HUMAN ACTIVITY RECOGNITION USING SENSOR FUSION

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Declaration

We declare that this written submission represents my ideas in my own words and where others' ideas or words have been included, we have adequately cited and referenced the original sources. We also declare that we have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. We understand that any violation of the above will be cause for disciplinary action by the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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Certificate

This is to certify that the project titled 'Human Activity Recognition Using Sensor Fusion' is submitted by KSA Pradyumn, Vikram Karthikay Putha and Chekuri Verma, CSE, SNIOE in the partial fulfilment of the requirements for the award of the degree of **Bachelor of Technology in Computer Science and Technology**. This work was completed under the supervision of Dr. Divya Lohani. No part of this dissertation/report has been submitted elsewhere for award of any other degree.

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Abstract

As wearable devices are widely used nowadays, Human Activity Recognition (HAR) has become an emerging research area in mobile and wearable computing. Recognizing human activity leads to a deep understanding of individuals' activity patterns or long-term habits, which contributes to developing a wide range of user-centric applications such as human-computer interaction, surveillance, video streaming, AR/VR, and healthcare systems. On-body motion sensors are commonly used in recognizing various activities. For example, mobile phone motion sensors have been a popular choice for activity recognition at the trouser pocket or equivalent position. Wrist-worn motion sensors are also being used for human activity recognition.

The position of on-body motion sensors plays an important role in human activity recognition. Most often, mobile phone sensors in the trouser pocket or an equivalent position are used for this purpose. However, this position is not suitable for recognizing activities that involve hand gestures, such as smoking, eating, drinking coffee, and giving a talk. To recognize such activities, wrist-worn motion sensors are used. However, these two positions are mainly used in isolation.

We evaluate 4 motion sensors (accelerometer, gyroscope, magnetometer, and linear acceleration sensor) at wrist or pocket positions. Using classifiers such as the KNN algorithm, we show that the combination of multiple sensors outperforms a single sensor alone, mainly at smaller segmentation windows.

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CHAPTER 1
INTRODUCTION

Human activity recognition (HAR) is the practice of using Machine Learning to recognise and name human actions from raw activity data collected from a variety of sources. It is a challenging time series classification task. The goal is to capture sensor data and associated behaviours for certain individuals, develop a model from these data, then generalise the model to categorise the activity of new, unknown subjects based on their sensor data.

The technique of combining data from several sensors to produce a more precise conception of the goal objective is known as Sensor Fusion. Nowadays, sensors are employed in practically every industry. We can find them in our smartphones, wrist watches, etc. Even while a single sensor may produce important data on its own, consider the data that might be gathered by integrating the output from several different sensors at once. If the whole is bigger than the sum of its parts, this would provide us with a far better comprehensive understanding of the process or situation with less uncertainty. We can achieve this feat using a mechanism called sensor fusion. The theory behind it is that each individual sensor has both advantages and disadvantages; the objective is to make use of each sensor's advantages and lessen any ambiguity to provide deeper insights which can then impact new, more intelligent, and more precise responses.

For example, the problem is that the accelerometer is generally very noisy when it is used to measure gravitational acceleration since the robot is moving back and forth. The problem with the gyro is that it drifts over time – just like a spinning wheel-gyro will start to fall down when it is losing speed. In short, you can say that you can only trust the gyroscope on a short term while you can only trust the accelerometer on a long term. In this case, by using sensor fusion, we can get the best of both sensors to get more precise data. The uses and applications of sensor fusion are wide-ranging. So it is our task to analyse the results of sensor fusion by performing different sensor fusions in each activity and try to increase the accuracy of results using sensor fusion.

CHAPTER 2
LITERATURE REVIEW

Basic Human Activity Recognition Based on Sensor Fusion in Smartphones [1]

In this paper a publicly available dataset was used which consisted of accelerometer, gyroscope and magnetometer readings collected by a mobile phone from four male subjects performing six physical activities. The participants performed walking, running, sitting, standing, walking upstairs and walking downstairs while the smartphone is placed in four locations on the body: right jeans pocket, belt, right arm, and right wrist. Data is collected at a sampling rate of 50 Hz, which was observed to be sufficient in recognizing physical activities in the past. The sensor stream was segmented by a sliding time window of two seconds with 50% overlap.
All evaluations are performed using 10-fold cross validation. The individual performances of the three sensors are evaluated as well as their collaborative effects on the recognition accuracy.

CNN-based Sensor Fusion Techniques for Multimodal Human Activity Recognition[2]

The dataset used in this research paper was acquired at the Robert Bosch Hospital (RBK) in cooperation with Bosch Healthcare Solutions GmbH and approved by the ethics committee of the University of Tubingen. It includes 31 subjects with a mean age of 62 years (range: 22-87 years; sex: 18 female, 13 male). Class distribution and number of available training samples within the dataset. Each participant was asked to complete a predefined course consisting of different daily life activities such as walking inside and outside, stair climbing, etc. Data were acquired from six sensor nodes attached at both wrist and ankle positions of each subject as well at the left and right side of the waist. Each node recorded 3D acceleration (ACC) and gyroscope (GYRO) data via a BNO055 sensor (sampled at 100 Hz; ACC: 14 bit resolution, range ±8 g; GYRO: 16 bit resolution, range ±2000 deg /s2).
To investigate the optimal sensor fusion technique, they considered three normalization techniques: Z-normalization (zNorm), Batch normalization (BN), Pressure mean subtraction (PMS).

Complex Human Activity Recognition Using Smartphone and Wrist-Worn Motion Sensors[3]

In this paper, a dataset was collected for thirteen human activities. During this data collection, all participants carried two mobile phones in their right pocket and at their right wrist. A smartwatch or wrist-worn device is emulated by using a smartphone at the wrist position. The Data was collected at 50 samples per second from the phone's accelerometer, its (virtual) linear acceleration sensor and its gyroscope. Linear acceleration is obtained by removing acceleration due to gravity from the accelerometer measurements. The orientation of motion sensors can affect the recognition performance of various activities. To counter such effects, we use the magnitude of these sensors as an extra dimension besides the x, y and z axes.
Three classifiers, which are commonly used for practical activity recognition: Naive Bayes, k-nearest neighbour (KNN) and decision tree were selected for classification.
Finally, for performance evaluation, 10-fold stratified cross-validation was used. In this validation method, the whole dataset is divided into ten equal parts or subsets. In each iteration,

nine of these parts are used for training purposes and one for testing. This process is repeated ten times, thereby using all data for training, as well as testing.

Machine Learning Algorithms for Human Activity Recognition[4]

In this paper, for data collection, it collects the data from both training and testing dataset, and in testing the data collected through window time. Then the structural and statistical features are extracted. Finally it recognizes the physical activity and models it. The data generated from the accelerometer is time series data and it is denoted by AX, AY AND AZ along X, Y and Z-axis respectively.
Wearable sensors help in developing new applications. The following aspects are used to evaluate the HAR system.
Selection of sensors, Data collection and Clustering of Data, Feature extraction method(s), Learning algorithm(s), Recognizing model and activity.
The Models used for activity recognition and results in this paper are Hidden Markov Model (HMM), Artificial Neural Networks, and Dictionary Learning Algorithm.

Multi-sensor fusion based on multiple classifier systems for human activity identification[5]

The paper's proposed multiple sensor modalities fusion for human activity identification consist of six steps:
These steps include data collection, signal processing, feature extraction and normalization, feature selection and classification of physical activity details.
The experimental evaluation steps consist of (1) single sensor analysis, (2) sensor fusion using feature concatenation and (3) multi-view stacking that combine the predictive probabilities of different sensor modalities before fusion.

