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Enhancing Human Activity Recognition With Different AI Models Using Mobile Sensor Data

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Abstract: Human Activity Recognition (HAR) plays a crucial role in health monitoring, smart environments, and human-computer interaction. This study investigates four machine learning models Logistic Regression, Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU) for activity identification using mobile sensor data. The dataset comprises gyroscope and accelerometer readings from smartphones. Preprocessing techniques such as feature extraction, noise reduction, and normalization are applied to enhance model performance. The results indicate that while Logistic Regression provides a reliable baseline, ANN, LSTM, and GRU models outperform it, particularly in capturing temporal dependencies. Among the evaluated models, The GRU model delivers the best performance, achieving an accuracy of 97.2% and a loss of 0.28%.

***Index Terms* – Human Activity Recognition, HAR, Mobile Sensors, Logistic Regression, Artificial Neural Networks, Long Short-Term Memory, GRU, Deep Learning.**

I. Introduction

Our smartphones are the most useful devices we own for daily use, and as technology develops to meet customer expectations and wants, they are getting more and more powerful. Designers add new hardware modules and components to increase the devices' functionality and power. A wide range of built-in sensors is found in most smartphones, as they greatly enhance the device's functionality and its capacity to sense the environment [1]. This enables the collection of enormous volumes of information about people's daily lives and activities, as seen in Fig. 1. In addition, these gadgets have sensors for light, GPS, microphones, cameras, accelerometers, gyroscopes, compass, and proximity 1,2,3].

- Gyroscope: Tracks the smartphone's movements in three dimensions. Flipping the phone over silences calls and other features, such as games and navigation.
- Accelerometer: The accelerometer is a key sensor in smartphones used to measure acceleration forces. Its primary function is to detect the device's orientation and motion in three dimensions.
- Proximity Sensor: Utilizes electromagnetic fields to detect nearby objects without direct contact. It helps prevent accidental touches on the phone screen and can also detect hand gestures.
- Brightness Sensor: It senses ambient light levels and adjusts the screen brightness accordingly, ensuring an optimal viewing experience while conserving battery life. In smart homes, these sensors are sometimes used to adjust lighting based on the environment [3].

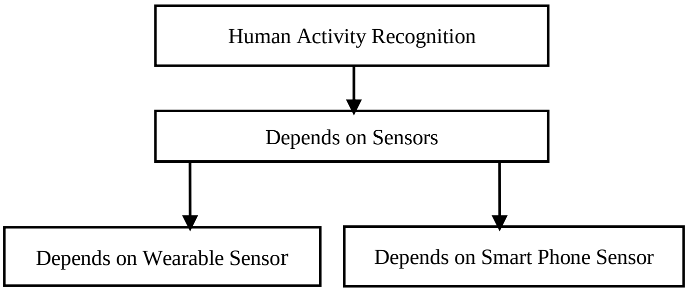

Fig. 1. Approaches employed for human activity recognition through Sensor

1.1 Challenges in Activity Recognition Through Smartphone's

The quantity of sensors to select: Selecting the appropriate sensors for activity recognition requires careful consideration of multiple factors. These considerations include user comfort, power consumption limitations, accuracy requirements, and environmental variability [2].

Place of wearable sensors and smartphones: Wearable sensor placement—on wrists, chests, or waists, for example—can have a big impact on the consistency and accuracy of data collection in activity recognition. Variability brought forth by user location variations in sensors may have an effect on the dependability of activity recognition systems. This variation highlights the requirement for uniform rules for sensor positioning or flexible calibration techniques in order to preserve dependability among a wide range of users [4].

Sensor requirements: The precision and accuracy of sensors (such gyroscopes and accelerometers) have a direct impact on the caliber of the information gathered. The consistency and dependability of activity recognition might be impacted by differences in sensor quality between various smartphone models or sensor manufacturers [1].

II. Literature Review

In their study [7], the authors applied a Multi-Layer Perceptron Classifier to categorize human activities using the UCI HAR dataset, focusing on principal components. They observed that using 70 principal components, the Multi-Layer Perceptron achieved an accuracy of 96.17%, whereas using 561 original features, the accuracy rose to 98.11%. This reduced the model building time from 658.53 seconds to 128.00 seconds.

