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Efficient Human Activity Monitoring Using Feature Based Deep Learning Techniques

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Abstract
Segmenting behavior-based sensor data and detecting the activity represented by the data are critical elements in any human activity learning applications such as health monitoring, security, and intervention. By recognizing activity transitions, we improve activity recognition. Activity segmentation can be used to increase the performance of activity identification in addition to giving useful activity information. We propose exploiting data obtained from smart homes to identify human activity using machine learning and deep learning methodologies. On data acquired from the five smart homes, we test our suggested segmentation-enhanced activity detection algorithm.

Keywords: Human Activity Detection, Health Monitoring, Deep Learning, Smart Home.

1. INTRODUCTION

The difficulty of anticipating a person's movement, generally inside the house, based on sensor data, such as an accelerometer in a smartphone, is known as activity recognition. Learning human activity models from streaming sensor data is a critical issue for the effective implementation of intelligent settings. Human activity learning tries to learn and interpret observed behaviors and events in an environment, and it is beneficial for a variety of applications and services such as health monitoring and emergencies, early illness detection, home automation, security, and behaviors intervention. Activity learning comprises useful features such as activity recognition, detection, segmentation, and forecasting. We focus on the activity segmentation problem, or the challenge of segmenting behavior-based sensor data into sub-sequences, in our study. The primary disadvantages of the prior existing system were that it employed image sensors, which interfere with a person's privacy, and it also used the LSTM module exclusively, with an accuracy of no more than 60-70 percent. However, in our system, we use a Bi-LSTM module that provides roughly 97\% accuracy, with each matching to a specific activity. Activity Recognition systems are classified into two types: video-based systems and sensor-based systems.

We examine the topic of activity segmentation in this study. Activity segmentation is the process of identifying activity boundaries and categorizing observed data into discrete activities. We deploy our suggested method in the context of smart houses that gather sensor data as people do unscripted, ordinary activities like brushing their teeth, sleeping, and stepping out of the house. Human Involvement The difficulty of recognizing a physical activity performed by a human based on a trace of movement inside a certain context is known as recognition. Our objective is to analyze the smart home dataset and develop a generic classifier that can predict the user's physical activity using deep leaning model. Activities such as leaving the house, taking medicine, sleeping, relaxing, eating, cooking, bathing, toilet, personal hygiene, watching TV, drinking, and so on are categorized as regular bodily motions and constitute our class of activity that must be registered. Sensors such as environmental sensors acquire data while the activity is being conducted to record movement.

First, we are taking the data from sensors of a smart home from CASAS [1]. In the data extraction phrase, the collected raw data contains the data like the sensor name, sensed time and date, the activity performed from these data and we are extracting data like activity change, sensor counts, the activity performed, last sensed hour, last sensed second, complexity and so on. After this, the extracted data is subjected to feature selection where the less frequent activities with values zeros are avoided and other data are loaded like ELearning data. This is done to avoid the model's accuracy loss and high variance to find the activity. In the next process the major activities are selected and taken as target data. Module is model training. Before we had used Artificial neural network but using artificial neural network the accuracy was very low so we started training in LSTM module. LSTM module also didn't give us the desired result so we have used a bidirectional LSTM because of its accuracy.

This paper is organized as follows. Related works are described in the section 2. The techniques of our models are presented in Section 3. Section 4 has the experimented setup. In section 5, we conducted research and its findings. Finally, we summarize our findings and suggest ways to improve our work in section 6.

2. RELATED WORK

In this section Activity recognition studies that had happened in the past are explained

2.1. Activity Monitoring Using Wearable Sensors

Sruti Das Choudhury and Tardi T Jahjad [2] had conducted a study on Gait recognition of motion and shape analysis using wearable sensors. This system was developed based on sensors. The sensors were placed over the human body. The sensors will detect the activities from the movement based on the human body. Yongwon Cho et al. [3] used a 3-axis accelerometer and a ambient sensor (wearable) to conduct their research. The system they developed was based on an accelerometer and ambient sensor. The accelerometer will detect the motion that and human-made ambient sensor will recognize the movement of the human body. Oscar D Lara [4] had done a human activity recognition survey system with the help of wearable sensors. This system was developed based on wearable sensors. The sensor was mounted on the Human body to recognize the activity of the person. The sensors will record heart rate, GPS, the temperature of a person and motions, etc.

