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Machine Learning Empowered Multimodal Sensor Fusion for Enhanced Human Activity Recognition

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Abstract

In this work, we lead an efficient examination of the particulars of information gathering and on-body sensor area for Human Activity Recognition (HAR) frameworks. We develop a testbed with eight Inertial Measurement Units (IMU) sensors on the body and an Android mobile gadget to catch activity information. To work with the preparation of a deep learning model on human activity information gathered in both controlled and genuine settings, we make a Long Short-Term Memory (LSTM) network structure. As per the trial's discoveries, activity information from four sensors at the midsection, right lower leg, and the two wrists at a testing pace of just 10 Hz is satisfactory to recognize activities of daily living (ADLs), like eating and driving. We utilize a two-level ensemble model to total the class-probabilities of a few sensor modalities, and we show that characterization execution might be upgraded by utilizing a classifier-level sensor fusion procedure. We foster custom loads for multimodal sensor fusion that consider the novel attributes of individual activities by evaluating the exactness of every sensor on different kinds of activity. Perceiving human activity is critical for various applications. This examination presents an element choice-based structure for human activity recognition. Tracking down the most essential attributes to recognize human activity is the objective. To enhance the broadly utilized factual highlights, we first build a bunch of extra qualities (alluded to as actual elements) in view of the *actual parts of human movement. A solitary layer highlight determination structure is inherent request to deliberately look at what the actual properties mean for the recognition framework's presentation.*

Keywords: *Machine Learning, Multimodal Sensor Fusion, Human Activity Recognition, Mobile Sensing, Sensor Position, Classifier-Level Ensemble, Long Short-Term Memory Network, Deep Learning.*

1. INTRODUCTION

1.1. Machine Learning and Human Activity Recognition

Human Activity Recognition (HAR) has emerged as a new field of study in mobile and wearable computing due to the increasing usage of wearable technology. Understanding people's patterns of behaviour or ingrained habits through the recognition of human activity is crucial for the creation of numerous user-centric applications, including AR/VR, video streaming, human-computer interaction, surveillance, and healthcare systems. While a great deal of examination has been finished in the field of PC vision on activity recognition, its utilization is confined to explicit circumstances where pre-introduced cameras have a predefined point of view and enough goal.

On the other hand, because wearable sensors are widely used and do not require infrastructure support, they enable continuous sensing throughout daily activities without spatiotemporal limitations. Despite the fact that wrist-mountable fitness trackers and smartwatches are more popular in the marketplace because they are more convenient to use, there is still disagreement about where the sensors should be placed and how exactly their data is acquired. For example, there are numerous publicly accessible datasets that gather information from Inertial Measurement Units (IMU) mounted on the arm, leg, waist, ear, and chest with different parametric configurations.

The specifics of data gathering may change based on the kinds of activities that are the subject of the study. For instance, a waist-mounted sensor with a modest sample rate would be adequate to identify basic motions (i.e., coarse granularity) like sitting and walking. Then again, a solitary midsection mounted sensor probably won't give a satisfactory level of execution for distinguishing

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combinatorial activities with better granularity, like eating and driving. In this work, we limit the extent of recognition to major human activities that incorporate activities of Daily Living (ADLs), like eating and driving.

Through the examination on the fundamental unit of activity, we desire to secure a more logical and underlying comprehension of daily schedules or individual lives. Past HAR writing depends on stochastic interaction and measurements prescient demonstrating strategies (e.g., choice tree, kNN, SVM). Therefore, in order to analyse data and extract features that accurately reflect the characteristics of activity datasets, a high level of expertise in medical and social research related to human activities is required.

In this work, we utilize a deep brain network engineering to distinguish human activity from natural information input. This design has shown empowering results when used to decipher human activity without the requirement for broad information pre-handling to separate elements. This exploration presents an underlying examination concerning the best area for sensors and the points of interest of their information gathering involving a deep learning calculation for HAR. Our objective is to identify the best locations for on-body sensor combinations and data sampling frequencies that will have the least negative impact on the data collection process.

Eight IMU sensors are mounted on various regions of the human body as part of our testbed system, which gathers activity data in controlled and real-world conditions. Then, a Long Short-Term Memory (LSTM) brain network classifier is utilized to prepare and dissect it. We utilize the spinner and magnetometer notwithstanding the accelerometer information to utilize a classifier-level sensor fusion procedure on multimodal sensor information. The base-student forecast yields are combined with preparing information from each kind of sensor on the LSTM network to make a stacked meta-include.

