Human Activity Classification using Radar

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EE4675 Object Classification with Radar · 6/18/2024

Content

Project Description

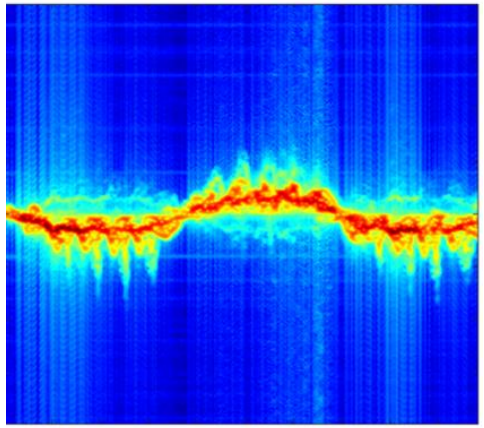
Data Processing

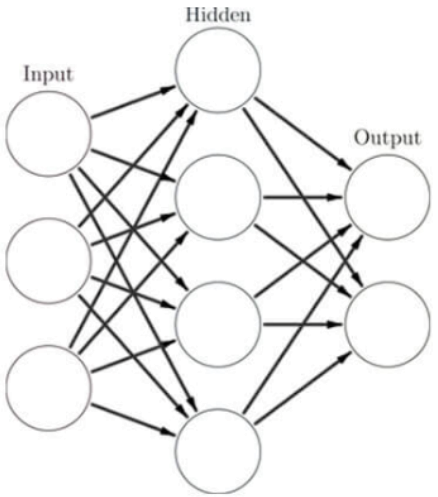
Neural Network

Conclusion

Future Work

Project Description

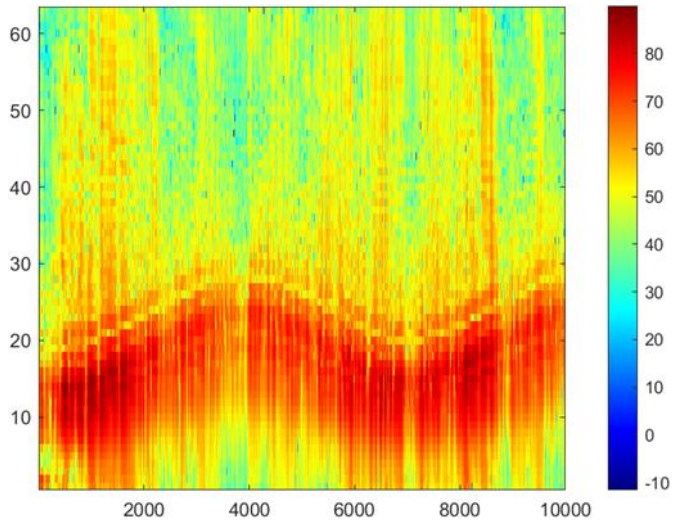




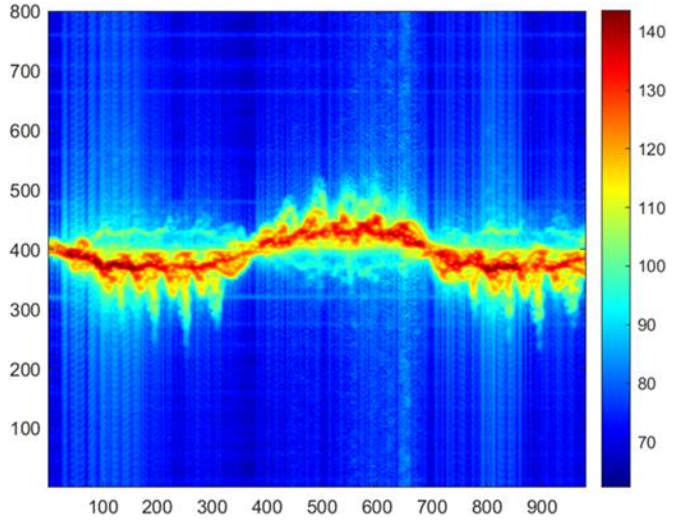
Classification Result

https://eprints.gla.ac.uk/223726/1/223726.pdf

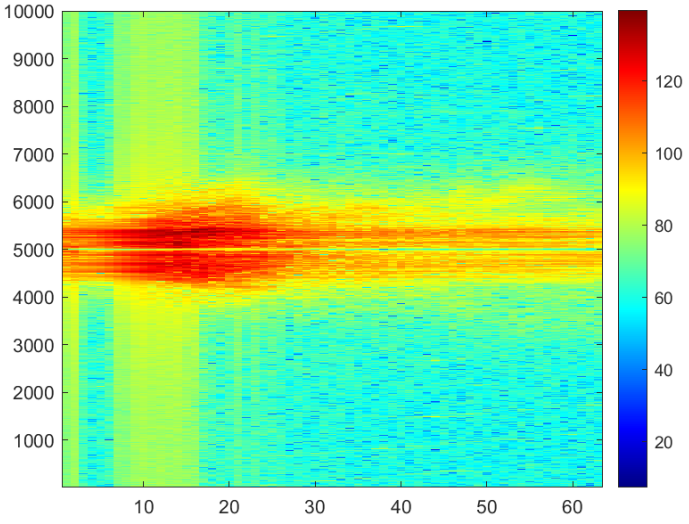
Data Processing



Range – Time (RT)