The author [8] selected Nearest Neighbor as the lightweight classifier, and sensor fusion increased its overall accuracy. An accelerometer and gyroscope combination produced the greatest results, and it concluded that a selection of eight characteristics was adequate for identification. The K-nearest Neighbor technique was used by the authors of a study in to categorize six distinct human activity identification tasks. An Android smartphone with an accelerometer was used to gather the data, which MATLAB was used to process.

The author [9] extensively examines how motion sensors behave when detecting human activity using smartphones. They use a cycle detection technique to segment the data sequence into activity units. These units are then characterized using features from time, frequency, and wavelet domains. The evaluation assesses effectiveness through F-score metrics across different sensor placements, user sensitivities, stability with various sensor combinations, and effects of data imbalances. The analysis is based on 27,681 sensor samples collected from 10 participants. The results indicate that each person has distinct movement patterns, with the customized model achieving an F-score of 95.95% and the generalized model achieving 96.26%.

The author [10] introduces a new unsupervised learning method for Human Activity Recognition (HAR) using smartphone sensor data, particularly in scenarios where the number of activities is ambiguous. The study shows that this approach achieves high accuracy in activity recognition by dynamically selecting parameters or the number of clusters (k) based on the CH index.

In this study, [11] the accelerometer sensor that is built into smartphones was utilized by the author as a method for activity identification. The frequency and temporal domains are used to select the signal's features. The most important aspects that can be utilized to categorize human activities are then extracted using Principal Component Analysis (PCA), which lowers the dimensionality of the features. The observed results, with rates of 96.11% and 92.10%, respectively, demonstrate that although frequency-domain features are more accurate, the identification rate of features based on PCA is greater.

III. METHODOLOGY

As demonstrated in Fig. 2, The architecture of the Human Activity Recognition (HAR) system consists of four primary components: Data Acquisition, Data Preprocessing, Feature Extraction, and Activity Classification.

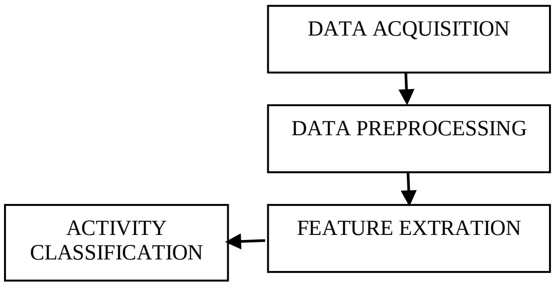

Fig. 2. Proposed Methodology

3.1 Data Acquisition: Data collection entails the core task of gathering and saving sensor data, illustrated in Fig. 3 [2, 5, 8].

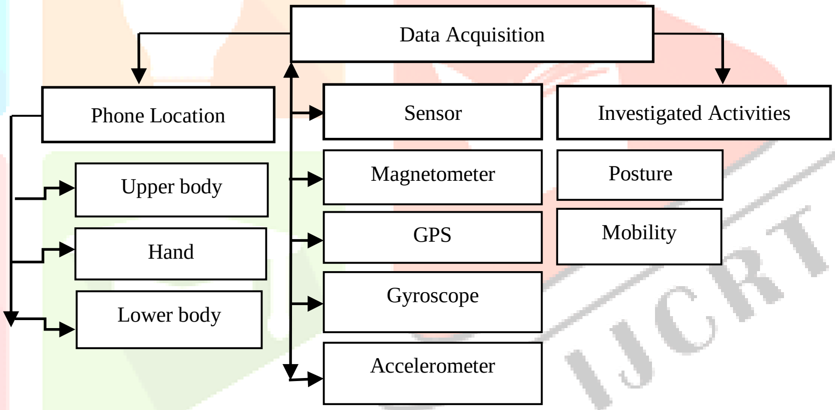

Fig. 3. Data Collecting Technique using mobile phones

3.2 Data Preprocessing: During the data preprocessing phase, the main objective is to filter signals in order to eliminate irrelevant or redundant information [6, 9].