Sensor Data Acquisition and Multimodal Sensor Fusion for Human Activity Recognition Using Deep Learning[6]

The key contributions of this research are:
• Building a testbed system and collecting activity data in both real-world and lab environments that contain high variations in the signal patterns.
• Analyze activity data to empirically study the data acquisition details regarding the sensor position and parametric settings, and investigate the characteristic of each sensor modality on detecting different types of ADLs.
• Perform sensor fusion on multimodal sensor data by implementing a two-level ensemble model that combines single-modal results from the deep learning activity classifier.
In Data Analysis and Evaluation: Deep Learning Architecture, Sensor Fusion was used and Impact of Sampling Rate, Impact of Sensor Position and Combinations, Impact of Multimodal Sensor Fusion were the key aspects.

Towards Physical Activity Recognition Using Smartphone Sensors[7]

In this paper, data was collected for six different physical activities. They are walking, running, sitting, standing, walking upstairs and downstairs. Four participants were asked to perform these activities for a few minutes. As these are repetitive activities, the amount of time for each activity was kept between 3-5 minutes per participant.
The collected data was divided into small segments for feature extraction using a sliding

window approach. The selection of an appropriate window size is important and different values can be set for it. Approach for Preprocessing of Data was explained. Experimental design i.e., seven commonly used classifiers (in activity recognition's state of the art) were evaluated for performance analysis and comparison.
Roles and importance of accelerometer, gyroscope, magnetometer clearly explained for HAR.

Analysis of Multi-Sensor Fusion for Mobile and Wearable Sensor Based Human Activity Recognition[8]

Evaluated the performance of the multi-sensor fusion in three basic experiments. First evaluated the seven (7) classifiers on each of the single sensors (Accelerometer or Gyroscope). Next, the fusion of accelerometer and gyroscopes at each sensor positions (ankle, chest, hip and wrist) were evaluated with the classifiers. Finally, the fusion of the accelerometer and gyroscope at different parts of the body were evaluated. For instance, combine an accelerometer on the ankle with a gyroscope on the chest, accelerometer on chest with gyroscope from the hip etc. Also, Analysis of Single Sensor Modality, Analysis of Different Sensor Modalities on the Same Location Placement, Analysis of Sensors Modalities Fusion on Different Locations Placement were done.

The Kalman Filter and Related Algorithms[11]

This paper is an introduction to the Kalman Filter and several related Bayesian state estimators. Kalman Filter is explained in detail.
he algorithm is structured in a predictor-corrector format. The general idea is to project the state forward, using a state transition function. Then this state is corrected by incorporating a measurement of the system's observable quantities. The algorithm can be divided into two distinct phases: a time update phase and a measurement update phase.
The total time complexity of a single application of the Kalman Filter is O(9n2.376 + 10n2 + 5n) ∈ O(n2.376).

Data Fusion with 9 Degrees of Freedom Inertial Measurement Unit To Determine Object's Orientation[12]

Given 9 Degrees of Freedom (DOF) Inertial Measurement Unit (IMU) composed of 3-axis Magnetometer, 3-axis Accelerometer, and 3-axis Gyroscope are processed to yield the object's rotations in 3 dimensions. While the magnetometer (compass) is used to determine the heading angle, accelerometer is used to determine tilt axis, gyroscope can be process to calculate the angular velocity. Each sensor has its own advantages under different static or dynamic scenarios. By analyzing each sensor separately, the angle output computed from each sensor is then fused with angles from other sensors using filter algorithms. For data integration Kalman Filter is used.

Sensor Fusion for Recognition of Activities of Daily Living[13]

Most earlier work in accelerometer-based activity recognition performed their experiments by placing multiple sensors on several parts of the subjects' body. Hip, wrist, arm, ankle were usually selected to attach sensors. Nowadays, Android-based cell phones mostly contain tri-axial accelerometers. The acceleration in three spatial dimensions with the magnetometer sensor and Earth's gravity can detect the orientation of the device. An accelerometer-based activity recognition system identifies the physical activity a user is performing, such as walking, jogging, climbing stairs, sitting, and standing. This section is to determine the phone's attitude and the walking direction by combining multiple types of sensors in addition to accelerometers. Some practical real-world situations are worthy of taking account. Even holding in one's palm, it does not really reflect motion direction. It is possible to detect a stride while distinguishing whether the phone is heading in directly the same motion direction or totally the opposite is another challenge.

Data Fusion and Multiple Classifier Systems for Human Activity Detection and Health Monitoring[14]

Topics written in this open research Directory which were referanced are:
Data Fusion Methods, Kalman Filtering, Fusion based on Sensor Modalities, Inertial Measurement Unit (IMU) Sensor Fusion, Multi-modal Sensors Fusion,
Sensor modalities, applications, strengths and weaknesses, Feature Fusion for Human Activity Recognition, Handcrafted Feature Fusion, Feature Types, Feature Selection Methods, Machine Learning Algorithms for Feature Fusion,
Multiple Classifier Systems for Human Activity Recognition, Data Partitioning, Fusion Strategies, Random Initialization, Class Label.

Motion Measurement Using Inertial Sensors, Ultrasonic Sensors, and Magnetometers With Extended Kalman Filter for Data Fusion[15]

A sensor system for position and orientation determination has been developed using complementary accelerometers, gyroscopes, magnetometers, and ultrasonic sensors. A gyroscope that is able to measure transient rotation is used to compensate the digital compass in case of rotation or translational acceleration. This combination takes the advantages of the digital compass in accumulated error-free measurement in static state and the short-term accuracy of the gyroscope in dynamic state. Experimental results demonstrate that the multi-sensors can measure position and orientation with lower uncertainties after EKF(Extended Kalman Filter) data fusion.

A method is presented to compensate the drift and the accumulated errors of inertial sensors using ultrasonic sensors and magnetometers for motion tracking. The contributions include two aspects. First, gyroscopes are used to extend the applicability of a digital compass in orientation determination from static state to dynamic state. Second, we use ultrasonic sensors in conjunction with accelerometers for position determination to compensate the drawbacks of each other, such as low sampling rate and large accumulated errors.

CHAPTER 3

DATASET AND ITS ATTRIBUTES

Data Collection and/or Data is the most important aspect of any ML-related Project. It's basically a collection of various types of data stored in a digital format. Machine learning models depend on data. Without a foundation of high-quality training data, even the most performant algorithms can be rendered useless. So, the selection of a good dataset was our first step in this project.

Few important points for finding a good dataset are as follows:

1. The Dataset must be vast so that the training of the ML algorithms is done considerably well.
2. A good data set is disaggregated (raw) data.
3. The attributes of the dataset must align with our interests in the process of the project
4. Dataset was cited under the research paper we wanted to follow.

After reviewing many research papers and considering all the above points we selected a dataset which is cited from [3].

ATTRIBUTES:

The attributes used for HAR are known as IMU (Inertial measurement unit) sensors, these sensors basically provide data on the physical movements of a human when attached to them either on a wrist or when it is put in a pocket.

The 4 attributes (i.e., the sensors) that we are going to use are the accelerometer (x, y, z), gyroscope (x, y, z), magnetometer (x, y, z), Linear Acceleration (x, y, z) as shown in the below picture from column B to M Figure (1). Columns A and N are the timestamps and classes of a particular data instance respectively.

This dataset contained 13 different activities in which we will be only considering 4 or 5 different activities to work on for our project. The reason for selecting the accelerometer and gyroscope was that most of the research papers we studied had these both sensors as a standard for predicting human activities. The other two sensors play a crucial role in predicting complex activities as well.

1. **Accelerometer.**

   An accelerometer is a type of electrical sensor used to detect the acceleration forces acting on an item to pinpoint its location in space and track its motion. There are two types of acceleration forces: static forces and dynamic forces. Static forces are forces that are constantly being applied on the Human (such as friction or gravity). Dynamic forces are "moving" forces applied by humans at various rates. Because we want to know the changes brought by these forces, we use an accelerometer.

2. **Gyroscope.**

A gyroscope sensor is a tool that can measure and keep track of an object's orientation and angular velocity. Gyroscope sensors are also called Angular Rate Sensor or Angular Velocity Sensors. Compared to accelerometers, they are more modern. While accelerometers can only monitor linear motion, they can measure the tilt and lateral orientation of the item.