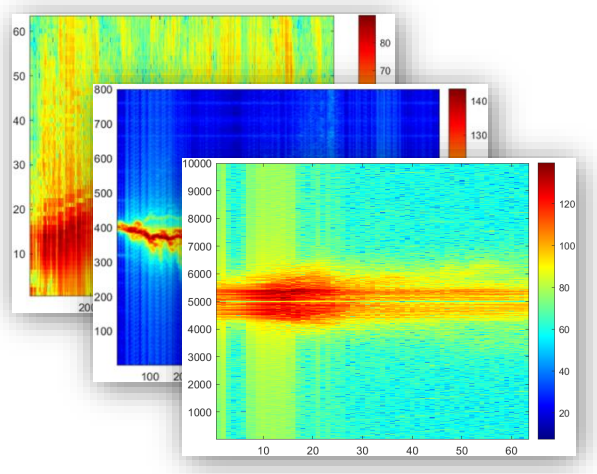


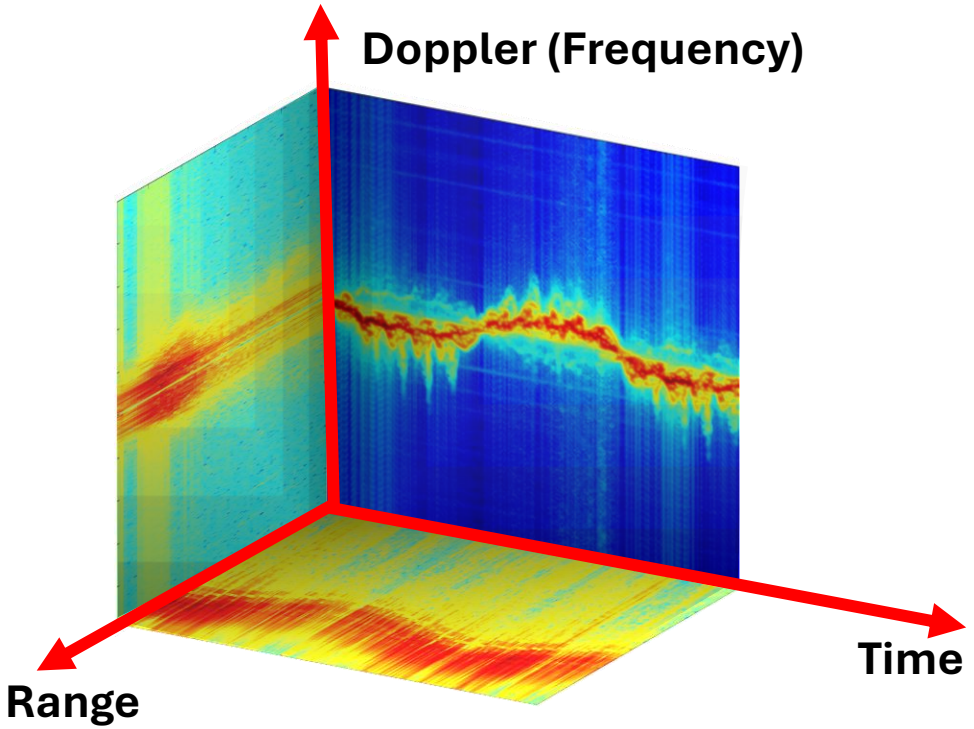
Doppler – Time (DT)



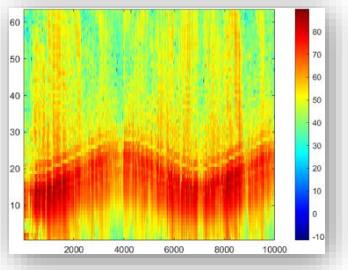
Doppler – Range (DR)