The meta-student trains on the meta-highlights by using an Irregular Backwoods choice tree as an aggregator model. Eventually, utilizing the refreshed multimodal sensor information, our two-level stacking and casting a ballot ensemble model gives expectations. We evaluate the recognition exactness of every sensor methodology on different activity types to reflect shifted attributes while

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distinguishing ADLs utilizing numerous modalities. We then process a modified weight that best suits every remarkable activity.

1.2.Objectives

- To make areas of strength for a learning system for multimodal sensor fusion determined to work on the accuracy and steadfastness of the discovery of human activity in different settings.
- To enhance the real-time performance of multimodal sensor data integration for human activity recognition through the optimisation of feature extraction and fusion approaches within a machine learning framework.
- Toresearch cutting-edge machine learning architectures and techniques to enhance multimodal sensor fusion.
- Toincrease the machine learning models' interpretability and explainability when used in multimodal sensor fusion, encouraging openness and confidence in the system that recognises human activities.

2. LITERATURE REVIEW

Mannini et al. (2013)recommended utilizing support vector machine (SVM) classifiers related to activity information accumulated from sensors arranged at the wrist and lower leg. Given the results that were acquired, it was found that the data taken at the ankle was superior to the data collected at the wrist by a factor of ten percent.

S. Balli, E. A. Sağbaş, and M. Peker (2019) Footsteps, gyroscope acceleration, and heart rate were among the information that was used in order to identify human activities. Principal component analysis (PCA) was the technique that was utilised in order to extract the features. In C4.5, random forest (RF), K closest neighbours algorithm (KNN), and support vector machine (SVM) were the classification algorithms that were utilised.

Aiguo et al. (2016)compared the use of k-nearest neighbours and Nave Bayes classifiers to the usage of accelerometers and gyroscopes independently. Experiments have shown us that combining accelerometers and gyroscopes increases categorization accuracy. Compared to KNN,

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Naive Bayes produced an overall accuracy of 90.1% and 87.8%. Although wearing a lot of sensors all the time would be impractical, a lot more sensors could enhance accuracy. The system would cost more if additional sensors were included.

Biagetti et al. (2018)a human activity recognition system that is composed of wireless sensor network nodes (biological and accelerometer) and is transferred to a computer for the purpose of data processing was proposed. When the KNN classifier was applied, the results attained an overall accuracy of 85.7%.

Yang and Zhang (2018)suggests a wearable system that is operationally categorised and looks like a wristwatch. This system would be worn on the hand. Following the extraction of the time and recurrence space properties of the accelerometer information, the choice tree approach is then used to break down the information. Additionally, their modelling can be carried out in real time on the low-power microcontroller known as the STM32L. Even though there are only a few actions taken into consideration (walking, sitting, jumping, cycling, and jogging), the accuracy is lower than fifty percent.

Bao et al. (2004) There were five biaxial accelerometers that were worn by the members of the research team in a range of places, including the hip, wrist, arm, ankle, and thigh area. The decision tree classifier was able to accurately classify twenty different activities with an accuracy rate of 84%. On the other hand, the restriction was the increasing number of sensors, the data on moving objects, and the accelerometer that was set to the orientation that was defined.

Piyush Gupta et al. (2015) developed a method for activity identification and feature selection using a 3-axis accelerometer worn on a belt. They found that wrapper-based feature selection outperformed filter-based feature selection using Nave Bayes and KNN. Only seven volunteers were used for the data gathering. Each was young (ages 22 to 28). In recent years, a number of scientists have investigated the potential of using a single accelerometer to gather the signal required for activity identification.

3. RESEARCH METHODOLOGY

3.1.Testbed System

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We build a testbed framework that purposes on-body IMU gadgets to gather persistent movement information. We utilize an IMU sensor called MPU-9250, which can test information from a tri-hub accelerometer, spinner, and magnetometer at up to 100 Hz recurrence. Every IMU gadget is carried out on an ESP8266 Miniature Regulator Unit (MCU) with a Wi-Fi networking and nRF24L01 RF module, as delineated in Figure 1a. The MCU is controlled by a miniature USB battery-powered Li-Po battery that reaches from 3.7 V to 1200 mAh. It has been observationally affirmed that the significant battery limit guarantees at least 12 hours of persistent information assortment at the most elevated testing recurrence. IMU gadgets are expected to be joined to a guinea pig's midsection, chest, upper arms, and lower legs notwithstanding their wrists. Gadgets are affixed to the body utilizing clinical Velcro lashes to limit signal commotion.