A gyroscope senses change in orientation of a device, and when paired with an accelerometer, is an excellent tool for measuring the orientation of an object in 3D space.

3. **Magnetometer.**

A magnetometer is a device used to measure the magnetic field, particularly with respect to its magnetic strength and orientation. It is used to identify the magnetic field's direction, intensity, or relative fluctuation at a certain site.

4. **Linear Acceleration.**

Linear acceleration is defined as the uniform acceleration caused by a moving body in a straight line. Linear acceleration sensors, also called G-force sensors, are devices that measure acceleration caused by movement, vibration, collision, etc. The Linear Acceleration Sensor interface of the Sensor APIs provides on each reading the acceleration applied to the device along all three axes, but without the contribution of gravity.

Linear accleration is an sensor fusion in itself.

Time stamp, accelerometer (x, y, z), linear acceleration sensor (x, y, z), gyroscope (x, y, z), Magnetometer (x, y, z), Activity Label(11111,11112, etc)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	1.39E+12	-3.1327	-10.188	-1.0488	-3.0399	-0.43163	-0.06148	-2.9783	-0.4948	-0.81215	21.24	42.72	15.42	11111
2	1.39E+12	-5.9249	-10.978	1.0079	-5.3538	-1.2218	1.821	-3.6328	-0.64599	-0.56016	21.12	42.6	15.78	11111
3	1.39E+12	-6.96	-12.136	0.28603	-5.4353	-2.4642	0.84062	-2.9557	-0.34147	-0.60598	20.82	42.6	16.74	11111
4	1.39E+12	-3.9635	-15.568	-3.3778	-2.325	-5.9283	-2.6294	-1.9743	-2.2758	-0.76908	20.64	42.36	17.34	11111
5	1.39E+12	-0.05448	-15.677	-4.4402	1.2882	-6.0468	-3.1649	-2.7388	-3.08	-0.89247	20.4	42.06	18.36	11111
6	1.39E+12	0.35413	-13.048	-2.5742	1.5373	-3.4059	-1.2346	-2.7419	-0.46853	-0.94287	20.34	42.06	19.02	11111
7	1.39E+12	-0.21793	-9.9156	-0.44947	0.89146	-0.25524	0.82205	-2.0119	0.2474	-0.85765	20.16	41.82	19.68	11111
8	1.39E+12	-0.65378	-7.7091	0.70826	0.39132	1.9886	1.7239	-2.0388	-0.40256	-0.72265	19.44	41.28	21.3	11111
9	1.39E+12	-1.076	-7.3822	-0.25879	-0.00681	2.3174	0.7132	-2.2437	-0.80909	-0.66859	19.26	41.04	22.14	11111
10	1.39E+12	-1.3893	-6.2245	-1.0624	-0.25859	3.4642	-0.05238	-2.1698	-0.78038	-0.69608	18.96	40.8	22.98	11111
11	1.39E+12	-1.8387	-2.3563	-1.4438	-0.4687	7.2799	-0.24517	-1.3705	-0.63316	-0.76877	18.54	39.96	24.78	11111
12	1.39E+12	-1.7298	-1.6889	-1.1305	-0.20064	7.9107	0.16506	-0.95356	-0.53054	-0.80634	18.42	39.6	25.8	11111
13	1.39E+12	-1.2803	-1.7843	-0.0681	0.36539	7.7992	1.2046	-0.04612	-0.49908	-0.82558	18.24	39.24	26.4	11111
14	1.39E+12	-1.0215	-2.8603	0.96704	0.69358	6.7322	2.0686	0.28497	-0.62583	-0.72052	18.12	39.06	27.18	11111
15	1.39E+12	-0.9398	-3.7728	1.0896	0.84937	5.845	1.7727	0.70372	-0.72907	-0.65607	18.24	38.52	28.26	11111
16	1.39E+12	-1.0896	-2.9829	0.6674	0.7786	6.6284	1.218	1.2437	-0.80451	-0.59712	18.12	38.58	28.62	11111
17	1.39E+12	-1.7025	-2.4108	-0.8036	0.35355	7.1555	-0.14953	1.8925	-0.50885	-0.40103	18.12	38.64	29.04	11111
18	1.39E+12	-1.7298	-8.6081	-8.5263	0.40102	0.68357	-6.2251	2.4655	-0.09682	-0.26725	17.94	38.82	29.52	11111
19	1.39E+12	-1.4438	-13.607	-12.163	0.40229	-4.5926	-8.7707	1.5391	0.35583	0.36896	18	39.18	29.64	11111
20	1.39E+12	0.74912	-19.45	-14.519	2.6613	-10.324	-11.481	-0.37843	-0.81734	0.17532	18.12	39.6	29.28	11111
21	1.39E+12	-0.61292	-16.508	-11.931	0.17295	-8.052	-7.0272	-1.171	-1.4187	-0.3879	18.24	39.78	29.16	11111
22	1.39E+12	-1.866	-9.3163	-5.775	-0.99628	-0.88045	-0.85059	-0.84666	-0.63805	-0.71654	18.36	40.02	28.98	11111
23	1.39E+12	-0.44947	-9.5206	-3.2144	0.41196	-0.96134	1.4938	-0.18326	-0.37935	-0.65607	18.66	40.8	28.44	11111
24	1.39E+12	-0.88532	-15.677	-1.6889	-0.05977	-6.871	2.5471	-0.09499	-0.38149	-0.56872	18.84	41.16	28.08	11111
25	1.39E+12	-4.3721	-16.753	-2.6423	-3.2987	-7.7997	1.212	0.021686	1.6945	0.013134	19.02	41.4	27.84	11111
26	1.39E+12	-2.8603	-9.6023	-0.89894	-1.4748	-0.4573	2.3597	-0.20495	1.0211	-0.17868	18.96	41.88	27.36	11111
27	1.39E+12	-1.9341	-3.4051	4.4675	-0.39935	5.8711	7.2545	0.52046	0.79901	-0.19792	18.72	42.18	27.18	11111

Fig: 3.1 DATASET[3].

CONCEPTS/IDEAS

The following are the concepts we learned and/or trying to learn and apply further down the procedure:

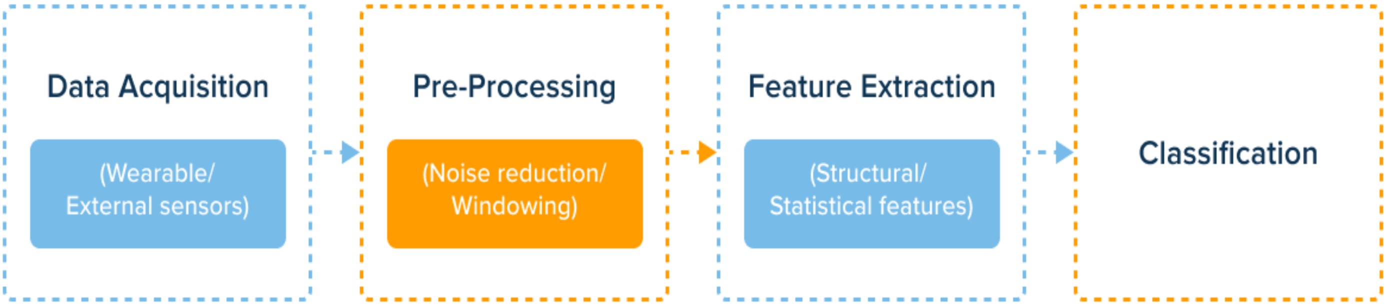

Fig: 3.2 CONCEPTS/IDEAS FLOWCHART

3.1 ***<u>Data/Attribute Selection and Extraction:</u>***

- The First step of our project was to decide upon a dataset that is used for HAR and then decide upon its attributes based on how important they are in determining the output of a prediction.
- The Second step was Extraction using a programming language (python in our case with pandas and NumPy) so that we can manipulate and use the data for computational purposes.

