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Recognising Human Activity from mobile sensor data using recurrent neural networks

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ABSTRACT: SMARTPHONES became an integral part of our daily lives due to its numerous benefits for our everyday lives such as communications, research, social interactions and many others.Smartphones evolved from having simple set of sensors into having sophisticated sensors such as GPS Navigation systems, Proximity Sensors, Accelerometers, Gyroscopes.Activity Recognition(AR) involves capturing , cleaning and analysis of the actions performed by the humans by using the sensors in the smart mobiles. The framework that collects the raw sensor data and tries to make a prediction on the human movement using the deep learning approach.The deep learning models are proven to provide us with better accuracy with low error when it comes to handling large amounts of unstructured data.In the architecture, a dataset of UCI-HAR for Samsung Galaxy S2 is used for various human activities.We analyze the data set and separate the different activities using Numpy and Pandas modules.RNN is an efficient and lightweight model that has shown high robustness and better activity detection capability than traditional algorithms .A HAR system has major areas of applications, such as interaction among humans and computers, remote monitoring, military, healthcare, gaming, sports, and security.

KEYWORDS: SmartPhones, Recurrent Neural Network, Sensors , Activity Recognition,HealthCare.

I INTRODUCTION

Smart phones have become a very useful tool in our daily lives of communication and advanced technology has provided intelligent assistance to the user in his daily activities. Attention to creating lifelogs, which refers to the use of technology to capture and record large amounts of user life on mobile devices, has grown exponentially. A good example of lifelogging is taking a number of daily steps using a smartphone. Lifelogs can be used to record simple physical activities such as walking, running, sitting, etc. or complex activities such as eating, working out, exercising, etc. This has a wide range of uses in various fields of research such as medicine, a fact that is unpopular with taxpayers. , computer-to-person interaction, security and targeted advertising. A lifelog can be used to extract information and provide information about a user's lifestyle and help improve quality of life by providing personalized recommendations and services.Portable computer-based interface and application, application programming interfaces (API) for external tools and applications, cell phones with brightness such as cameras, GPS, web browsers etc., and installed sensors like accelerometers, gyroscope and Magnetometer which allows for improved applications by looking at a specific client location, movement and context. In order to develop a smart phone smart app, it is important to use the context awareness and status of the gadget client. Activity Recognition is one of the platforms for these devices that can deal with subconscious sensations and is used in a variety of areas such as business, medical services, security, transportation and more. Different types of sensors include portable sensors that can detect movement and a Bluetooth sensor that enables the exchange of information from one gadget to another using information communication channels. Discovery and recording are possible through these portable sensors that help detect topics further. Tasks can also be removed when hired in a preferred location.Personal Movement Recognition is an important but challenging test site with many applications for health care, smart environment and national security. A developmental approach is to process information from sensory unit sensors that are worn on the client's body or processed on the client's cell phones to track their movements. The model is constructed equivalent to seeing different functions under real-world conditions using information collected by a single triaxial accelerometer built into the phone. A triaxial accelerometer that reverses the acceleration gauge near the x, y and z axes where the velocity and movement can be checked. Awareness can be used as an example by using data obtained from inertial sensors. On some smart devices, the sensors are automatically integrated with a set of physical functions such as standing, positioning, moving, sitting, scrolling up and scrolling by manipulating the independent markers of uninfected computers. The overall performance of the controls with controlled reality training is considered in terms of limited memory accessible to smart gadgets. Collection of training records is also often used directly in the phase steps, which reduces weight for clients. A simple smartphone can help solve the problem of writing a detailed history of the user's daily activity. Advances in in-depth learning and methods for the selection of features and the inclusion of various sensors can suppress the limits of recognition of human activity at deeper ontological levels.

II RELATED WORK

Min et al [14] designs two models, in which one uses only acceleration sensor data and other uses location information in addition to acceleration sensor data. Before feature extraction, the acceleration sensor data is divided into time segments which is said to be temporal segmentation. Inorder to handle streaming of data, sliding window technique is used.

The component vector of the time window is utilized as the contribution to the classifier. Utilizing area data, a progressively explicit and itemized area based classifier can be connected. The location information is not gathered from the framework and it is derived from different kinds of activities. In the Artificial Neural Network [ANN] classifier, the Xavier and ReLU are commonly utilized to decrease learning time in the field of machine learning. The learning rate is set to 0.01, and the Adam streamlining agent is utilized since it is known to accomplish great outcomes quickly. Finally, the model with location information shows an accuracy of 95% and the model without location information does 90% accuracy.