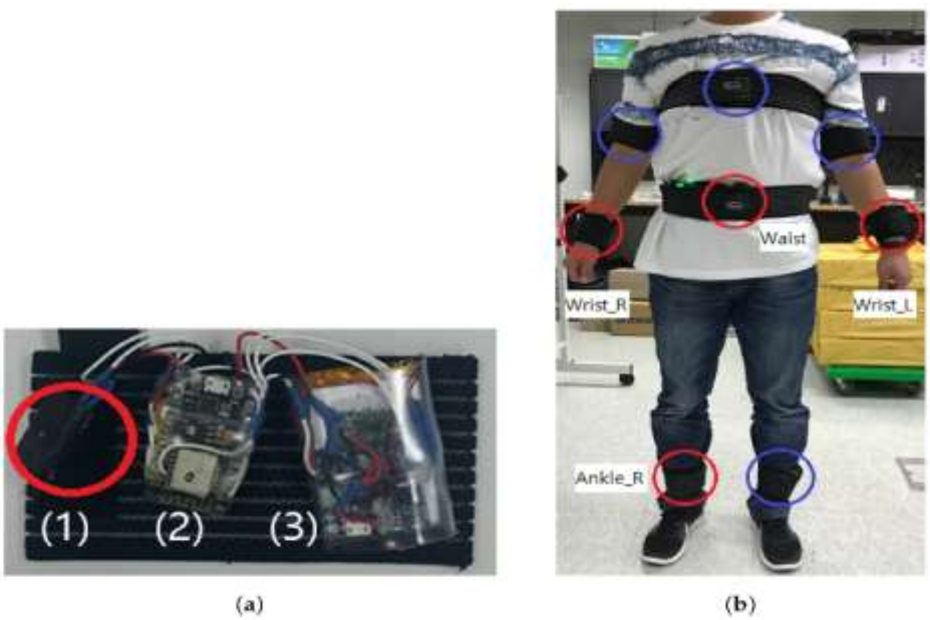

Figure 1: Arrangement of the testbed. (a) A body-worn Inertial Measurement Unit (IMU) gadget is contained three sections (b) Out of the eight body-worn sensors (displayed as circles).

We set up a transfer module that fills in as an IMU gadget to gadget center for information gathering. Since each IMU gadget gathers a ton of activity information, we chose to utilize the Wi-Fi convention to guarantee dependable and fast information transmission over high limit network channels. To begin time-synchronized one-to-numerous correspondence channels between IMU gadgets, the hand-off module first transceives activity orders between IMU gadgets utilizing the

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RF convention. Using the soft-AP choice, the hand-off module can make an impromptu Wi-Fi network and afterward recover activity information from every IMU gadget. Endless supply of information assortment, the hand-off module utilizes the Wi-Fi network to send the arranged information to an Android mobile gadget.

3.2.Experiment Protocols

We assembled activity information from five scientists at an exploration foundation as a test project. Two men and three ladies, ages 35 to 50, and levels going from 158 to 177 cm, made up the guineas pigs. Each participant had no physical disabilities and was right-handed. The test volunteers gave their informed consent before beginning the experiment and were told to walk freely to carry out their daily tasks. Three separate business days were utilized for the examination, yielding a sum of three hours of activity information for each subject. Two distinct methods for collecting data were created: one for a controlled setting and the other for the real world.

Two trials in a certifiable setting were done during people groups' standard mid-day breaks. Since the guineas pigs were not given any guidelines on the investigation method, they acted normally and to the surprise of no one. The whole investigation meeting was, a physically named the seen by a teacher marks for the connected activities. Table 1 gives an outline of the successive activities named all through a full circle between the work environment and a café.

Table 1: Protocol for the experiment in a real-world setting (two iterations).

No.	Activity	Duration (min)
1	Walking Downstairs	4
2	Walking	6
3	Driving or Moving	4
4	Sitting	6
5	Eating	19
6	Driving or Moving	4
7	Walking	11
8	Sitting	4

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9	Walking	21
10	Walking Upstairs	4
	Total	83

Then again, during the controlled climate situation, a teacher gave directions for each target activity, and guineas pigs complied. To accumulate the activity names displayed in Table 2, one cycle of the analysis is completed.