3.2 ***<u>ML Algorithms Application:</u>***

- The Next step is to apply the ML algorithms on the dataset, for training the algorithm to predict a human activity as precisely and accurately as possible.

- One of the algorithms is KNN which involves calculating the Euclidean Distance, sorting them, and prediction of the class.

- The other repetitive algorithm being used in research papers is the decision tree. The Decision Tree algorithm is a Greedy Algorithm.

3.3 ***<u>Sensor Fusion, Classification and Cross Validation:</u>***

- Once we can predict human activity, we can start focusing on the main aspect of the project i.e., sensor fusion. As discussed above, we learned why sensor fusion was important.

- After we can determine a prediction either individually or after sensor fusion, we must be certain whether the prediction is accurate or not, for that purpose Classification Rate Tables are jotted down using stratified cross-validation.
- Cross Validation means using the same dataset to both train and test the data on an ML algorithm and compare the results to check the accuracy of the algorithm; these accuracies are basically classification rates.
- Classification rate Tables can be derived for various types of combinations of data for example for the KNN algorithm and Decision Tree algorithm, single sensor prediction, and sensor fusion prediction for Example look at Figure (2).
- After the application of sensor fusion, we expect to come up with better results than before sensor fusion was applied according to theory.

<u>Window size:</u>

It is the number of instances of data taken per time. In the finalized dataset the data is gathered such that 50 instances are recorded per second so while taking the data for application purposes we can take window size as a parameter for analysis of different classification tables.

Process of Sensor fusion.

The Sensor fusion is used to overcome limitations of an individual sensors. In our case we estimate quantities that are not directly measurable like Euler angles(roll, pitch, yaw) by using data provided by the sensors. Euler angles describe the orientation of an object which is more optimal to use in HAR.

<u>Axis and rotation’s definition.</u>

Let's specify the reference for three sensors and their rotational axis before getting into the specifics. Using the definition of the right hand rule and its axis and positive rotation representation:

Your index finger is pointing in the direction of the letter X.

Now point your middle finger in the direction of the Y.

Finally, raise your thumb towards Z's direction.

Now, the positive rotation is defined as when the object rotates clockwise around each axis look from the origin toward the positive direction.

Rotate clockwise around x-axis, that is roll (+).

Rotate clockwise around y-axis, that is pitch (+).

Rotate clockwise around z-axis, that is yaw (+).

Type of sensors and their features.

Three type of sensors: Accelerometer, Gyroscope, and Magnetometer will be covered in this section. Each come with their advantages and disadvantages in the method of how to calculate the roll – pitch – yaw angles using each sensor.

a) Accelerometer.

From accelerometer we can get roll and pitch.**[12]**

```
roll = float(math.atan2(acc_data[1], acc_data[2]))

pitch = float(math.atan2(-acc_data[0],
math.sqrt(acc_data[1]**2 + acc_data[2]**2)))
```

No matter what yaw angle you rotate around the z-axis, it always measures az = 1g and ax = ay = 0. Therefore, we need another sensor to calculate the yaw angle that is magnetometer.

b) Magnetometer.

From magnetometer we can get yaw.**[12]**

```
Mx = mag_data[0]*math.cos(pitch) +
mag_data[2]*math.sin(pitch)

    My = mag_data[0]*math.sin(roll)*math.sin(pitch) +
mag_data[1]*math.cos(roll) -
mag_data[2]*math.sin(roll)*math.cos(pitch)



    yaw = float(math.atan2(My,Mx))
```

c) Gyroscope.

From gyroscope we can get its own individual

Angle = angular velocity * time.**[12]**

```
delta_t = 0.02
    roll_angle = math.degrees(gyro_data[0]*delta_t)
    pitch_angle = math.degrees(gyro_data[1]*delta_t)
    yaw_angle = math.degrees(gyro_data[2]*delta_t)
```

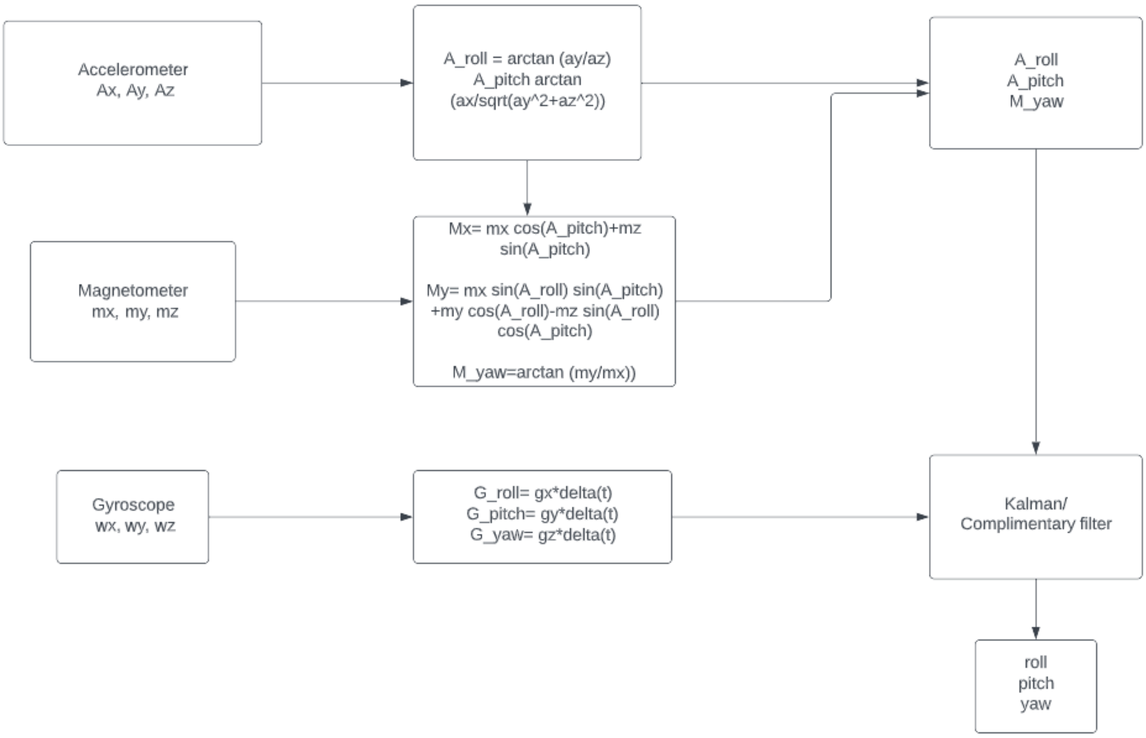

Figure 3.3 : Process of sensor fusion.

Kalman Filter

The Kalman Filter is a very rare algorithm, in that it is one of the few that are provably optimal in our calculation for sensor fusion of roll, pitch, and yaw.

When an object is stationary on Earth, the roll and pitch angles may be properly computed because the accelerometer has high long-term accuracy.However, when the sensor is moving, the moving acceleration will impact the rotation calculation. However, if we apply a low pass filter to the output of the accelerometer, most of the noise and the external force acceleration will be removed, the filtered value is then used to integrate with other sensor (gyroscope).

The gyroscope's calculation drift over time as a result of integration is the only issue. A slight measurement inaccuracy made at one point will be perpetuated by the integral. Additionally, the gyro - rates won't return to zero when the object is at rest because of inertia. For instance, the value measured will differ from if the raw data is measured at a value of, your object was moved, and then it was returned to its standstill state. Gyroscopes are extremely accurate in the near term, though. Therefore, after obtaining the angular rate from the sensor, users typically apply a high pass filter to the gyroscope data.

So, in kalman filter the three angles of accelerometer and magnetometer will be integrated with the three independent angular calculation from the gyroscope to form a more accurate result.