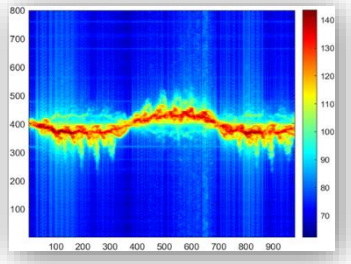
Data Processing

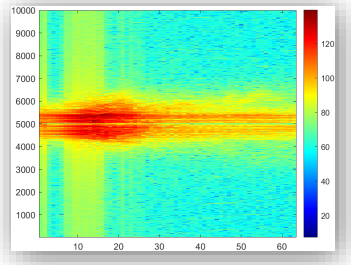




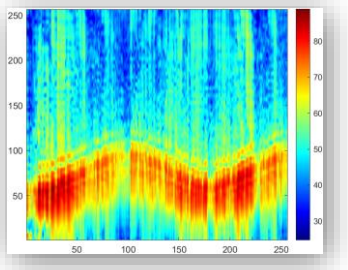
Data Processing

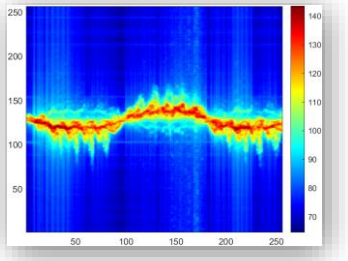


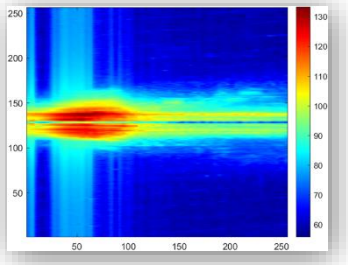




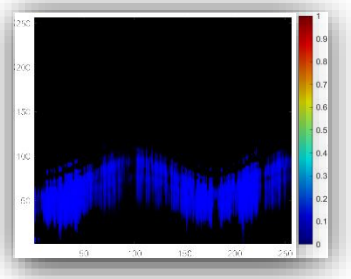
Resize to [256,256]