Yoshizawa et al. [5] studied accelerometer data in the frequency domain to segregate data from wearable sensors by creating a threshold that shows when activities transition from static to moving. Nyan et al. [6] divided the accelerometer data into three categories: walking, climbing, and descending stairs with the help of wavelength decomposition. for finding the matching start and end location she provided the explicit ground truth segmentation giving a gap between two activities for a few seconds. A hidden Markov model is used to label the appropriate activity in the second stage. One significant flaw in this study is that all of the data was gathered from a single person. All of these solutions employ a supervised approach to detect transitions and were designed for usage solely in scripted situations. Participants in such environments follow directions and the start and end of each activity are predetermined. The activity transition detection and recognition methods that follow are quite different from evaluating sensor activities in real-world situations with streaming sensor data, where obvious boundaries between various activities may not exist naturally.

2.2. Activity Monitoring Using Light Sensors

On a dataset acquired in a programmed environment with ambient sensors, Cho et al. [7] used LSTM, a sort of recurrent neural network, to identify if an activity is stopped or is it still happening. From accelerometer data, a two-step supervised classifier was constructed to distinguish ambulation activities and transitions. An artificial neural network classifies moving and non-moving activity in the initial stage. Emily B. Fox and Michael C [8], had proposed a non-parametric Bayesian approach, their model discovers dynamical behavioral latent set shared among the sequence and segmenting each time series into regions and sharing pattern both inferred form data. The inference algorithm efficiently avoids to consider a truncated model by adding and removing behaviors with the help of split-merge moves and data-driven birth and death proposals.

2.3. Activity Monitoring Using Image Sensors

George Demiris et al. [9] are the authors of a paper that has a study with dataset of older adults with the aim of having elderly care for older adults in future. This system was developed based on computer vision recognition where the system takes a snapshot of the movement that is human-made and feeds it to the machine learning model to analyze the motion of the person. UnADevs is an unique unsupervised technique for finding activity clusters in streaming sensor data that correlate to periodic and stationary activities. the method they use is regulate sensitivity and discover cluster overlapping to deal with deviation from nominal behaviour. Video segmentation or

segmenting a mix of video and accelerometer data were the subject of early investigations on human activity segmentation.
The challenge of activity segmentation from sensor data has become the key focuses of interest in the IoT age, thanks to advancements in smart homes, wearable devices, and ubiquitous computing. Here in this emerging area we have conducted a review work for those factors.

2.4. Activity Monitoring Using Motion Sensors

Narayanan Chatapuram Krishnan and Diane J Cook [10] had used a streaming sensor data for realisation of intelligent environment. Human activity learning tries to learn and interpret observed behaviours and events in an environment and is beneficial for a wide range of applications and services such as health monitoring and emergencies, early illness detection, home automation, security, and behavior intervention. According to statistics, Europe's population is ageing, and human help for the elderly will become prohibitively expensive in the not-too-distant future. The prospects for implementing a supervision system capable of monitoring a person's behaviour in his or her house without invading privacy are examined in this research.

Anubhav Nataniet al. [11,12] have conducted research on the topic smart home technologies and activity recognition for effective energy consumption Advances in smart home technology and Internet of Things (IoT) devices have made it possible to track human behaviors for health and energy efficiency. Machine learning has shown to be an effective method for predicting human behavior [13,14]. However, because there is no direct link between sensor readings and resident activities, multi-resident activity detection remains a hurdle. With the advancement of consumer electronics, there has been a rise in desire for more granularity in separating and analyzing human everyday activities[15]. Furthermore, the power of machine learning, particularly deep learning, has become clear. While research on applications such as monitoring the elderly progresses, and Surveillance in public spaces to discover suspicious individuals and items. To segment transition-aware human activity recognition of physical activity using smartphones[16]. Two implementations were offered, each with a different prediction approach for dealing with transitions: direct learning or viewing the probabilistic output of sequential activities as unknown activity. To accomplish the approach's result, support vector machine prediction and heuristic filtering are coupled.