Below is the python code for Kalman filter.**[17]**

```
def KalmanFilter(newAngle, newRate, looptime):
    global x_bias
    global P_00
    global P_01
    global P_10
    global P_11

    delta_t = float(looptime)/1000
    x_angle = delta_t * (newRate - x_bias)

    P_00 += - delta_t * (P_10 + P_01) + Q_angle * delta_t
    P_01 += - delta_t * P_11
    P_10 += - delta_t * P_11
    P_11 += + Q_gyro * delta_t

    y = newAngle - x_angle
    S = P_00 + R_angle
```

```
    K_0 = P_00 / S
    K_1 = P_10 / S


    x_angle += K_0 * y
    x_bias += K_1 * y
    P_00 -= K_0 * P_00
    P_01 -= K_0 * P_01
    P_10 -= K_1 * P_00
    P_11 -= K_1 * P_01


    return x_angle
```

Here in code,

"newAngle" is either roll, pitch, and yaw of accelerometer.

"newRate" is either roll, pitch, and yaw of gyroscope.

"looptime" is window size.

"Q_angle, Q_gyro, R_angle" are Covariance Gyro Bias

"x_angle" is estimated angle of our sensor fusion.

"P" is error covariance matrix.

"K" is kalman gain.

CHAPTER 4
ANALYSIS

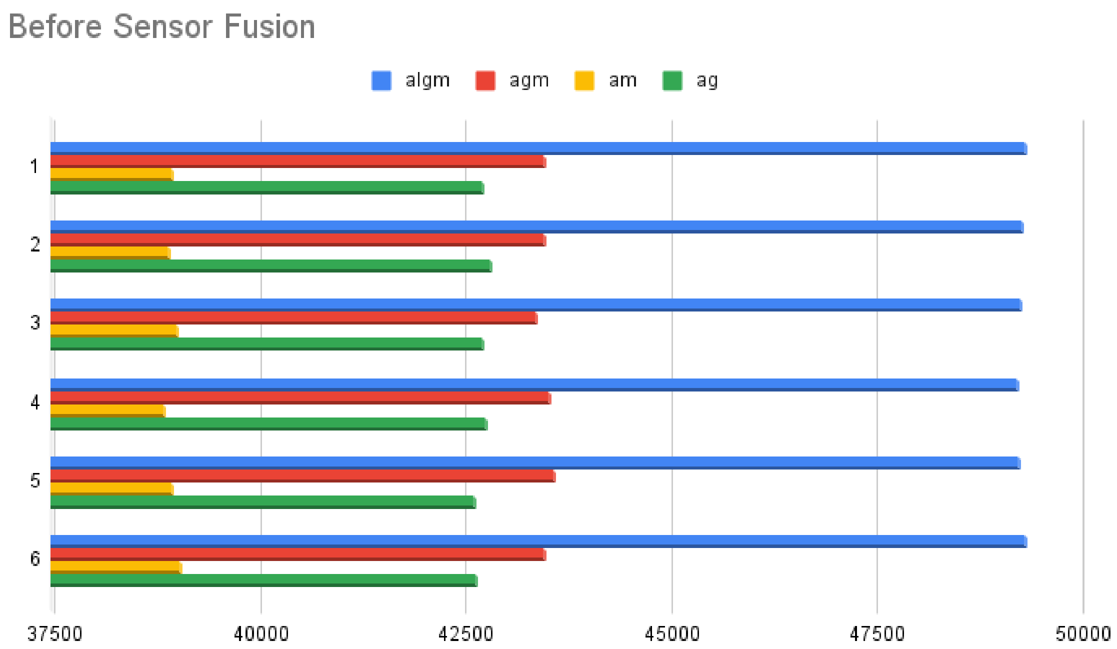

Figure 4.1 BEFORE SENSOR FUSION ACCURACIES

As expected, increasing the number of attributes increased the classification rate of the HAR algorithm used. When talking about head to head difference in increase, it can be seen when only 2 attributes are used, the addition of Magnetometer data results in lesser increase than the addition of Gyroscope data. Other such comparisons can also be made in the future. For reference, the total testing size of each data set was 54000 for these tests, but changing the size did not result in a big change of accuracy, so the largest size possible was chosen.

before						
Attributes	**1**	**2**	**3**	**4**	**5**	**6**
algm	49318	49282	49269	49217	49237	49326
agm	43467	43472	43379	43537	43582	43478
am	38952	38903	39005	38839	38948	39042
ag	42728	42815	42722	42756	42629	42639

Table 4.1 BEFORE SENSOR FUSION ACCURACIES

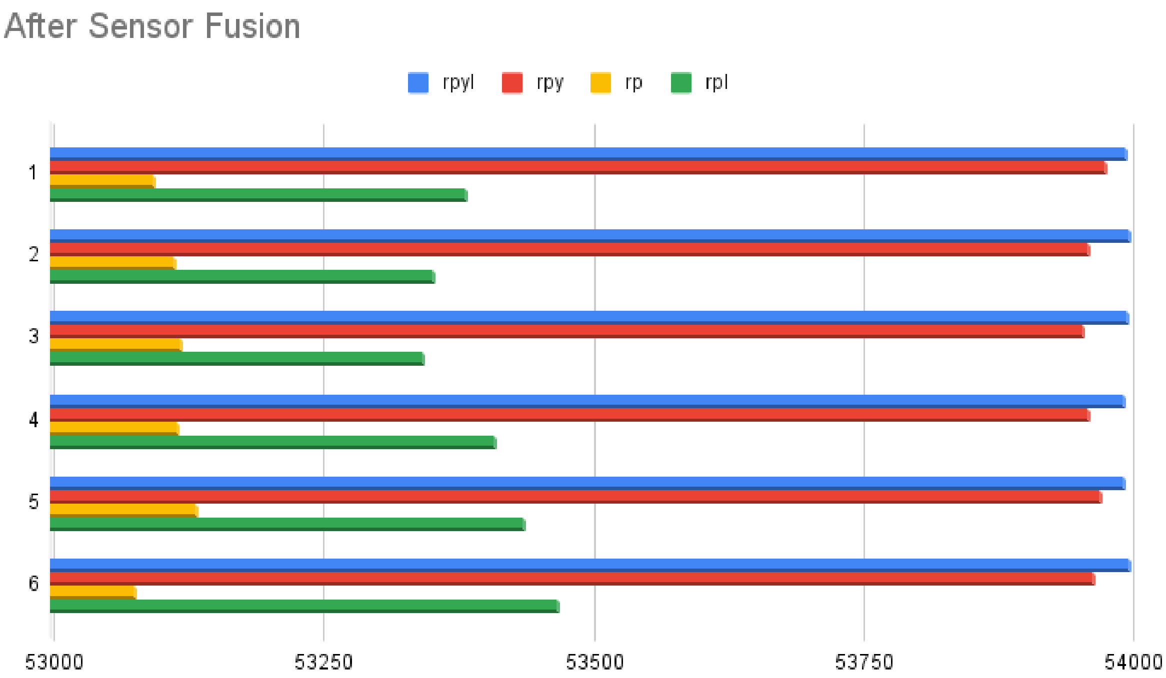

Figure .4.2 AFTER SENSOR FUSION ACCURACIES

Comparing with the previous graph, a clear increase in the accuracy of the HAR algorithm can be seen. The jump is from 39000-49000 to a staggering 53000-54000. Which is 72-90% before sensor fusion to a whopping 99% after sensor fusion. Like mentioned before, the testing size of the datasets is 54000, and changing the size did not result in much change in the accuracies, so we went with the largest size possible. 9 dataset permutations with cross validation were being obtained, but only the first 6 were used, so as to get better visibility of data in the plots. The accuracy in those remaining permutations was also identical.

after						
Attributes	**1**	**2**	**3**	**4**	**5**	**6**
rpyl	53995	53998	53997	53993	53994	53998
rpy	53976	53960	53955	53960	53972	53965
rp	53093	53113	53119	53116	53133	53076
rpl	53383	53353	53343	53410	53436	53468