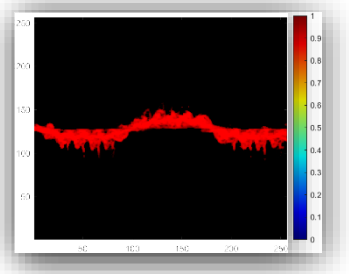


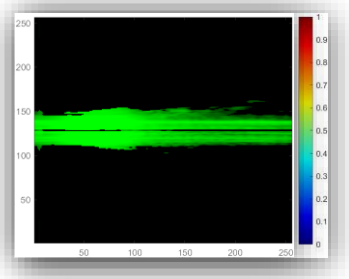




CFAR

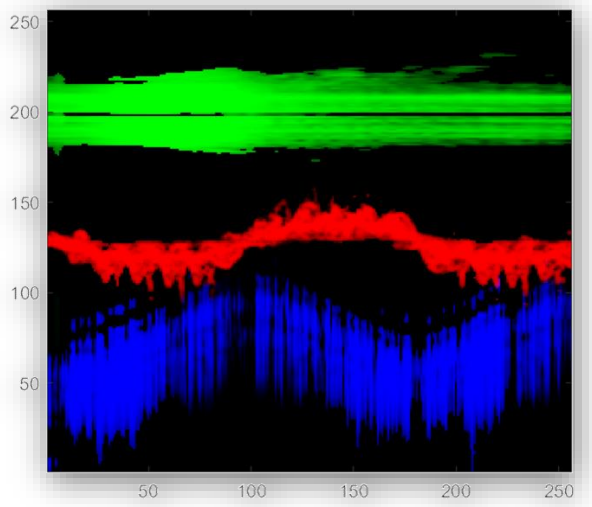






Channel Encoding

Combine



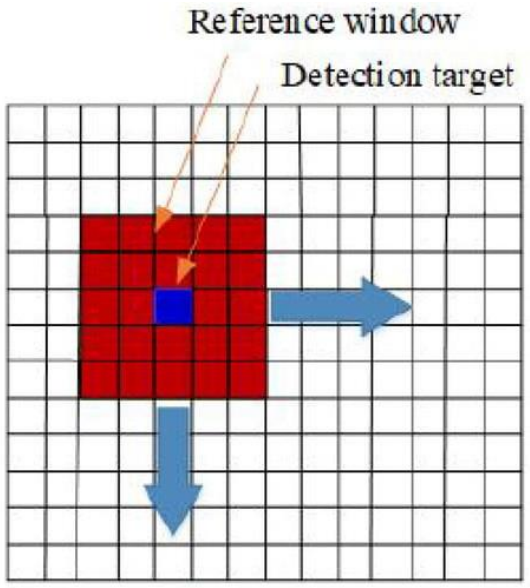
Processed Radar Data

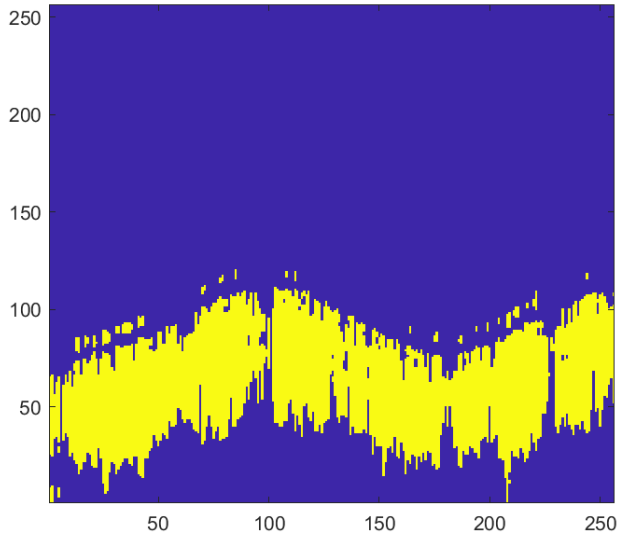
14GB → 34MB
Compression Rate:
406%

Small and Explainable

CFAR

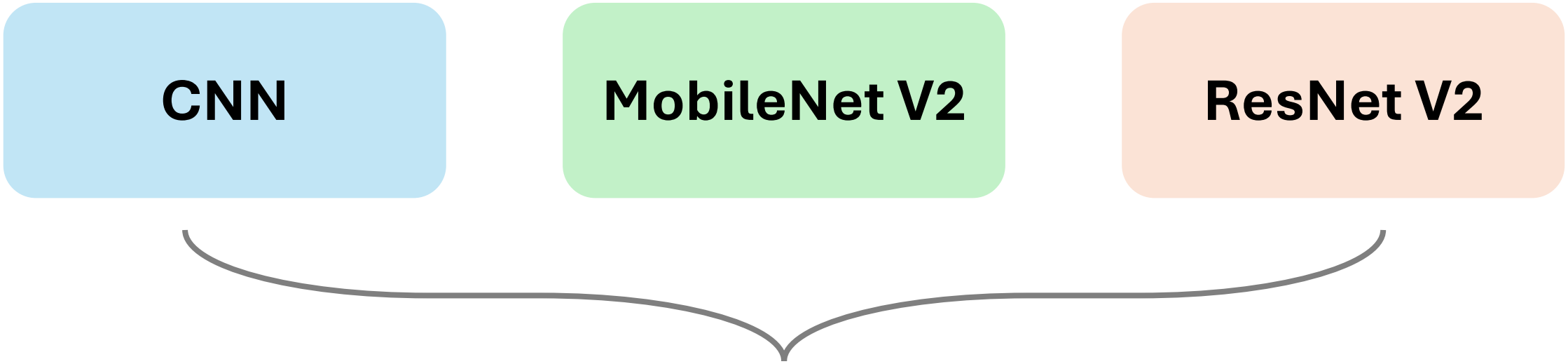
Detect targets by **dynamically adjusting the detection threshold** based on the average power of surrounding cells, thereby maintaining a consistent false alarm rate despite varying noise and clutter conditions.





CFAR Detection Result for Range time plot

Neural Network



Same Radar Processed Data and Train-Validation-Test Split

CNN

Layer (type)	Output Shape	Param #
conv2d_21 (Conv2D)	(None, 256, 256, 32)	2,432
max_pooling2d_9 (MaxPooling2D)	(None, 128, 128, 32)	0
conv2d_22 (Conv2D)	(None, 128, 128, 64)	18,496
max_pooling2d_10 (MaxPooling2D)	(None, 64, 64, 64)	0
conv2d_23 (Conv2D)	(None, 64, 64, 128)	73,856
max_pooling2d_11 (MaxPooling2D)	(None, 32, 32, 128)	0
conv2d_24 (Conv2D)	(None, 32, 32, 128)	147,584
max_pooling2d_12 (MaxPooling2D)	(None, 16, 16, 128)	0
conv2d_25 (Conv2D)	(None, 16, 16, 64)	73,792
max_pooling2d_13 (MaxPooling2D)	(None, 8, 8, 64)	0
conv2d_26 (Conv2D)	(None, 8, 8, 32)	18,464
max_pooling2d_14 (MaxPooling2D)	(None, 4, 4, 32)	0
dropout_4 (Dropout)	(None, 4, 4, 32)	0
flatten_4 (Flatten)	(None, 512)	0
dense_8 (Dense)	(None, 512)	262,656
activation_4 (Activation)	(None, 512)	0
dense_9 (Dense)	(None, 6)	3,078