Table 2: Protocol for the experiment in a controlled setting (one iteration).

No.	Activity	Duration (min)
1	Standing	6
2	Sitting	4
3	Eating	11
4	Lying	4
5	Walking Downstairs	4
6	Walking Upstairs	5
	Total	34

3.3.Final Testbed Configuration

We created eight body-worn sensors in the early stages of the system design, as seen in Figure 1b. In the early research, we found that using too many sensors interferes with the process of determining the distinctive feature of each activity record. Furthermore, there was no discernible difference between the two ankle sensors' ability to identify the different activities. As a result, we adopted the sensor on the right ankle and disregarded the sensors on the upper arms for the same reason. The chest sensor caused a great deal of discomfort for the participants, therefore we removed it from the final testbed design to ensure its viability.

4. DATA ANALYSIS AND RESULT

We remove the marks related with the activity information, and afterward utilize a fixed-width sliding window with a 51% cross-over to section the information. An essential unit for information

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examination that can be perceived as the activity goal is the sliding window size. On the off chance that discrete activities are contained in a solitary section of activity information, we might have the option to deal with a surge of activity information as one stage and find long-term examples or patterns by utilizing an extended window size, yet we will most likely be unable to extricate particular properties of every activity.

Alternately, a little window size may be suitable for zeroing in on additional fragile crude movements that happen rapidly, especially with regards to low-level hand signals like reach, snatch, and delivery. We want to distinguish coarser-grained developments related with movement, which normally goes on for a couple of moments. 5.11 s-long window size was exactly utilized in before work in the HAR writing. Utilizing the regular free-living rhythm of 75 ± 5 stages each moment as a pattern, we use one walk cycle's length, which differs somewhere in the range of 1.45 and 1.70 s. Hence, we utilize an alternate sliding window beginning from 1.4 to 5 s to quantify the recognition precision. The 2.5 s-long sliding window performs better compared to other boundary values in our dataset, as shown by the outcome in Figure 2.

Table 3: Accurate recognition depending on sliding window length.

Window size (sec)	Sampling rate = 100Hz
1.4	91.32
2.5	92.67
5	90.79

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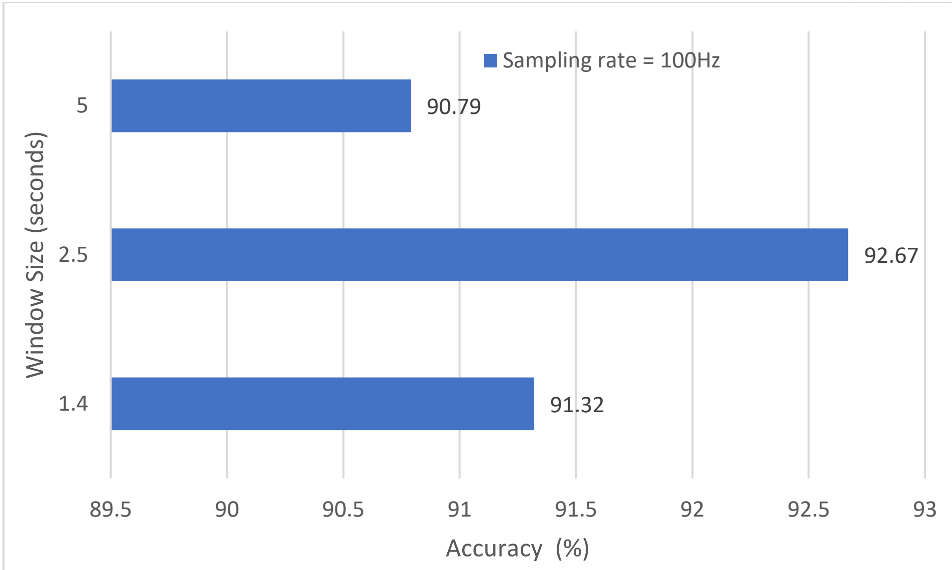

Figure 2: Accurate recognition depending on sliding window length.

Compared to feature data, which typically results in a drop in classification accuracy due to pre-processing transformations, raw sensor data can yield higher inference results from deep learning classification models. In this way, without the requirement for additional component designing, crude sensor information is provided straight into LSTM cells for offline activity grouping.