Table .4.2 AFTER SENSOR FUSION ACCURACIES

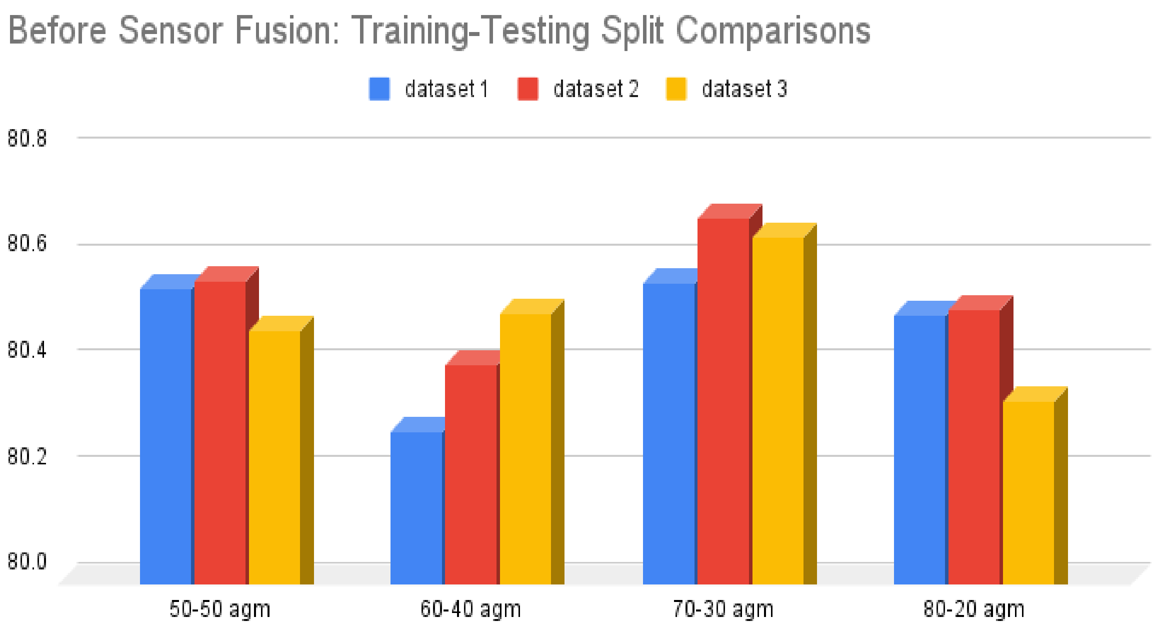

Figure 4.3 BEFORE SENSOR FUSION TRAINING/TESTING SPLIT

After trying different combinations of attributes for both before and after sensor fusion, the next factor we chose to analyze was the training/testing split of the dataset. 4 splits were chosen, 50-50, 60-40, 70-30 and 80-20. The earlier trials were all done on 80-20 splits. All the current trials were done using 3 attributes only (a, g and m).

Before Sensor Fusion, the change in the training/testing split didn't cause much change in the accuracy of the HAR algorithm, but looking at the plots, it can be seen that 70-30 is a better split than the rest, by a small margin.

The accuracies all hovered around 80%.

dataset	50-50 agm	60-40 agm	70-30 agm	80-20 agm
1	80.545	80.273	80.554	80.494
2	80.56	80.4	80.677	80.503
3	80.465	80.497	80.64	80.331

Table 4.3 BEFORE SENSOR FUSION TRAINING/TESTING SPLIT

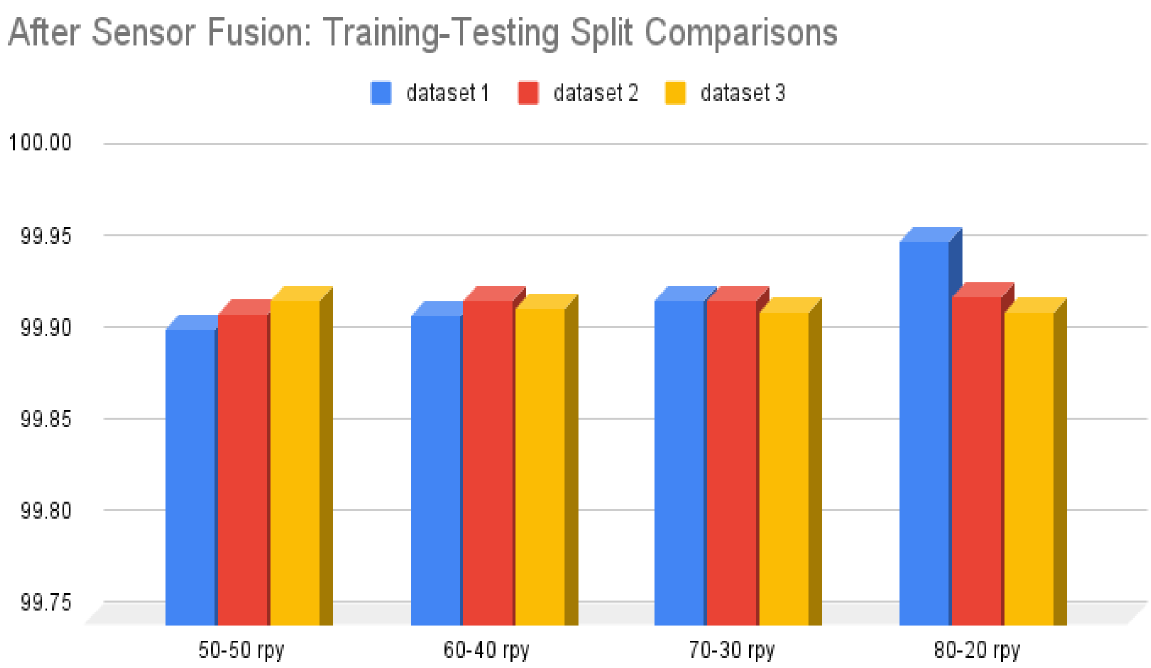

Figure 4.4 AFTER SENSOR FUSION TRAINING/TESTING SPLIT

Similar to Before Sensor Fusion, After Sensor Fusion results between various training/testing splits did not show much difference either, but the best one of the bunch would be the 80-20 split.

Even for After Sensor fusion, only 3 attributes were chosen (r, p, y).

The accuracies all hover around high 99%.

With more time, and different datasets, we can further test out if this trend continues or not.

Train/Test Split	1	2	3
50-50 rpy	99.907	99.915	99.923
60-40 rpy	99.914	99.923	99.918
70-30 rpy	99.923	99.922	99.916
80-20 rpy	99.955	99.925	99.916