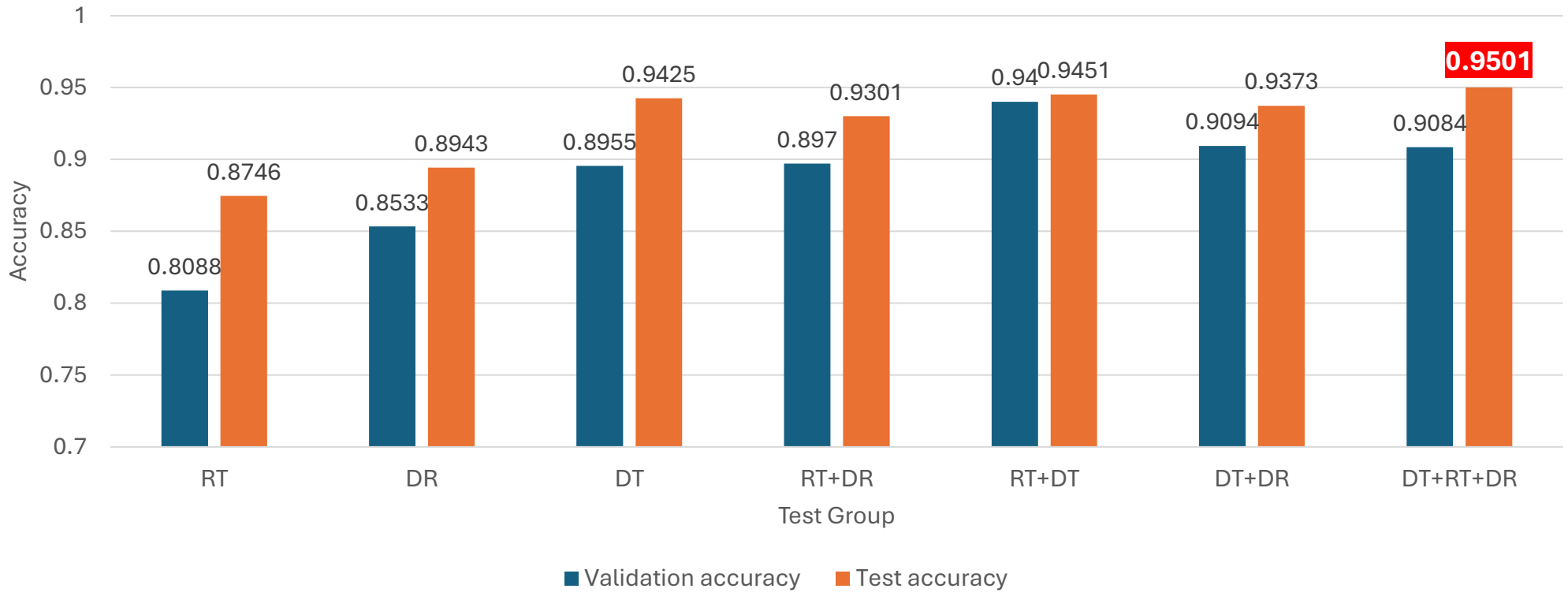
Total params: 600,358 (2.29 MB)
Trainable params: 600,358 (2.29 MB)

- 6 Convolutional Layers (Relu)
- 6 Max – Pooling Layers (2,2)
- 1 Drop – Out Layer (40%)
- One Flatten Layer (For Dense)
- One Dense Layer(Relu)
- Final Dense with Result (Softmax)
- 600,358 Parameters in total

CNN Result

Highest Test Accuracy: 95.01%
Test Group: DT+RT+DR

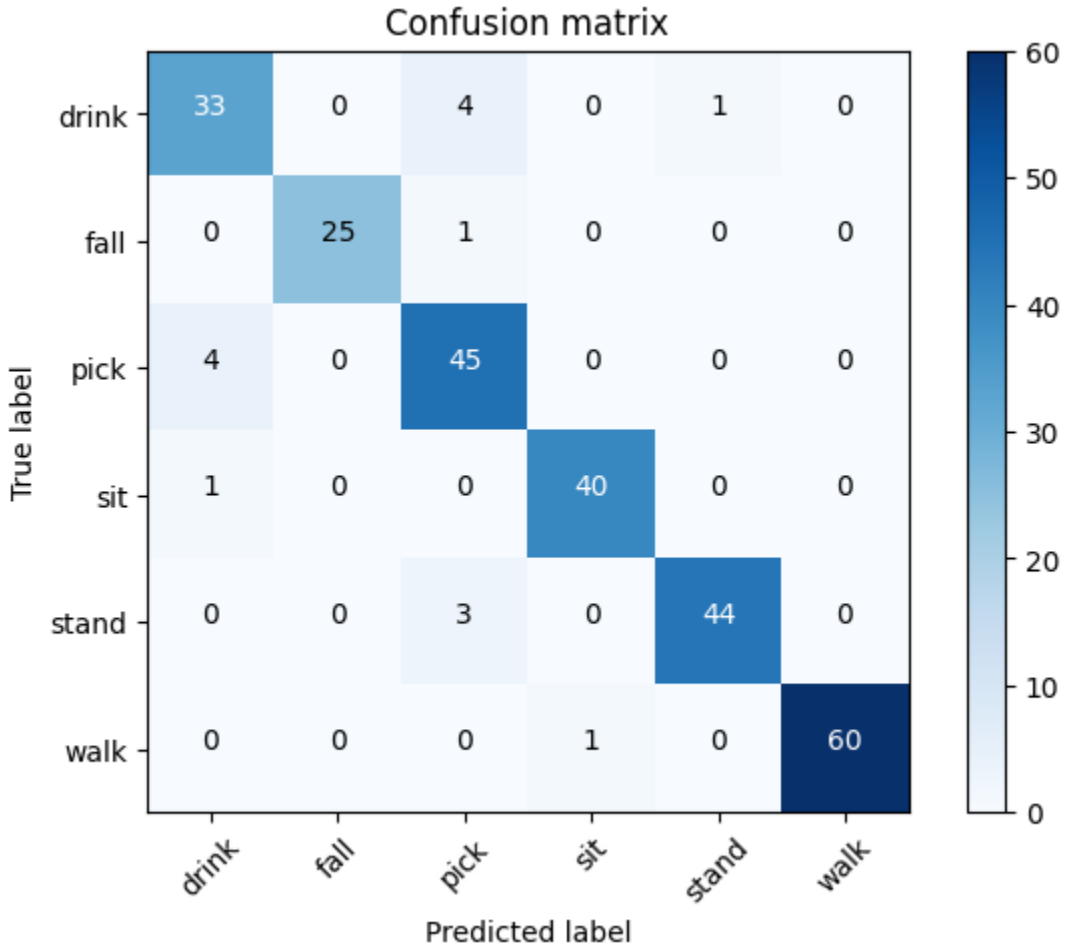
DT alone scores very high!