Qingzhong et al [18] proposes a method for activity recognition in two steps. In step 1, accelerometers provide unrefined sensor data which recognizes the actions and the course of mobile phones indicating the gyroscope senses rotational movements which are large to detect by people. In step 2, feature extraction method is performed for the sensed data. Machine learning models worked for action recognition, at that point the profound learning model dependent on convolutional neural systems. The results are demonstrated to indicate consistency, it is expected that the scope of activities recognition can be extended with the utilization of gathered information with multi-class dataset. The experimental results demonstrate that LibSVM performs better in all arrangements than FLD in terms of precision. From the results, it tends to be reasoned that accelerometer sensor (A-sensor) reading contributes more compared to G-sensor reading (Gyroscope sensor) but can increase the accuracy of the detection by utilizing both AI and profound learning calculations.

Akram et al [1] analyzes different activities of a person, using which a classification model is built based on the feature selection. In Weka toolkit, Multilayer Perceptron, Random forest, LMT, SVM, Simple Logistic and LogitBoost are compared as individual and combined classifiers then it was validated using K-fold cross validation. The recognition is analyzed as mobile in hand and pocket position. The efficiency is obtained as SVMprovides better precision in hand and Random forest dictates highest accuracy. Mobile phone in-hand position, the fusion of Multilayer Perceptron, Logit Boost and SVM classifier yields an accuracy of 91.15% but meanwhile in-pocket position, Multilayer Perceptron, Random Forest and Simple Logistic with 90.34% accuracy. A single triaxial accelerometer was used to obtain accurate recognition of 91.15% on daily activities

III SENSORS IN SMARTPHONE

From face recognition and fingerprint reading to GPS and automatic lighting, your smartphone relies on many special sensors to let you use apps, features, and services that make your life easier.The sensor is a small device or module that analyzes your surroundings. and reported quantity rating to the developer. Smartphone sensors measure a variety of features around them, including ambient light, device shape, movement, etc. Every smartphone has a 3-dimensional connection system. Based on this program, the sensors on your smartphone detect and record

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changes in real time.All the different sensors of your smartphone operate based on these axes. However, note that the connection system remains stable depending on the default configuration of the phone. It does not change when you hold your phone in landscape mode or tilt it in any direction.

- **Accelerometer**:

The accelerometer is one of the most important gears in smartphones and a smart wardrobe. An important limitation is the identification of changes in the smart gadget path in relation to the data and the adjustment of the introduction to suit the conclusion of the client research. For example, when you scan a site page with a wider range, you can find this group to see it from changing phone layout to level. A unique approach Camera mode additionally converts the scene into a representation or image into an event when there is a change in gadget/camera orientation. Over time, this sensor undergoes 3D rotation (X, Y, and Z) [21] to increase the speed of the device relative to the free fall.

- **Gyroscope**

The use of the Gyroscope to maintain and control space, level, or shape depends on the level of precision. In any 'Gyros' used an adjacent accelerometer indicates progress from the 6-Axis, for example, right, left, up, down, forward, and distortion. Distinguishes movement, tone, and yawning. Yaw, Roll, and Pitch precise minutes seen on 3-Axis. Using the development of MEMS (Micro Electrical and Mechanical System), gyroscopic sensors aid in line thinking and visual acuity structures used on smartphones and tablets. Figure 1 shows the Sensors on the smartphone

- **GPS**

Global Positioning System (GPS), at first made and set up for military tasks and was made available for everyone in the1980s by the Government. GPS is a system which tracks the goal or 'explores' the things by picture or guide with the help of GPS satellites. Several mobile phones support GLONASS (Globalnaya Navigatsionnaya Sputnikovaya Sistema) GPS structure for navigation highlight

- **Compass Sensor**

Smart Compass is a standard gadget for viewing the topic in relation to the north-south shaft of an attractive stadium. The help of a compass on a cell phone is an unexpectedly growing sensor called a magnetometer. It is used to assess the quality and course of attractive fields. By breaking the earth's magnetic field, the sensor enables the gadget to select its shape with high accuracy. Compass sensor buoy number somewhere in the scope of 0o and 360. It starts from 0o as the north directly indicates the point between the current mobile course and the total north value by the clock. Speedometer and option to send GPS intellectuals via SMS or email modes. The information flow from the compass sensor is a number of moving numbers that reflect the holy messenger, goofy (i = D 1, 2, 3, ... 0 degree <= campy <= 360degrees). Compass reading can be used to differentiate existing changes in client mobility.

