HUMAN ACTIVITY RECOGNITION

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ABSTRACT

Human Activity Recognition,familiarly called HAR . It is a field of study concerned with detecting a certain movement or activity of individuals using sensor data. This collected sensor data was in the form of images, radar, videos or other wireless methods. Smartphone sensors such as the accelerometer, gyroscope, and other sensors produce data that is used to train Supervise Predictive Models of Machine Learning utilising techniques like as Decision Learning, Support Vector Machine, and Random Forest. This can be used to identify the kind of movement being performed by the person and can be further divided into categories such as Walking, Sitting, Standing,Sleeping etc.

INTRODUCTION

In todays day to day life ,physical movements have become an issus of concern and therefore it becomes difficult to maintain a balanced and healthy life, so scientists are finding ways to know and study in large about the link between physical exercise and health. All of their actions must be meticulously documented as part of their study. For development of activity identification software we can use the above data. In practical use of these gadgets ,doctors make the very use of it in keeping track of their patients.

One more growing worry is the stationary lifestyle that several persons lead as a result of the modern world's shift in lifestyle, when work and leisure are less physically demanding .As a result, recommender systems can employ activity recognition to assist day by day activities which involves bodily motions by assisting users in tracking them and motivating them to enhance their physical activity. Unobtrusive and transportable activity recognition has become possible because to recent advancements in wearable technologies. With this technology, gadgets such as smartwatches and smartphones are readily accessible, with a variety of sensors which are in-built and a great amount of compute power. Generally, the technology tools are in place to create a transportable, retiring, and error free system for detecting human actions. As a result, it is now possible to recognize people's physical activity as they are going about their regular routine. The use of light-weight gadgets for identifying human activities was examined. It should be able to distinguish activities in real time, first and foremost. This necessitates that the categorization features be computed in real-time. In addition, to avoid a delayed reaction, small window durations must be used. Finally, in order to run on hand-held devices, classification algorithms should be simple, light-weight, and computationally affordable.

LITERATURE SURVEY

Shahroudy et al. (2016) investigated recent strategies for high to bottom primarily based human movement assessment and showed the quality of 3D depiction for activity category classification.
There are several drawbacks to existing depth-based and RGB+D-based activity detection standards, including the lack of preparatory testing ,unambiguous category names, camera angles, and a good vary of subjects. This analysis conferred a large-scale dataset for human action recognition that enclosed fifty six,000 video tests and four million edges from forty totally different individuals. It includes sixty totally different activity classes, as well as daily, shared, and wellness-related activities.
Another long-term neural system structure is planned to illustrate the long-term transient association of all body parts' highlights and to employ them for accurate activity classification. Finally, the advantages of employing deep learning approaches over the most recent hand, which includes cross-subject and cross-assessment criteria for the dataset in question., were incontestable .
According to Oyelade et al. (2010), the flexibility to trace the progress of understudies' studious performance may be a important concern for the scholastic network of upper learning. A framework is represented for breaking down understudy outcomes supported cluster examination and using typical quantitative formulas to mastermind their scores info by the dimension of their execution. Cluster analysis and customary applied mathematics techniques area unit applied to the evaluated student dataset containing student scores from one semester to live the tutorial accomplishment of the scholars. The chosen random samples area unit given the amount of clusters to be obtained as input. The first moment of every cluster is calculated, and therefore the method is perennial till the information points don't modification. For the chosen semester with 9 courses provided, the performance is evaluated employing a settled model, and a fuzzy model is

employed to predict their educational accomplishment.
NP-hard is a perfect learning Bayesian system but learning-improved innocent Thomas Bayes has gotten heaps of attention from scientists. Improved computations and a hidden innocent Thomas Bayes model area unit projected during this study (HNB). In HNB, every characteristic incorporates a veiled parent that unites the results of all alternative properties. The gullible Thomas Bayes, specific Bayesian classifiers, innocent Thomas Bayes tree, tree-expanded guileless Thomas Bayes tree, and tree-expanded guileless Thomas Bayes tree are all compared to HNB. Bayes, Thomas, and known the medium price of one-reliance estimators exploitation the thirty six UCI informative collections chosen by maori hen (AODE). Associate correct category likelihood estimation and classification area unit utilized in a range of knowledge mining applications.
Aggarwal and colleagues (2011). coordinate system volume techniques and sequent ways that to differentiate activities from input pictures were mentioned. [9] the bulk of those area unit applications that necessitate the automatic acknowledgment of abnormal state exercises, created of a range of materials People's straightforward (or nuclear) activities. this can be a commentary concerning provides a point-by-point diagram of assorted best-in-class candidates investigate papers on acknowledging act. it's set to use a methodology-based scientific classification. examines every person's points of interest and limitationsmethodology. Low was mentioned by Eneaer et al. (2016). RGB-D sensors in police

investigation at a coffee price, and a human-computer The skeletal joints' interaction and calculated options The skeleton options were wont to produce the bar graph. was denoted by many necessary poses. the present state of affairs Minor AI estimates were the main focus of the techniques.don't hand it over.