Table 4.4 AFTER SENSOR FUSION TRAINING/TESTING SPLIT

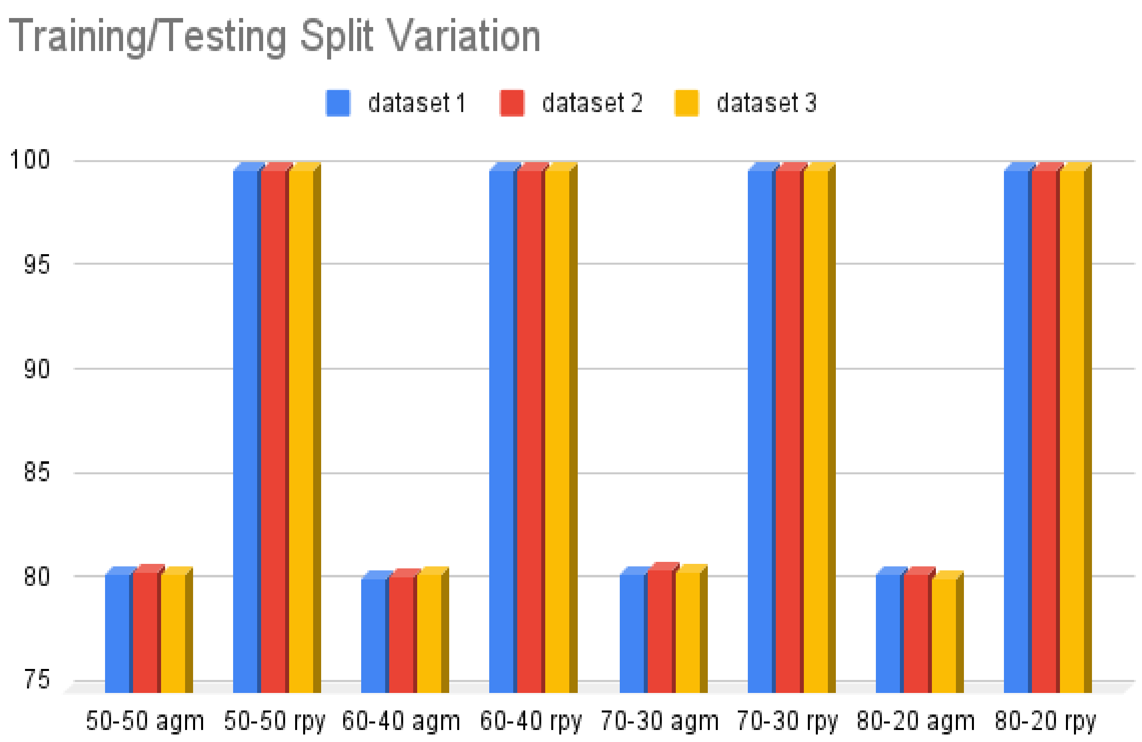

Figure 4.5 TRAINING/TESTING SPLIT VARIATION

Same data as earlier, just put together to highlight just how much difference there is between the accuracies before and after sensor fusion.

Here the difference between the before and after is almost 19% in accuracy.

dataset	50-50 agm	50-50 rpy	60-40 agm	60-40 rpy	70-30 agm	70-30 rpy	80-20 agm	80-20 rpy
1	80.545	99.907	80.273	99.914	80.554	99.923	80.494	99.955
2	80.56	99.915	80.4	99.923	80.677	99.922	80.503	99.925
3	80.465	99.923	80.497	99.918	80.64	99.916	80.331	99.916

Table 4.5 TRAINING/TESTING SPLIT VARIATION

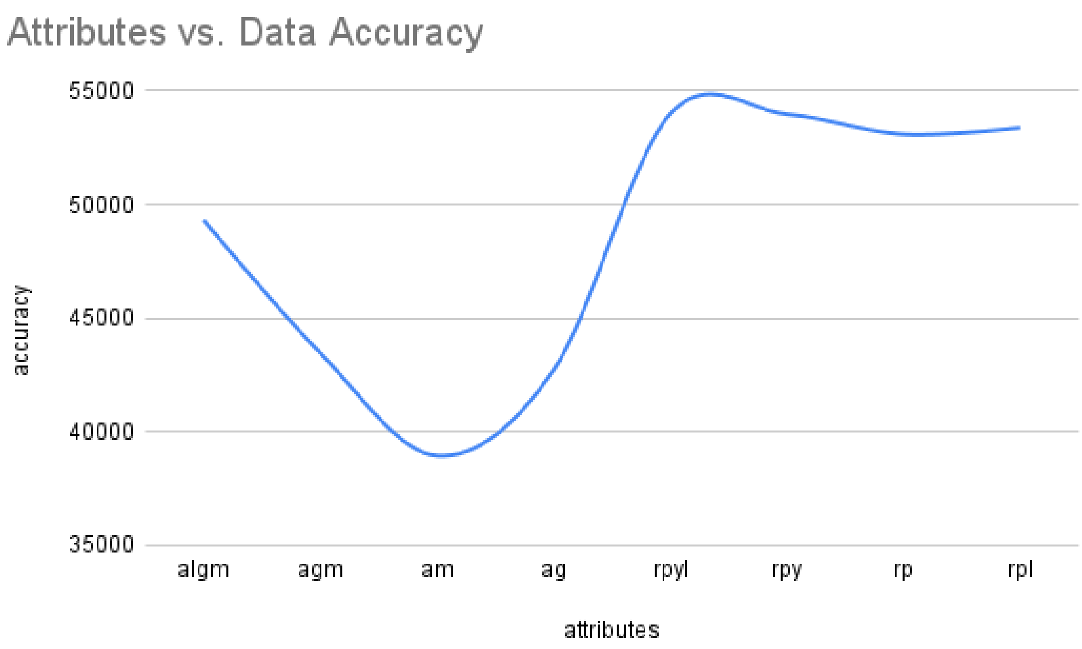

Figure 4.6 ATTRIBUTES VS DATA ACCURACY

Taking 2 permutations of a dataset of size 54000 and running the HAR algorithm with and without sensor fusion, and altering the number of attributes in both the before and after, the following data was obtained.

Clearly there is a big difference between the HAR accuracy before and after sensor fusion, but there is also significant change occurring when the number of attributes are changed before sensor fusion. This change isn't as significant for after sensor fusion.

The peak accuracy is achieved at RLPY while the lowest point is at AM. This supports both the claims that sensor fusion should result in higher accuracy of prediction and that more attributes also results in higher accuracy of prediction.

attributes	data 1	data 2
algm	49318	49282
agm	43467	43472
am	38952	38903
ag	42728	42815
rpyl	53995	53998
rpy	53976	53960
rp	53093	53113
rpl	53383	53353

Table 4.6 ATTRIBUTES VS DATA ACCURACY

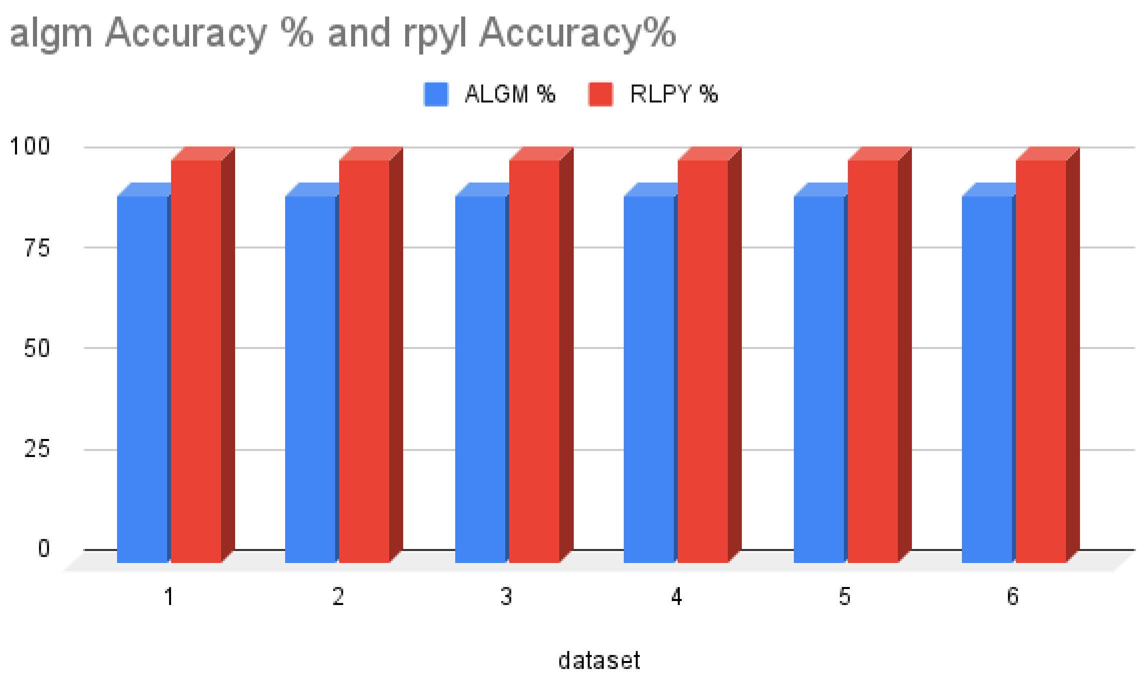

Figure 4.7 ALGM VS RLPY ACCURACY %

The peak accuracies were achieved when 4 attribute data was used in both before and after sensor fusion.

For before, the peak is roughly 91% when A, L, G and M are all used.

For after, the peak is roughly 99.9% when R, L, P and Y are all used.

