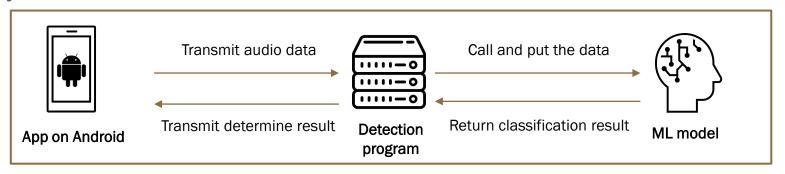




Sequence diagram, Use Case diagram



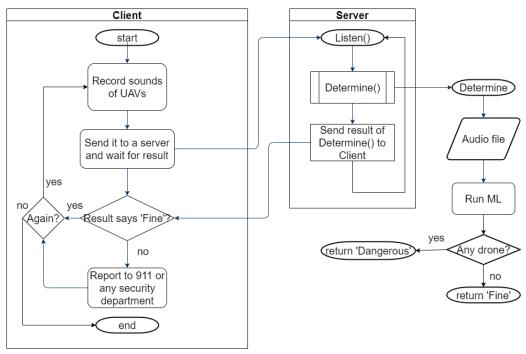
System Flow



- 1. Transmit audio data to detection program.
- 2. Run Machine Learning model and put received data.
- 3. Binary Classification with input data.
- 4. Detection program transmit classification result to the app.



System Flow Chart





System Requirements







Android device (version 11.0~)

Cloud Server

Machine Learning

- 1. Android Device to use the app
- 2. A Cloud server for transmitting and saving ML model
- 3. TensorFlow for running Machine Learning model
- 4. Trained Machine Learning model for classification.



Real-time UAV Detection using Smartphones

Each member's current progress



Selecting Features of Audio data

- Efficient to train ML models than raw data
- In another research[1], researchers select5 features that have more than 2 shapes.
- Librosa library is fit for extracting features.

Name of features	Num of Shape
mfcc	40
mel	128
contrast	7
chroma_stft	12
tonnetz	6

[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



Verifying Feature Extraction

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

```
df = pd.DataFrame(index = ['MFCC', 'mel', 'chroma_stft', 'contrast', 'tonnetz']
                  ,columns = ['Shape'])
## 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)
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]
```

	Shape
MFCC	40
mel	128
chroma_stft	12
contrast	7
tonnetz	6

[Program for verifying feature extraction]

[Results of program]

[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



Selecting Algorithm

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

Name of Algorithm	Hyperparameters	
NN (Neural Network)	Learning rate = 0.001, epochs = 30	
GNB (Gaussian Naïve Bayes)	Default	
KNN (K-Nearest Neighbor)	N_neighbors = 6, others are default	
SVM (Support Vector Machine)	C = 6, 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



Structure of Neural network model

- Neural network model structure
- High flexibility, depends on developer
- 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)]	0
dense_3 (Dense)	(None, 128)	16512
activation_2 (Activation)	(None, 128)	0
dropout_2 (Dropout)	(None, 128)	0
dance 4 (Dance)	(Name 120)	16512
dense_4 (Dense)	(None, 128)	16512
activation 3 (Activation)	(None, 128)	0
activation_3 (Activation)	(None, 128)	•
dropout_3 (Dropout)	(None, 128)	0
a. opout_3 (b. opout)	(110110; 120)	J
dense_5 (Dense)	(None, 1)	129
	(**************************************	
=======================================		
Total params: 33,153		
Trainable params: 33,153		
Non-trainable params: 0		

[Structure for NN model]