2.5. Goals for Our Project

Now, as we have talked about what other researcher has done in the field of HAR we are here to discuss about what our goals are for doing this project. The main goal is to limit the number of mistakes done due to human error which could have a serious consequences and help the people to identify what is happening in their house when they are not available. It also involves a matter of security in their house hold. Similarly, for hospitals and schools we propose this research and project so as to monitor everything that is being done in their property this will improve the efficiency of the organization as well.

3. PROPOSED METHODOLOGY FOR HUMAN ACTIVITY RECOGNITION

3.1. Dataset

The CASAS dataset this dataset was generated with the help of a lot of volunteers residing in different homes and performing different activities, every individual had participated in carrying out at least 15 activities. There were some activities which could be done alone and some with involvement of other participant. The ceiling was equipped with motion sensors for analyzing the movement and each item was installed with contact switches. During the data set collection at least two participants had to be present in the house. A mess network was formed for the sensors to interact with each other and these sensors were interacting on ZigBee Pro protocol, all the sensors were battery powered and used as a leaf node. Similarly, the always-on devices were acting as branches.

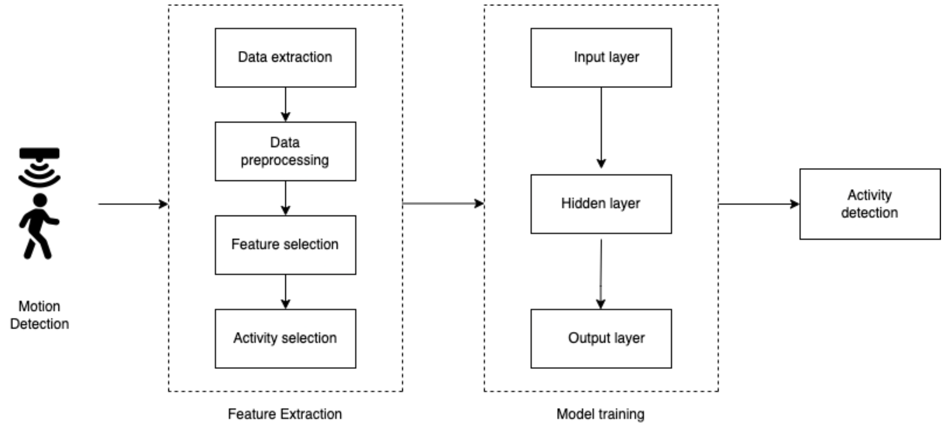

Figure 1: Overall System Architecture

3.1.1. The Raw Data Format

The (Date) (Time) (Sensor) (Translate01) (Translate02) (Message) (SensorType) (Activity)
\begin{itemize}

- (Date) is YYYY-MM-DD, in local time.
- (Time) is HH:MM:SS.ms, 24-hour and in local time.
- (Sensor) is the name of the sensor, this can be found on the sensor map.
- (Translate01) is the room-level sensor location.
- (Translate02) is more detailed, usually identifying what in the room the sensor is aimed at or sensing.
- (Message) is the message generated by the sensor
- (SensorType) what type of data a sensor is sending is determined by the sensor type before it was identified by their names but later the field of the data was used to identify the sensor data.

Table 1 Sensor and their associated actions

Sensors	**Actions**
MotionSensor	Laundry, Watching TV, Bed to Toilet Transaction, Eating, Sleep
LightSensor	Drinking, Laundry, Take Medicine, Personal Hygiene, Relaxing
TemperatureSensor	Cooking, Bathing
LightMotionSensor	Entering Home, Leaving Home

3.2. Data Extraction

After data collection we will extract the data from it there are number of features was available in the dataset.