3.3 Feature Extraction: Feature extraction is a key step in the transformation of segmented data, which is especially important when working with inertial sensors. These sensors' raw data, which are shown as signals, are inappropriate for usage directly with machine learning algorithms [5]. The objective of this procedure is to extract the signal's temporal and frequency domain features, which are crucial for identifying activities. Frequency-domain properties include things like peak power, peak frequency, spectral entropy, and different frequency bands, whereas time-domain qualities include things like median, skewness, kurtosis, variance, average, and range [6][20].

3.4 Activity Classification: Activity Classification, addresses strategies for learning that leverage the preprocessed data effectively.

III. DATASET

UCI-HAR Dataset

The Dataset involved Twenty-Eight participants aged Nineteen to Forty-Eight, each wearing a Samsung Galaxy S II phone around their waist. They performed six tasks: Walking, Sitting, Standing, Lying, and Walking Up and Down. The smartphone's combined accelerometer and gyroscope recorded 3-axial angular velocity and 3-axial linear acceleration at a constant rate of 50Hz [16][21]. Video recordings were used for manual labeling of the data. The dataset was randomly split, with 70% used for training and 30% for testing. The sensor's acceleration signals integrated body motion and gravitational components, segmented into body acceleration and gravity using a Butterworth low-pass filter.

IV. MACHINE LEARNING ALGORITHMS

4.1. Logistic Regression

This classification method models the relationship between multiple independent variables and a dependent variable [17,18]. Its effectiveness makes it a popular choice for classifying data into distinct categories. Logistic regression is a supervised machine learning algorithm primarily used for binary classification tasks. It estimates the probability of an outcome, event, or observation, producing a binary result limited to two possible categories, such as yes or no, 0 or 1, true or false. The algorithm examines the relationship between one or more independent variables and assigns data to distinct classes. It is widely applied in predictive modeling to determine the likelihood that a given instance belongs to a particular class.

4.2 Neural Networks

To effectively recognize body positions using sensor data, an algorithm must handle nonlinear data, adapt to system changes, and tolerate noise. Prominent recognition algorithms include artificial neural networks, fuzzy frameworks, genetic algorithms, and neuro-fuzzy systems, all influenced by biological principles [15][18]. Artificial neural networks, explored extensively, require testing various topologies by experimenting with varying numbers of hidden layers and neurons, the goal is to identify the optimal performance for specific applications [Fig. 4]. MATLAB's quickest backpropagation algorithm was used for training, employing the Mean Squared Error (MSE) function to calculate network Efficiency.

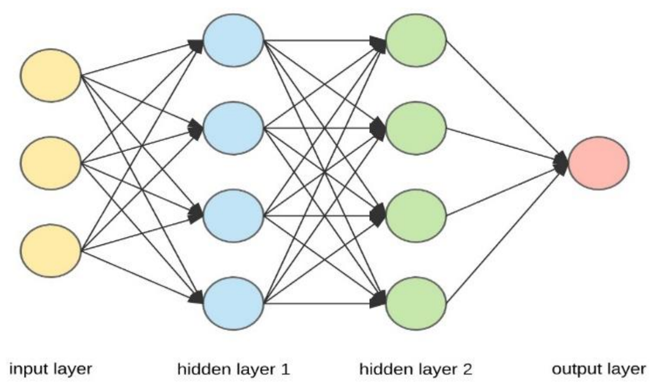

Fig. 4. Architecture of Neural Network

4.3 Long Short-Term Memory

An LSTM, a type of recurrent neural network (RNN), stands out due to its specialized memory cells, surpassing convolutional neural networks in effectively extracting features from sequential data [13]. Each LSTM cell comprises four gates: forget, input,
state, and output [Fig. 5]. By analyzing subsequences of input sensor data, the LSTM predicts the appropriate activity class for each time step, and these predictions are aggregated to forecast the subsequent activity for each window [14][19].