Code for model training

- scikit-learn library is used (v 1.0.2)
 - SVM, GNB, KNN models

- 'TensorFlow' library is used (v 2.10.0)
 - NN model

```
# Modeling
## SVM(Support Vector Machine)
def svm_base(X,y,C,kernel='linear'):
    svm_model = svm.SVC(C, kernel=kernel)
    return svm model
## GNB (Gaussian Naive Bayes)
def gnb base(X,y):
    gnb model = naive bayes.GaussianNB()
    return gnb model
## KNN (K-Nearest-Neighbor)
def knn_base(X,y, n_neighbors=6):
    knn model = neighbors.KNeighborsClassifier(n_neighbors=n_neighbors)
    return knn model
## NN(Nueral Network)
def neural base(shape):
    input tensor = Input(shape=(shape))
    x = Dense(128)(input tensor)
    x = Activation('relu')(x)
    x = Dropout(rate=0.1)(x)
    x = Dense(128)(x)
    x = Activation('relu')(x)
    x = Dropout(rate=0.1)(x)
    output = Dense(1, activation='sigmoid')(x)
    model = Model(inputs=input tensor, outputs=output)
    model.summarv()
    return model
```

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Server program

```
[joonki@localhost ~]$ telnet 192.168.227.131 7367
Trying 192.168.227.131...
Connected to 192.168.227.131.
Escape character is '^]'.
HI!
This is Joonki Rhee!
I'm testing server on Linux!
Connection closed by foreign host.
```

TCP/IP Server for data transmitting

[Client]

- Able to withstand high network load
- Call ML model to classify
- Will be executed on Linux

```
Hello from SWATTER Server Socket Test!
Before While
In While, event count[1]
User Accept
In While, event count[1]
Recv Data from [7]
Client[7]: HI!
In While, event count[1]
Recv Data from [7]
Client[7]: This is Joonki Rhee!
In While, event count[1]
Recv Data from [7]
Client[7]: I'm testing server on Linux!
```

Solution 'TCPServer' (2 of 2 projects)

ServerCore

ServerCore

External Dependencies

Main

Memory

Network

EpollCore.cpp

EpollCore.h

Listener.cpp

Listener.h

NetAddress.cpp

[Server]

[Classes of Server program]



Real-time UAV Detection using Smartphones

Project's next steps



Training models with UAV audio data



- Finalize skeleton code for the program.
- Train the models with UAV sound data and save the models.
- Extract features of UAV sound data and run the models.



Completing Cloud Server development

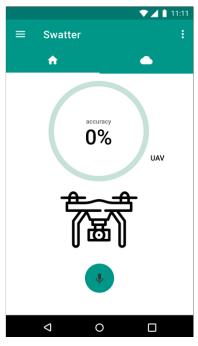


- Designing packets for communication
- Testing the communication and performance
- Uploading to cloud and executing it
- Balancing network load for smooth service

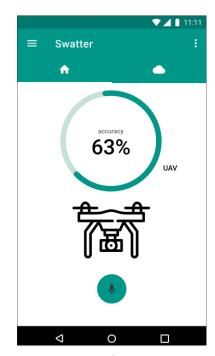


Developing Application for User

- Convert model using TensorFlow lite
- Requirement of development
 - Kotlin (java), Android API 24
- Developing application Three main Function
 - Record sound
 - Draw result of UAV Inference
 - Transmit sound data to cloud server



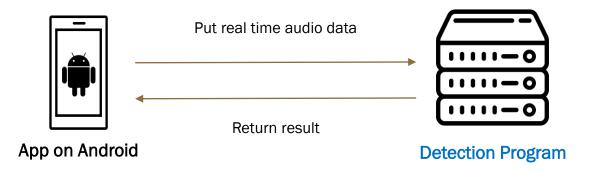
[Example UI before detection]



[Example UI after detection]



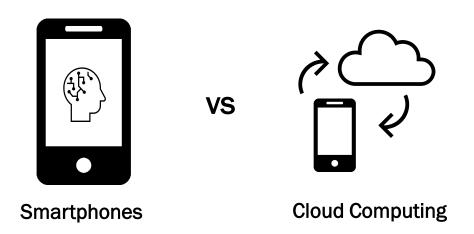
Using Machine Learning on Smartphones



- Implement ML model for UAV detection in real time.
 - -> Figure out a method to transmit and process data in real time.



Adjusting Models



- Test for comparing inference time and performance between two different method.
- Select better method for UAV detection.





Real-time UAV Detection using Smartphones



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Thank you!

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