CNN Result

Test Group: DT+RT+DR

Drink – Pick
Problematic Movements



MobileNet V2

Inspired by

Z. Xiaolong, etc. - A lightweight network model for human activity classifiction based on pre-trained mobilenetv2

Transfer Learning in MobileNet V2-140-224

140%
width multiplier

Processes **224x224** pixel images

6,000,000
parameters

Inverted Residuals
architecture

Optimizes accuracy and efficiency for **Mobile Devices**

Adjust the **input layer** and **output layer** to adjust out dataset

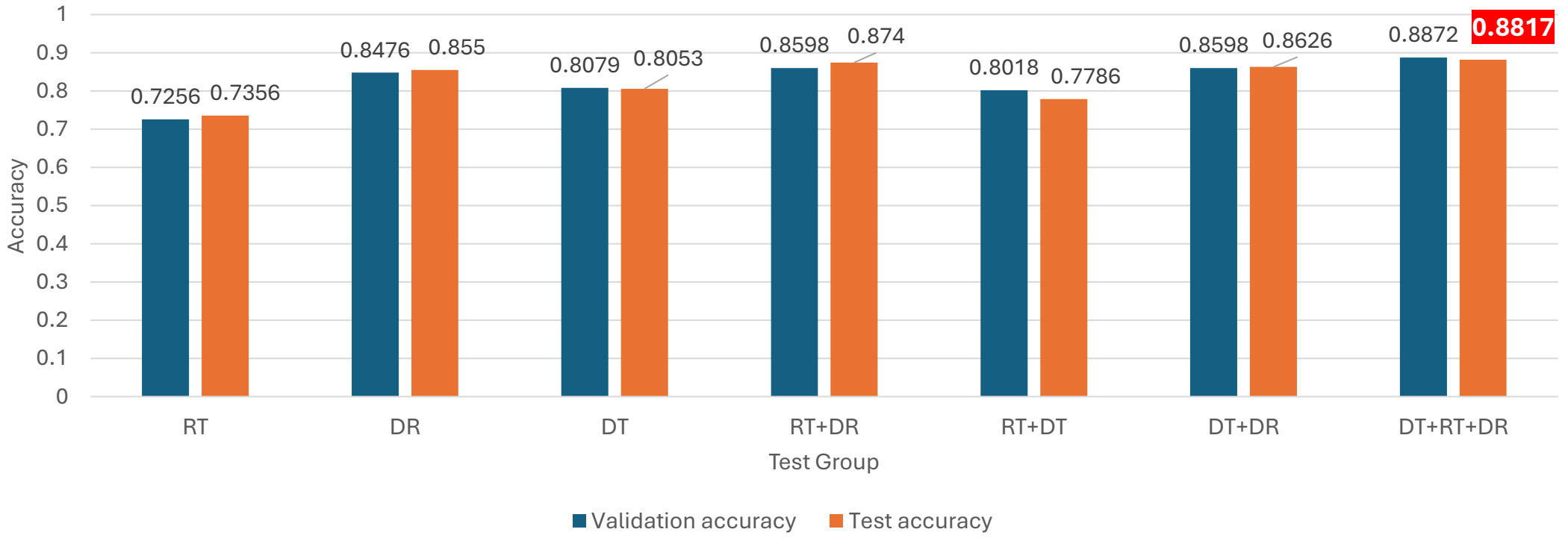
Change the **learning rate**

Adjust the **dropout rate**

MobileNet V2 Result

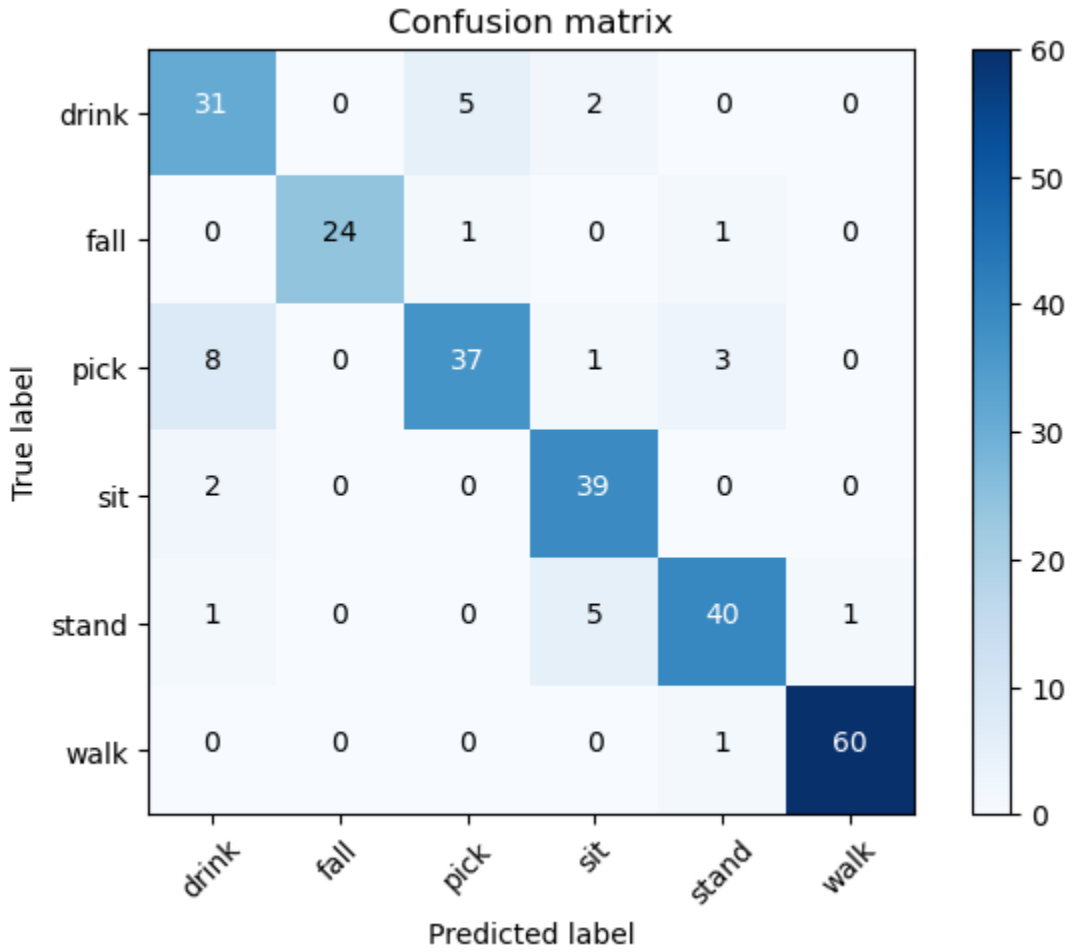
Highest Test Accuracy: 88.17%
Test Group: DT+RT+DR