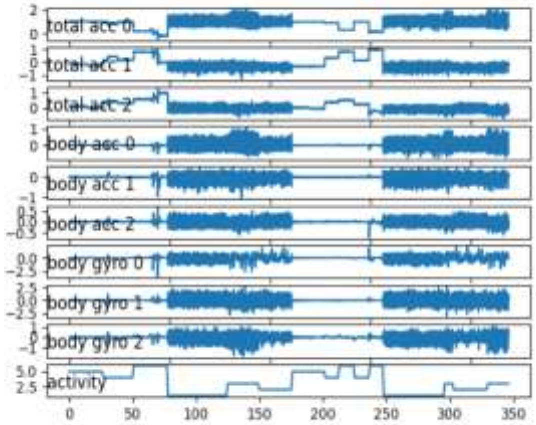

Figure 1 : Sample sensor data

IV METHODOLOGIES

The following are the machine learning and deep learning methods employed

A. Data Collection

The dataset is prepared by monitoring the activities of 30 volunteers within an age of 19-48 years. Each person performing six different kind of activities are listed below:

- WALKING
- WALKING_UPSTAIRS
- WALKING_DOWNSTAIRS
- SITTING
- STANDING
- LAYING

This data is collected at the UCI Personal Performance Recognition Machine [HAR] study store. Using an embedded accelerometer and gyroscope, it captures 3-axial line acceleration and a precise 3-hub speed with a constant frequency of 50Hz. The acquired data was randomly divided into two sets, of which 70% volunteers were selected as information preparation and 30% experimental information. Audio channels connected to the pre-captured sensor signals and subsequently tested on sliding windows with a fixed velocity width of 2.56 seconds and a half (128 read / window). Butterworth's slow-moving channel enters the body with speed and gravity. Gravity is expected to have low frequency segments and a 0.3 Hz break-in channel is used. In

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all windows, the brightness vector was obtained by obtaining features from time and place repetition. Finally the data set contains 2947 records with 561 highlights. For each record it is provided as follows:

- The estimated body and triaxial acceleration from the accelerometer
- Triaxial Angular speed from the gyroscope.
- Its activity label.
- An identifier of the subject who carried out the analysis.

B. Recurrent Neural Network with LSTM

A recurrent neural network(RNN) is a kind of synthetic neural community which makes use of sequential records or time collection records. These deep studying algorithms are normally used for ordinal or temporal problems, which includes language translation, herbal language processing (nlp), speech recognition, and picture captioning.They are prominent with the aid of using their "memory" as they take records from earlier inputs to persuade the modern enter and output. While conventional deep neural networks expect that inputs and outputs are impartial to each other, the output of recurrent neural networks rely upon the earlier factors inside the sequence. While destiny activities might additionally be useful in figuring out the output of a given sequence, unidirectional recurrent neural networks can't account for those activities of their predictions.There are two main things to consider

- An inclination is a fractional subordinate concerning its inputs. A slope estimates how much the yield of a capacity changes, on the off chance that you change the sources of info a tad.
- The higher the angle, the more extreme the slant and the quicker a model can learn. If the incline is zero, the model stops learning.

A long immediate memory (LSTM) system basically broadens their memory. The units of a LSTM are utilized as structure units for the layers of a RNN, that is then often referred to as a LSTM, allowing RNN to own their inputs for a protracted period. LSTM' empower RNN' to recall

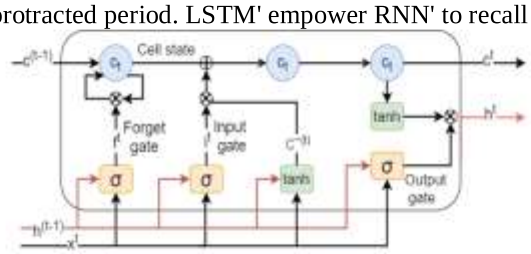

Figure 2 : Structure of LSTM

V SYSTEM ARCHITECTURE

Personal Activity Recognition is to recognize the functions performed by those people which include the following functions such as: walking, walking_up, walking_down, sitting, standing and positioning.Initially, a database called Human Activity Recognition [HAR] is collected in the UCI machine learning archive. Database is pre-processed using audio filters.After pre-processing, data is classified as static windows.Feal engineering strategy is applied to window data. Window data is classified as 70% training set and 30% test set. The engineering aspect has the following stages.By the main, data set is loaded with three main types of signals such as total acceleration, body acceleration and gyroscope. Then, upgrade your LSTM network model. LSTM can read and remember long sequences of data. The model can support multiple sequences of tasks. After modeling, you need to define, balance and evaluate LSTM. Then, the Recurrent Neural Network [RNN] is used with the LSTM model.

