

Classical Machine Learning Approach for Human Activity Recognition Using Location Data

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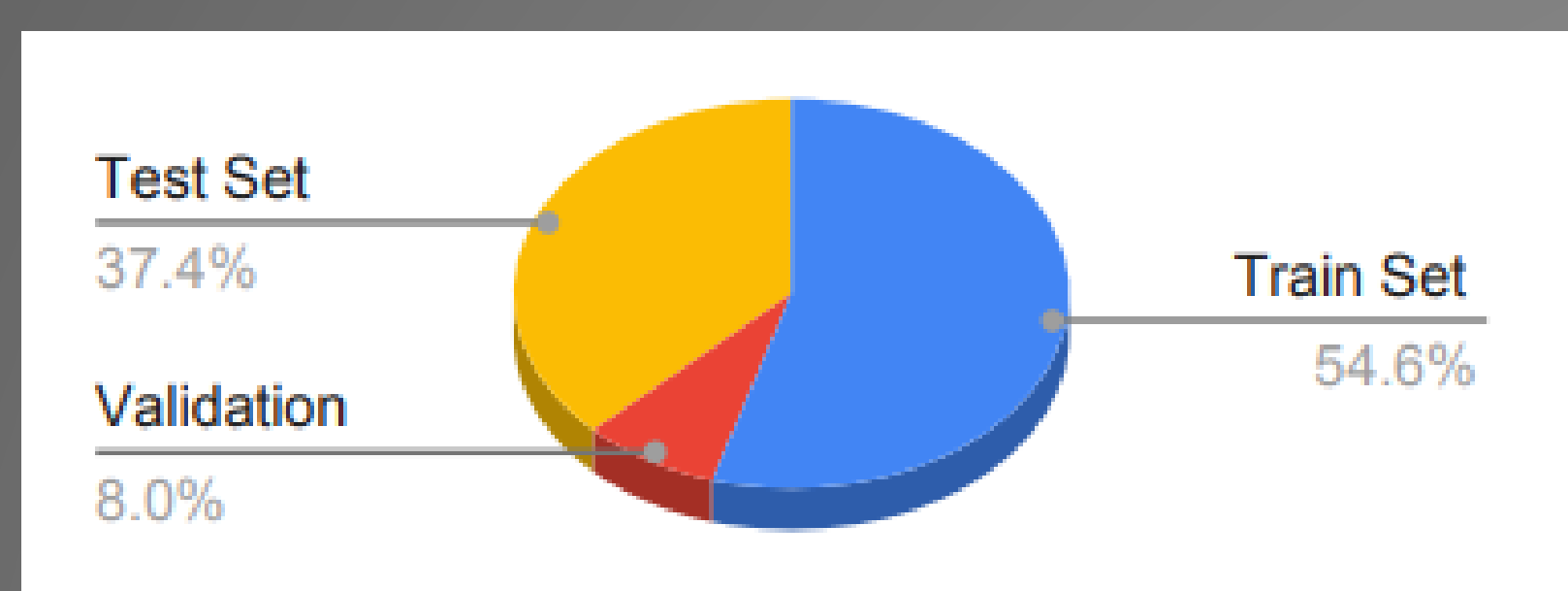
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Introduction

- Presented summary on Sussex-Huawei Locomotion-Transportation(SHL) dataset
- Extracted time domain features
- Random forest classifier performed best result
- The designed system is really simple and takes a little computational power to develop the system

Sussex-Huawei Locomotion-Transportation (SHL) Dataset

- Dataset included eight modes of locomotion and transportation- 1) Still, 2) Walking, 3) Run, 4) Bike, 5) Car, 6) Bus, 7) Train, 8) Subway
- The dataset consisted of radio data that included GPS reception, GPS location, WiFi reception, and GSM cells tower scans.



• SHL Train Set 2021 contained data from a phone located at the hips position of user-1 only for 59 days. SHL-Validation Set 2021 contained data from a phone as well and located at the hips position of user-2 and user-3 for 4 days. On the contrary, SHL-Test Set 2021 comprised of data from user-2 and user-3 for 39 days through a phone at same body position.

Methodology

We have got our best result while applying a traditional machine learning algorithm to the extracted feature. For prediction purpose, we used data interpolation if there was no location data for that instance.

Data Pre-processing

Label Matching: We matched the label depending on the Epoch time [ms] feature in the files. In the Label file, in between every timestamp(t) and the next one of that timestamp(t+1), if we found any timestamp in the GPS, WiFi, and Cells files; we labeled that timestamp of GPS, WiFi and Cells file with the given Label of the Label file's considered timestamp. The timestamp that was unlabeled while following the technique was dropped.