Class irregularity is a run of the mill issue in grouping since most datasets do exclude the very same number of examples in each class. This peculiarity is likewise present in regular human activity. A popular metric in situations when there is a class imbalance is the F1-score. However, in the context of multi-class classification, the accuracy measured by the ratio of properly predicted observations to total occurrences is similar to micro-averaging the F1-score. The imbalanced sample distributions across classes are reflected in Micro-F1, which gives the dominating classes greater weight. The large scale averaging F1-score, then again, represents both misleading up-sides and bogus negatives in view of a for every class normal and is a symphonious mean of precision and review measurements.

To fundamentally sum up the outcome to an autonomous dataset, we run the information by means of ten times cross-approval. The dataset is haphazardly separated into ten equivalent estimated subsamples; nine of the subsamples, or 89% of the all out information, are utilized as preparing

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information, and one subsample, or 11% of the activity information, is forgotten about as test information. The framework is tried utilizing a concealed dataset as such. Moreover, we use information expansion to perform leave-one-subject-out (LOSO) cross-approval for reference. This procedure is well known in deep learning research since it requests immense datasets for model preparation. As made sense of in for mark saving expansion, we utilize irregular boundaries and the jittering way to deal with create added substance sensor commotion. To reinforce the flexibility of our deep learning model, we deal with the restricted information accessibility and get a significant measure of preparing information along these lines. The remainder of this work makes benefit of the cross-approval results' mean presentation.

- **Impact of Multimodal Sensor Fusion**

We utilize a stacking ensemble with various blends of sensor modalities for multimodal sensor fusion. To prepare the characterization model, the meta-student acknowledges stacked class-probabilities of every sensor methodology. We utilize the Irregular Timberland calculation as a meta-student for stacking ensembles subsequent to looking at the presentation of kNN, SVM, and Irregular Backwoods, as shown in Figure 3. Moreover, we use casting a ballot ensemble as the meta-student that coordinates sensor information from the accelerometer, spinner, and magnetometer. The class name that the grouping models have anticipated the most often is the last class mark in hard-casting a ballot. On the other hand, soft-casting a ballot estimates the class names that have the most noteworthy class likelihood when the normal of the multitude of classifiers is thought about. While each sensor may perform differently based on the type of activity, weights are established based on each modality's accuracy. As a result, we develop weights based on the attributes of every action.

Table 4: The stacking ensemble's meta-learner models' performance and execution time.

Meta-learner algorithm	F1-score
Random Forest	0.853
kNN	0.848
SVM	0.857

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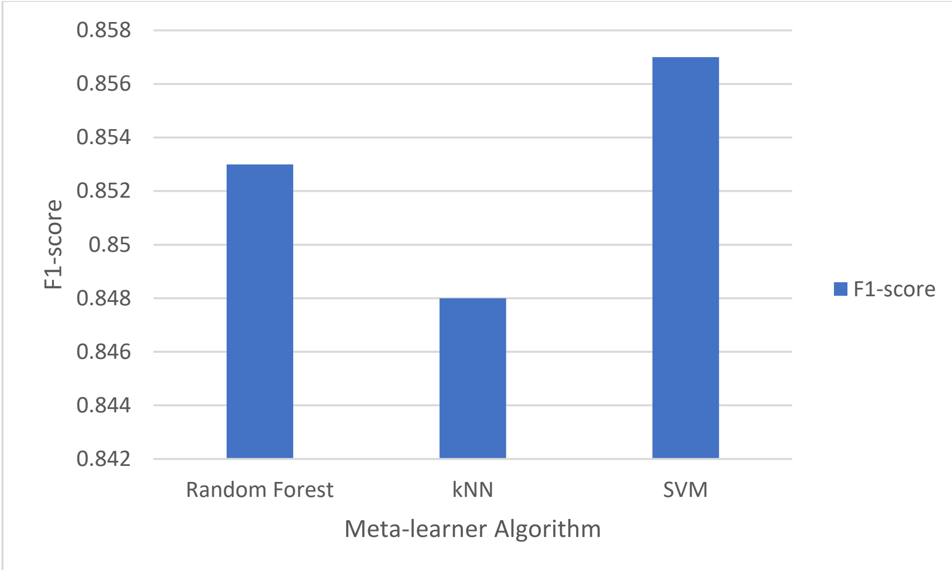

Figure 3: The stacking ensemble's meta-learner models' performance and execution time.