IMPLEMENTATION STUDY

Data Preparation

The primary step is to assemble variable time-series knowledge from the sensors on the phone and therefore the watch. never-ending frequency of thirty cycle per second is employed to sample the sensors. After that, the statistic is segmental exploitation the window technique, during which the statistic is separated into fixed-duration windows with no gaps between them . The window technique doesn't need the statistic to be preprocessed, creating it glorious for period applications.

Preprocessing

After that, the measuring device time-series knowledge is filtered to get rid of droning values and outliers, creating it appropriate for the feature extraction stage. The typical filter and therefore the median filter (Sharma et al., 2008) area unit the 2 most typical forms of filters utilized during this stage (Thiemjarus, 2010). as a result of the kind of noise being proscribed here is cherish the salt and pepper noise determined in pictures, that is, excessive acceleration values occurring in single snapshots interspersed across the statistic. to get rid of this kind of noise, a median filter of order three (window size) is employed.

Pre-processing Module

The network's input layer solely takes pictures of a precise size, therefore the first image is scaled to suit. The image is scaled exploitation the coordinate axis and coordinate axis scaling ratios. many different social control approaches may be utilized, however scale social control is one amongst the foremost economical, thence it absolutely was utilised during this model.Scale social control is employed to map the points within the original image to alternative points. Sy and sx are co ordinates and the picture is represented in both the opposite directions using these sx and sy scaling ratios.

Due to shadows, pictures can mirror a state of unequal distribution. Factors like as light and shadow wreak havoc on the feature extraction approach to beat this issue, greyscale values area unit averaged to realize associate just distribution. The bar graph feat (HE) approach is used during this paper . The technique changes the first image's bar graph to a good distribution.

Feeling recognition Module

Artificial neural networks, that area unit sculptured once the human brain, will learn from large volumes of knowledge. Basing on their connections, the CNN can group and identify objects. A CNN is also called as feed-FNN. It pulls crucial info from pictures for feeling detection and categorization. Network settings are usually optimized using backprogation techniques.

Feature Extraction

Every section is summarised by a set variety of options, i.e. one feature vector per section. The properties are extracted using both the time and frequency domains as a result of several activities, like walking and running, area unit repetitive, they include a series of actions that area unit perennial frequently. This dominating frequency, conjointly referred to as the frequency of repetition, may be a descriptive feature that has been taken into consideration.

Standardization

Because time domain options area unit measured in (m/s 2) and frequency domain options area unit measured in (Hz), all options ought to get on constant scale for a good comparison, as sure classification algorithms use distance metrics. The attributes area unit reworked to possess zero mean and unit variance exploitation Z-Score social control during this section.

$$xnew = (x-\mu)/ \sigma$$

where μ and σ area unit the attribute's mean and variance severally.

PROPOSED APPROACH

The ability to classify what activity a person is engaged in at any given time allows computers to provide support and instruction to that person before or throughout a task. The challenge arises from the diversity of our movements as we go about our daily responsibilities. There have been numerous attempts to accurately identify a person's activity using various machine learning algorithms, to the point that Google has released an Activity Recognition API for developers to use in their mobile app development.

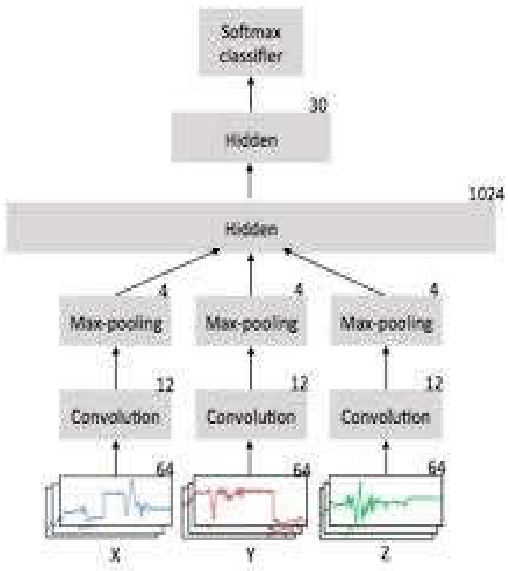

Fig 1 : Proposed Model

ALGORITHMS USED

Multi perception Neural Network

Firstly network's first layer i.e input layer takes the picture which is already pre processed. Only single layer of this picture from input layer is processed at that point of time. Each layer has two-dimensional planes. Their only work is to present maps, and many of them are there. The pixel value of images are generally used by computers to decode the code. The image is interpreted by neural networks from pixel to lines, curves, edges, and eventually, things comprehended by the human brain, after which the emotion is detected. The below are layers:

- Convolution layer
- Pooling layer
- Fully connected layer
- SoftMax layer

Layers involved in this model are:
Input->Conv(C1)->Pool(S1)->Conv(C2)
->Pool(S2)->Conv(C3)->Pool(S3)->FC->Softmax.