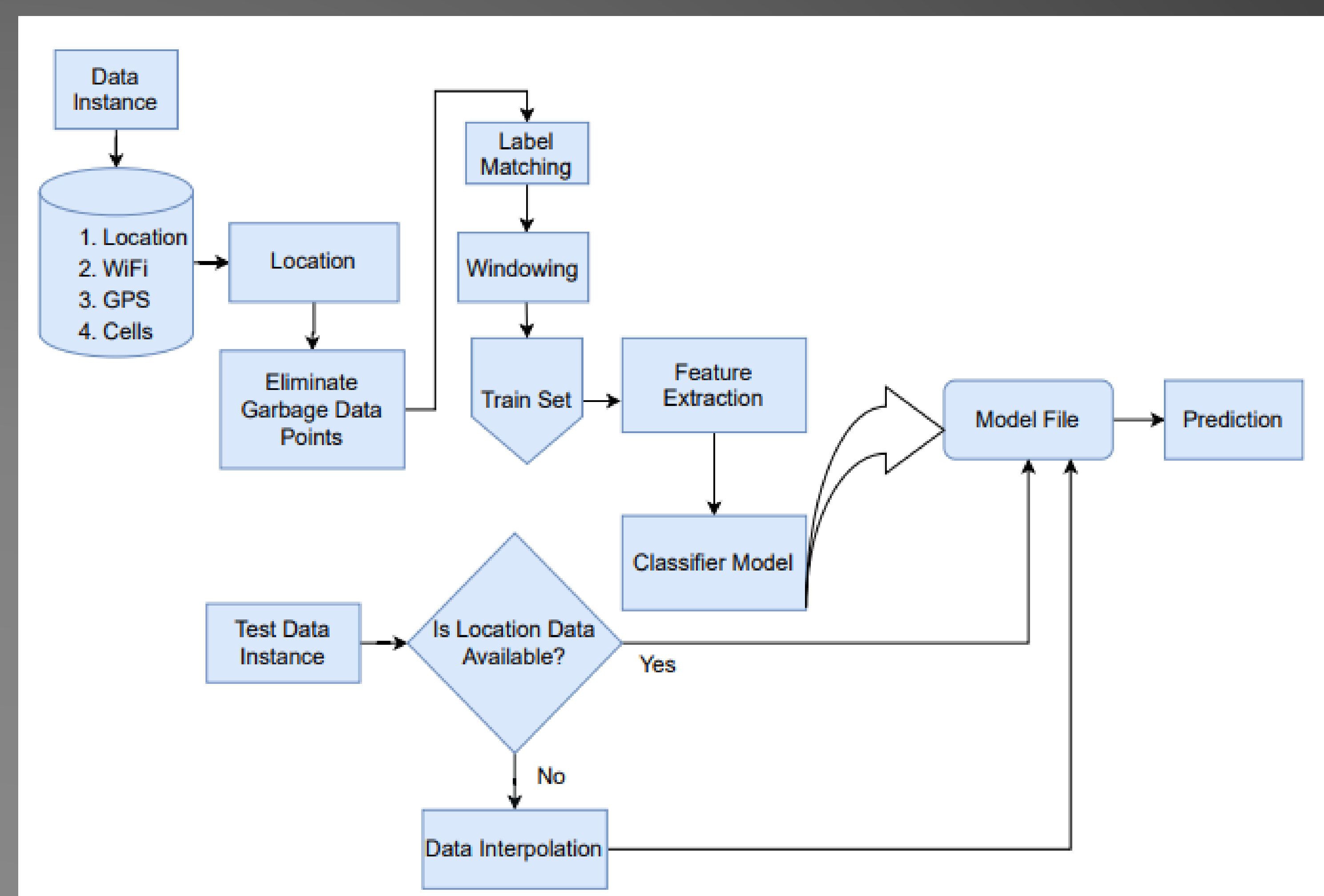
Feature Extraction

We have exploited two features: haversine distance and average speed. All the statistical features extracted using the window selection method as a part of feature extraction.