(A: Accelerometer, G: Gyroscope, M: Magnetometer., L: Linear Acceleration)

(R: Roll, P: Pitch, Y: Yaw)

Even on multiple tests, the respective accuracies remained identical.

dataset	algm	rpyl	ALGM %	RLPY %
1	49318	53995	91.32962963	99.99074074
2	49282	53998	91.26296296	99.9962963
3	49269	53997	91.23888889	99.99444444
4	49217	53993	91.14259259	99.98703704
5	49237	53994	91.17962963	99.98888889
6	49326	53998	91.34444444	99.9962963

Table4.7 ALGM VS RLPY ACCURACY %

RESULTS

The results after the completion of the project were as follows:

1. Successful, accurate, and precise prediction of Human Activities Based on a particular given HAR Dataset.

2. Classification Rate Tables of single and fused sensor values as well along with tables with respect to ML algorithms such as KD tree and base KNN based on different training/testing split.

3. Analysis of all the various results of all Classification tables and prove the superiority of Sensor Fusion accuracies over Individual Sensor accuracies.

CONCLUSIONS

So far the analysis shows a clear increase in the accuracy of the HAR algorithm when sensor fusion is implemented. This increase is the highest when 4 attributes (Roll, Pitch, Yaw and Linear acceleration) are all used in the prediction after sensor fusion. The change is almost identical in case of all training/testing splits.

Currently comparisons done to see which attributes contribute most towards the increase in accuracy, i.e., head to head comparison of attributes was not done to a very large extent due to time constraints, but with further collection and analysis of such data, we can come to proper conclusions as to which attributes are the most significant in increasing the accuracy of prediction.

From the acquired results, at the bare minimum it can be concluded that sensor fusion is indeed superior in prediction of activities.

FUTURE WORK

- Reworking our implementation to adapt real-time data collection and prediction to make the application more usable in real life cases.

- Implementing Ensemble Learning. This will also help us analyse just how much accuracy can increase while using different methods and ML algorithms.

- Adding more class labels or activities, to diversify the dataset which is being used for training and testing.

- Running more test cases to collect even more data for analysis and visualization of that data. One thing that can be done immediately is automating the data collection process for the classification rates.

ROLES

- **Chekuri Varma**:
  Working on types of sensor fusion and implementation of sensor fusion in python.

- **Pradyumn**:
  Research and work on the implementation of HAR algorithm in Python.

- **Vikram**:
  Analysis of the data after testing is completed, and its visualization.

TIMELINE

25/8/2022	Finalized Project Topic and Started Finding Research Papers.
8/9/2022	Finalized Datatset along with parameters and finalized other helpful parameters as well.
14/9/2022	Started studying research papers and identified topics/concepts. (written in Literature Review).
20/9/2022	Started Learning about ML algorithms i.e., why and how they are used on datasets and what are the different classifiers that are used for HAR.
30/9/2022	Worked on Data extraction of dataset using python, applied an ML algorithm(KNN) on the dataset to understand how it works.

MIDSEM

14/10/2022	Midsem Report and Presentation
October	IMPLEMENTATION
November	Results and Analysis

BIBLIOGRAPHY

[1] C. V. San Buenaventura and N. M. C. Tiglao, "Basic Human Activity Recognition based on sensor fusion in smartphones," 2017 IFIP/IEEE Symposium on Integrated Network and Service Management (IM), 2017, pp. 1182-1185, doi: 10.23919/INM.2017.7987459.

[2] Sebastian Munzner, Philip Schmidt, "CNN-based Sensor Fusion Techniques for Multimodal Human Activity Recognition", Nweke et al. Hum. Cent. Comput. Inf. Sci. (2019) 9:34, https://doi.org/10.1186/s13673-019-0194-5

[3] Muhammad Shoaib, Stephan Bosch Ozlem Durmaz Incel, Hans Scholten, "Complex Human Activity Recognition Using Smartphone and Wrist-Worn Motion Sensors", Department of Computer Engineering, Galatasaray University, Ortakoy, 34349 Istanbul, Turkey; 24 March 2016

[4] K.R.Baskaran, M.N.Saroja, "Machine Learning Algorithms for Human Activity Recognition", International Journal of Innovative Technology and Exploring Engineering (IJITEE), ISSN: 2278-3075, Volume-8 Issue-12S, October 2019

[5] Henry Friday Nweke, Ying Wah The, Ghulam Mujtaba, "Multi-sensor fusion based on multiple classifier systems for human activity identification", Nweke et al. Hum. Cent. Comput. Inf. Sci. (2019) 9:34

[6] Seungeun Chung, Jiyoun Lim, Kyoung Ju Noh, "Sensor Data Acquisition and Multimodal Sensor Fusion for Human Activity Recognition Using Deep Learning", Contents Basic Technology Research Group, Electronics and Telecommunications Research Institute, Daejeon 34129, Korea; kusses@etri.re.kr (J.L.); kjnoh@etri.re.kr (K.J.N.); ggkim@etri.re.kr (G.K.); Published: 10 April 2019

[7] M. Shoaib, H. Scholten and P. J. M. Havinga, "Towards Physical Activity Recognition Using Smartphone Sensors," 2013 IEEE 10th International Conference on Ubiquitous Intelligence and Computing and 2013 IEEE 10th International Conference on Autonomic and Trusted Computing, 2013, pp. 80-87, doi: 10.1109/UIC-ATC.2013.43.

[8] Henry Friday Nweke, Ying Wah Teh, Uzoma Rita Alo, Ghulam Mujtaba, "Analysis of Multi-Sensor Fusion for Mobile and Wearable Sensor Based Human Activity Recognition"

[9] M. Webber and R. F. Rojas, "Human Activity Recognition With Accelerometer and Gyroscope: A Data Fusion Approach," in IEEE Sensors Journal, vol. 21, no. 15, pp. 16979-16989, 1 Aug.1, 2021, doi: 10.1109/JSEN.2021.3079883.

[10] Gravina, R., Alinia, P., Ghasemzadeh, H. and Fortino, G., 2017. Multi-sensor fusion in body sensor networks: State-of-the-art and research challenges. Information Fusion, 35, pp.68-80.

[11] Montella, Corey. (2011). The Kalman Filter and Related Algorithms: A Literature Review.

[12] Data Fusion with 9 Degrees of Freedom Inertial Measurement Unit To Determine Object's Orientation By Long Tran, Senior Project Electrical Engineering Department, California Polytechnic State University, San Luis Obispo, June 2017.

[13] Sensor Fusion for Recognition of Activities of Daily Living, Jiaxuan Wu , Yunfei Feng , and Peng Sun, Department of Computer Science, Iowa State University, Ames, IA 50010, USA; College of Computer Science and Engineering, Northeastern University, Shenyang 110000, China.

[14] Nweke, Henry & Wah, Teh & Mujtaba, Ghulam & Al-Garadi, Mohammed. (2018). Data Fusion and Multiple Classifier Systems for Human Activity Detection and Health Monitoring: Review and Open Research Directions. Information Fusion. 46. 10.1016/j.inffus.2018.06.002.

[15] H. Zhao and Z. Wang, "Motion Measurement Using Inertial Sensors, Ultrasonic Sensors, and Magnetometers With Extended Kalman Filter for Data Fusion," in IEEE Sensors Journal, vol. 12, no. 5, pp. 943-953, May 2012, doi: 10.1109/JSEN.2011.2166066.

[16] Robottini, "Kalman filter vs Complementary filter", Blog: Robottini-Altervista, 2011. [Online]. Available: https://robottini.altervista.org/kalman-filter-vs-complementary-filter. [Accessed: 5-Dec-2022].

[17] Lauszus, "A practical approach to Kalman filter and how to implement it", Blog: TKJ Electronics, 2012. [Online]. Available: http://blog.tkjelectronics.dk/2012/09/a-practical-approach-to-kalman-filter-and-how-to-implement-it/#comment-57783. [Accessed: 5-Dec-2022].