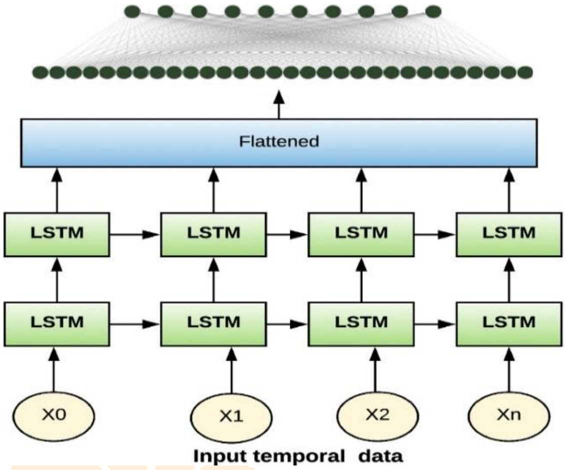

Fig. 5. Architecture of LSTM

4.4 GRU

A gated recurrent unit (GRU) is an RNN architecture that enables selective memory retention. It incorporates two gates update and reset into the hidden layer, allowing the model to decide which information should be retained or discarded. Like LSTM, GRU is designed to handle sequential data by selectively remembering or forgetting information over time. However, GRU is simpler in structure, with fewer parameters, making it more efficient in terms of training and computational resources. The key difference between GRU and LSTM lies in memory management: while LSTM maintains a separate memory cell state alongside the hidden state, updated via three gates (input, output, and forget gates) [22].

V. Result

UCI HAR benchmark dataset has been employed in this study, which is made up of Smartphone accelerometer and gyroscope data, for human activity identification. ANN, and LSTM models were employed in the study to identify six different human activities. In order to identify any data imbalances in the dataset, we first count each activity. Based on Fig. 6, it can be concluded that the classes are incredibly well-balanced.

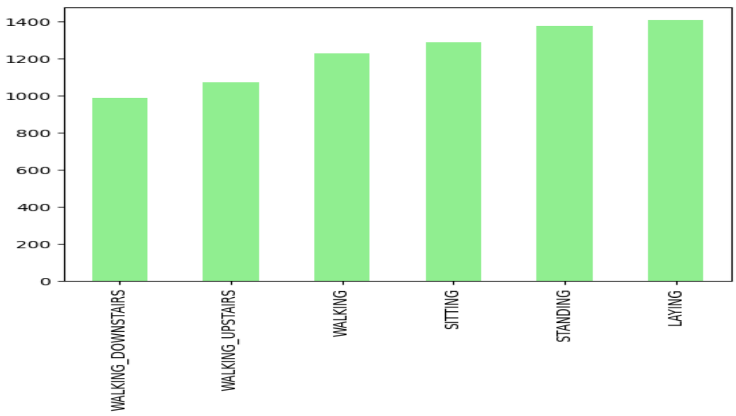

Fig. 6. Frequency of each activity in UCI HAR

In this study, we implemented multiple models to predict human activity recognition using the UCI HAR benchmark dataset. A logistic regression model achieved an accuracy of 94.83% with a loss value of 0.67. Additionally, a fundamental artificial neural network (ANN) model for predicting human actions was developed, achieving an accuracy of 95.12%. The experimental results also demonstrated that the LSTM model achieved an accuracy of 96.4%. Furthermore, a GRU model was applied to the UCI HAR dataset, achieving the highest accuracy of 97.2% according to the experimental data.

Table 1 summarizes the performance comparison of the Logistic Regression, ANN, LSTM and GRU with UCI HAR benchmark dataset for various activity classifications

Table 1. Performance comparison of proposed approach with state of the art

Classifier	Accuracy	Loss
Logistic Regression	94.83	0.67
ANN	95.12	0.52
LSTM	96.4	0.13
GRU	97.2	0.28

VI. Conclusion and Future Work

Logistic Regression, Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks are compared in this study for human activity recognition. The results show that the GRU performs better, with an accuracy of 97.2% and a loss of 0.28. On the other hand, the Logistic Regression attains a loss of 0.67 and an accuracy of 94.83%, ANN attains a loss of 0.52 and an accuracy of 95.12% and the LSTM attains a loss of 0.13 and an accuracy of 96.4%. This demonstrates how well GRU performs in comparison to Logistic Regression, ANN and LSTM models in accurately predicting human behaviors from sensor data.

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