Selected Features	
Channels	Time Domain Features
Epoch time[ms]	Minimum
Accuracy of this location[m]	Maximum
Latitude[degrees]	Standard Deviation
Longitude[degrees]	Average
Haversine Distance[m]	Variance
Average Speed[m/s]	Peak to Peak Range
Average Accelaration[m/s^2]	Max Rate of Change
	Average Rate of Change
	Standard Deviation of Rate of Change
	Mean Absolute Deviation
	Inter-Quartile Range
	Autocorrelation
	Mean Crossing Rate
	Linear Velocity

Classifier

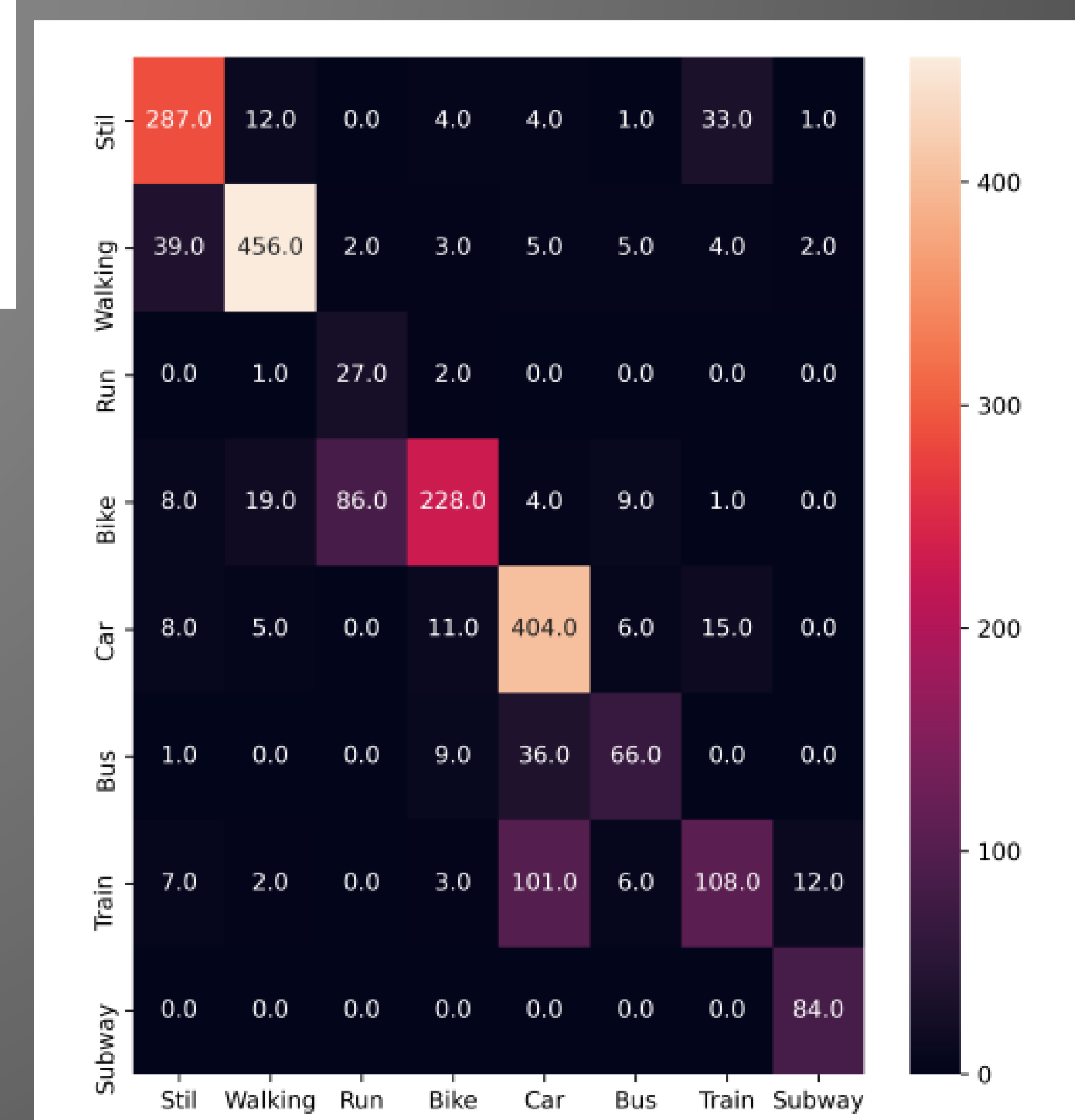
Random Forest Classifier- n estimators=300, min samples split=2, verbose=0, alpha=0.



Result and Analysis

This shows the results for different modalities. We got the best result using Location modality.

Modalities	Accuracy
GPS	32.97%
Wifi	30.99%
Location	78.14%
GPS + Location	75.56%



This shows the confusion matrix using Location.

Reference

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[2] Md Atiqur Rahman Ahad, Anindya Das Antar, and Omar Shahid. 2019. Visionbased Action Understanding for Assistive Healthcare: A Short Review. In CVPR Workshops. 1–11.

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