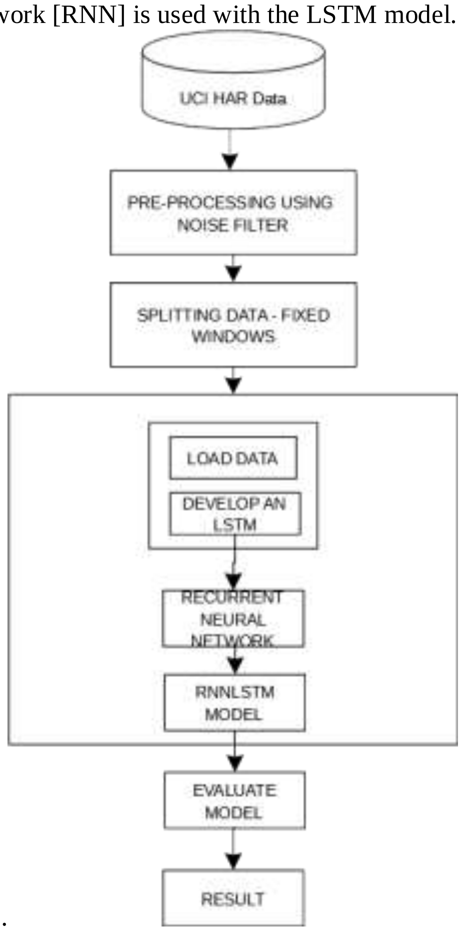

Figure 3 : Architecture

VI RESULTS

Performance Metrics Of The Classifier

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CLASSIFIER	ACCURACY(%)	MEAN ABSOLUTE ERROR	ROOT MEAN SQUARE ERROR	MEAN ABSOLUTE PERCENTAGE ERROR(%)
RNN With LSTM	93.89	0.0004	0.0024	4.78

TABLE 1 : Performance Metrics Of The Classifier

The experiments were performed in Python version 3. The results for the proposed model are shown in Table 1. The result shows that the recurrent neural network with short-term memory [RNN LSTM] offers better accuracy with a percentage error with the lowest absolute mean [MAPE]. RNN LSTM has a best-balanced accuracy of 93.89%, a mean absolute error [MAE] of 0.0004, mean square error [RMSE] of 0.0024 and mean absolute percentage error [MAPE] of 4.78%. Because of this, RNN LSTM can be used to detect human activities in real-world applications to reduce loss of human life.

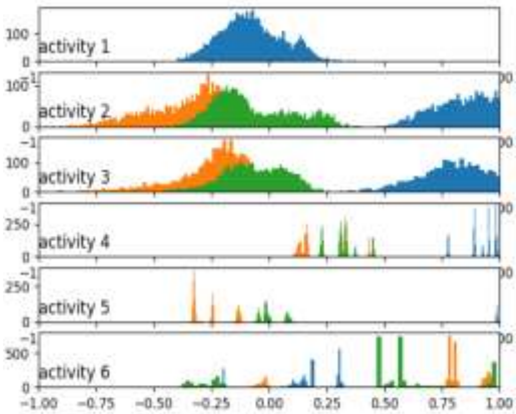

Figure 4 : Distribution of Different Activities

VII CONCLUSION & FUTURE SCOPE

Smartphones are ubiquitous and are becoming more and more modern. This has changed the scenario of people's daily life and opened the doors to fascinating data mining applications. The recognition of human action is a key obstacle behind these applications. It uses the sensor's raw data as a source of information and predicts a customer's movement. This experiment gives a comprehensive overview of ongoing developments which can predict human activities with an accuracy of up to 93.89% with PDA sensors. Using the Odds-Normal strategy proved to be the best classifiers for motion detection, outperforming all other classifiers. Furthermore, it could be shown that the recognition strategy can identify exercises independently of the position of the mobile phone. For future work, the motion detection task will be performed in different ways.First, start with a plan to get extra exercises. Second, you want to collect information from more customers of different ages. Third, try to remove more marks that could likely separate multiple exercises.

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