Accuracy of DR is Higher than RT and DT



MobileNet V2

Test Group: DT+RT+DR



ResNet V2

Transfer Learning in ResNet V2 - 152

152 Layers
Deep Residual Network

60,192,808
parameters

Good at
Image Classification

Residual Blocks
addresses the vanishing gradient problem

Adjust the **input layer and output layer** to adjust out dataset

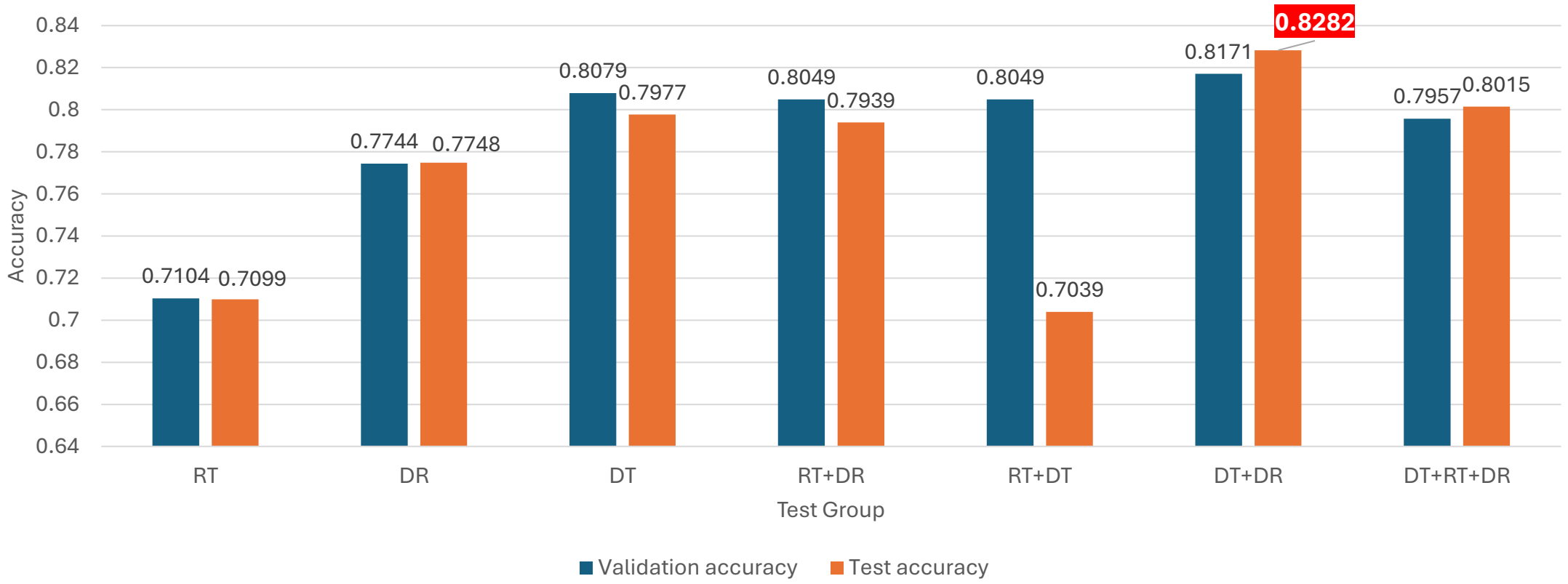
Change the **learning rate**

Adjust the **dropout rate**

ResNet V2 Result

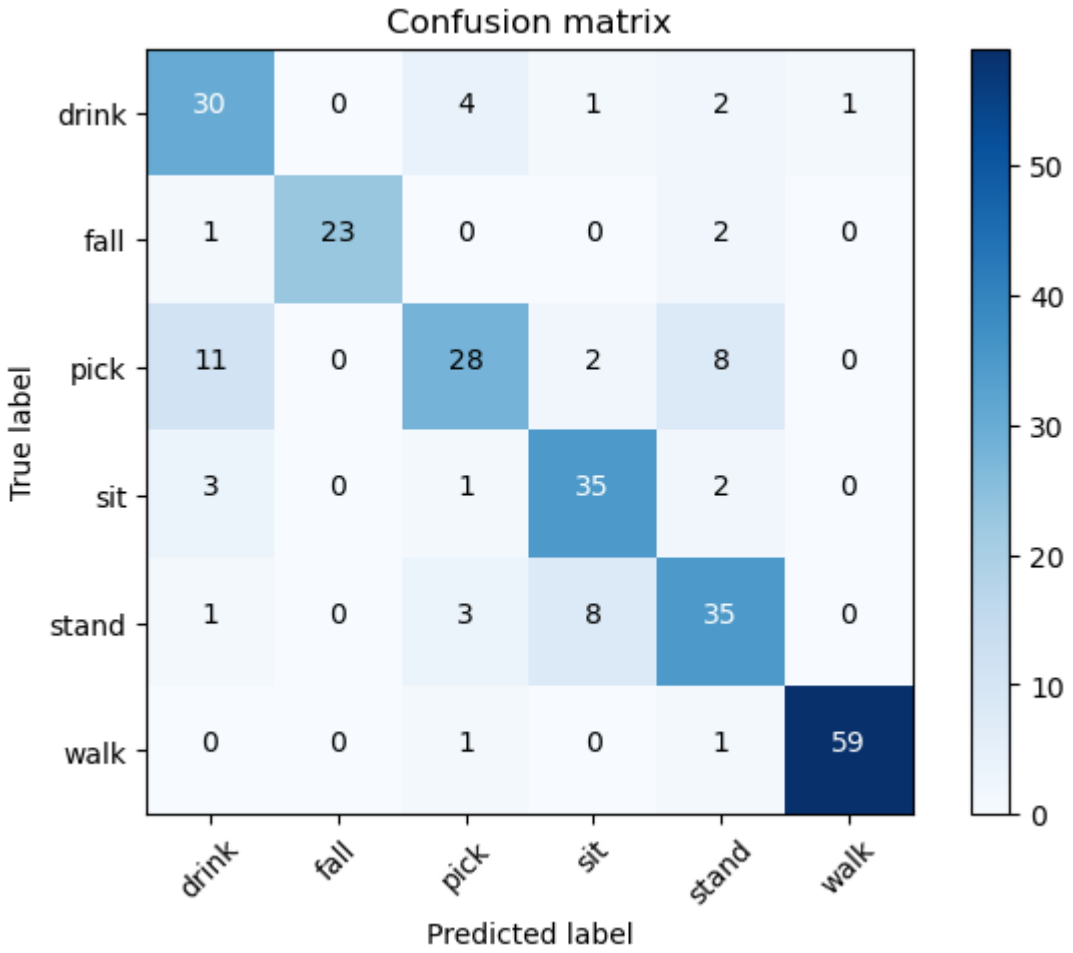
Highest Test Accuracy: 82.82%
Test Group: DT+DR

Need Fine Tunning to get better result



ResNet V2 Result

Test Group: DT+RT+DR



Conclusion

Model Size:

ResNet V2 > MobileNet V2 > CNN

Accuracy:

ResNet V2 < MobileNet V2 < CNN

Best Model:

CNNs can successfully classify the human activity with 95% accuracy.

Best Data and Data Group:

The DR and DT domain contains the most valuable information.
Combining the Data from different domain can increase the accuracy.

Future work

1. Complex Dataset Evaluation

Test channel encoding on complex/benchmark datasets to assess generalization and accuracy improvement over spectrograms.

2. Fine-Tuning the Models

Fine-tune models to evaluate accuracy enhancement with channel encoding.

3. Feature Importance Analysis

Generate heatmaps to identify significant plot features and gain insights into important characteristics.

Thank You

Alexandros Theocharous | Yanqi Hong