At first, we evaluate how well a solitary sensor methodology acts in activity recognizable proof. The recognition exactness of every sensor information applied to the LSTM base-student model is displayed in Figure 4. Among IMU sensors, the accelerometer plays out the best (93.20%), trailed by the magnetometer (84%) and spinner (75%). Since every sensor recognizes an unmistakable actual property, the commitment to the recognition of ADLs shifts relying upon the activity's qualities. An accelerometer, for example, can be utilized to recognize minute developments by estimating changes in area and speed. An accelerometer is likewise regularly utilized as a flat out direction sensor in the up-down plane by using different tomahawks. A spinner distinguishes changes in rotational speed and direction; notwithstanding, as a result of huge float, accuracy should be accomplished through alignment from a known direction. A magnetometer performs inadequately for fast developments, yet it is useful for determining outright direction from attractive north with negligible float after some time. Thus, the presentation of these multimodal sensors is ordinarily made up for by their mix.

Table 5: Using the LSTM network, determine each sensor modality's recognition accuracy and F1-score measurement.

IMU sensors	Accuracy	F1-score
Accelerometer	93.2	84

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Gyroscope	75	54
Magnetometer	84	65

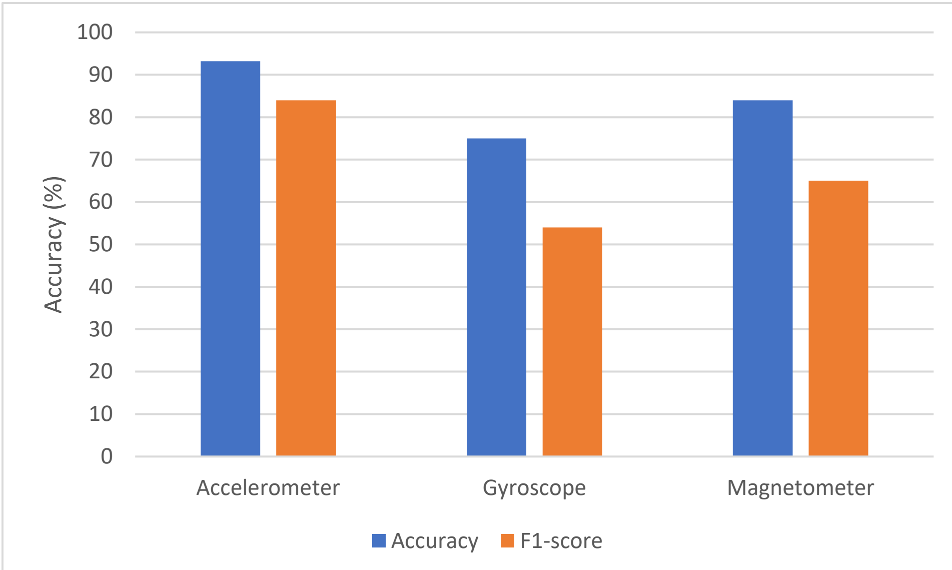

Figure 4: Using the LSTM network, determine each sensor modality's recognition accuracy and F1-score measurement.

5. CONCLUSION

In this examination, we direct an exact examination concerning the particulars of information gathering and on-body sensor area for HAR frameworks. We use a deep learning system to prepare the crude activity information got from both controlled and genuine settings. This framework naturally learns highlights through brain networks without the requirement for heuristic area skill. We determine that low testing rate — as low as 10 Hz — is adequate for the activity recognition by using the LSTM network, which changes transient conditions on the time-series activity information. Low example recurrence grants expanded information assortment for HAR applications, which normally run on asset hungry mobile gadgets, since it diminishes the framework trouble by safeguarding battery and capacity limit. The discoveries of our examination show that main two sensors — joined to the right wrist and right lower leg — can sensibly perceive ADLs, like eating and driving — either as a driver or a traveler. Put another way, it is educated that the functional parametric setting regarding sensor position for extra HAR research be one

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sensor on the top portion of the body and one on the lower half. Besides, we use a two-level ensemble procedure that incorporates stacking and deciding on the multimodal sensor information to look at the impact of sensor fusion and show the improvement in execution. We foster custom tailored loads for sensor modalities that can address the attributes of unmistakable activities by looking at the recognition precision of every sensor on different activity types.

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