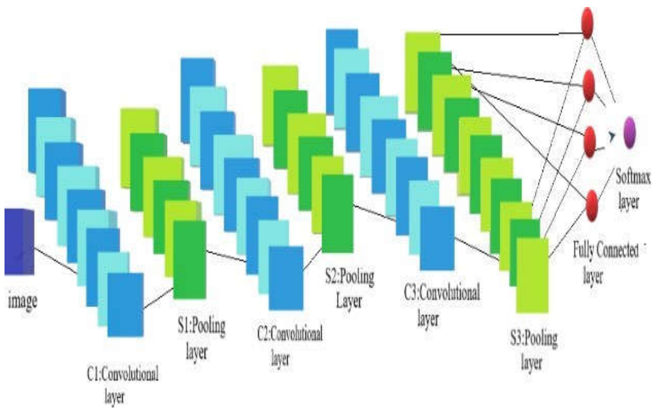

Fig 2 : Multi perception neural network for HAR

RESULTS & EVALUATION METRICS

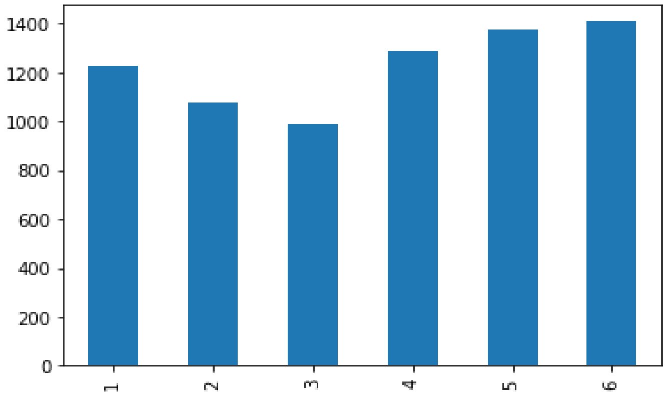

Fig 3: Comparison of different results

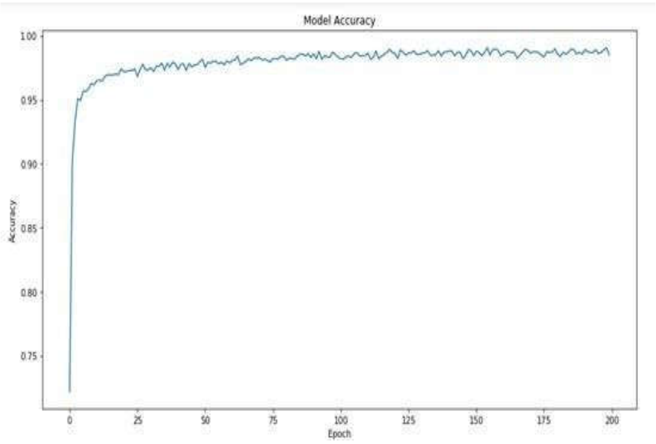

Fig 4: MLM Model Accuracy

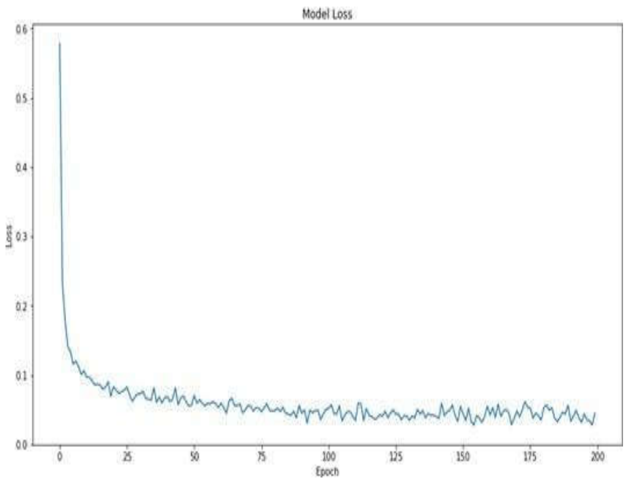

Fig 5: MLM Model Loss

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In [13]: pred = test_model(estimator, encoderTe, TeX)

In [14]: score(TeY, pred)
         Test Accuracy : 99.55%
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Fig 6: Snippets of Test accuracy

CONCLUSION

In this paper, a framework was suggested for classifying diverse human activities by combining sensors from smartphones and smartwatches. It detects and records activity in real-time. Furthermore, this approach is portable, lightweight, and cost-effective in terms of computing. The findings indicated that there is no clear winner, but that ignorance triumphs. The greatest efficiency and correctness was achieved by using bayes classification . The total accuracy ranges from 84.6 percent to 89.4 percent, with very few variances. As a result, this platform can distinguish a wide range of human behaviors. All of the tested classifiers, however, mixed up walking and stair climbing. The second finding is that including the smartwatch's sensor data into the recognition algorithm improves accuracy by at least 6%. Lastly, According to calculations, the best sample frequency is in the 10 Hz range. There are still some issues that need to be resolved.The most crucial step is to run larger tests with more people to make a more comprehensive evaluation to see whether one method is truly superior to the other, or whether any off-the-shelf method can perform well in this categorization task. More sensors (e.g., a heart rate sensor), recognition of high-level activities (e.g., shopping or eating dinner), and extrapolation of these trained classifiers to other people might all be added to this effort.

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