3.2.1 List Of Features Extracted From The Dataset

- Last sensor Event Hours: The Hour of a day was extracted from the dataset in localtime.
- Last sensor Event Seconds: The total number of seconds since midnight was calculated from localtime.
- Last sensor day of week: The Current sensor week was extracted from the raw-data in localtime.
- Window Duration: The time duration of the 30 sensor events sliding window in seconds.
- Time since last sensor event: The total number of seconds since the last sensor event activity.

- Last sensor Location: The Last Sensor event location ID was noted in current sliding window.
- Last motion Location: The Last motion event location ID was noted in current sliding window. Default -1 if nothing was found in current sliding window.
- Activity Change: Recording Change in activity levels between 2 halves of the sliding window
- Area transitions: Detecting Number of transactions between sensor locations in current sliding window.
- Sensor Count: The number for sensor event count was taken to the account in particular sliding window at particular hour for every sensors.
- Sensor Elevation Time: The total seconds since the current sensor last seen in current sliding window was calculated.
- Activity (Class label): The Activity for the current event was observed.

3.3. Data Pre-processing

Because deep learning is computationally costly, we used PCA transformation in this stage to restrict the number of dimensions the RNN has to deal with. On the other side, some of the housing examples are dreadful. These samples were originally labelled as "unknown." We've opted to keep these samples out of training, testing, and training after several failed attempts. We feel the percentage of unlabeled data is so little that it would have no effect on the accuracy balance. We used the following basic formula to clean the dataset:

$$D = \sum_{i=1}^{n} Da_i | (y_i ! = 0)$$

D stands for the sample to be processed. A label with a value of (0) denotes an unknown class and is thus eliminated from the dataset. Then, using basic random sampling, we separated the dataset into three holdouts: training (60 percent of the dataset), validation (20 percent of the dataset), and testing (10 percent of the dataset) (which accounts for 20 percent of the dataset). Finally, we used the z-score method to normalize the data. In this dataset we have various class labels frequency that mismatches with other class labels creates data imbalance. This data imbalance will gradually affect the model performance and accuracy.

3.4. Feature Selection

Here in feature selection, we decide which feature that fits to our model and gives reasonable accuracy. The feature that has more variance than other features was selected. we are selecting the feature with more variance because as the variance is more than the training of the model is done properly. some features such as other activity is neglected as those features overshadow the actual features in number as there are a lot of values of that feature and which is not assigned to any class thus it's of no use to our module. The features have less variance and static values are filtered out from the dataset.

3.5. Activity Selection

In Average of 30 homes there are 35 Different activities was present in each and every dataset. And the Frequency of every activity was changes based on different event happens in the particular homes. This will create a data imbalance in Our dataset like. Some of the activity was higher in count and some of the activity has lower in count. So, the common activities such as sleeping, eating, walking out, entering the hose etc. these activities were selected because they were variable data and was easier to train the module for future reference. over the 30 houses was selected and taken as a class label. And then we use Random under sampling technique was used to create a data balance.

3.6. Model Architecture

3.6.1. ANN

A computer model made up of several processing components that take inputs and outputs based on their activation functions is known as an artificial neural network (ANN). An input layer, many hidden layers, and an output layer make up an artificial neural network. The input layer takes data in a variety of forms specified by the programmer. Between the input and output layers is a concealed layer. It does all the math to uncover hidden features and patterns. Via the hidden layer, the input undergoes a sequence of modifications, culminating in output that is communicated using the output layer.

3.6.2. LSTM
Long short-term memory (LSTM) is a deep learning architecture which is used in the fields of artificial intelligence and deep learning. This is based on artificial recurrent neural networks (RNNs). In the LSTM, there exist feedback linkages. The LSTM contains feedback connections. It can deal with both full data sequences and single data points. LSTM cell is composed of an input gate, an output gate, and a forget gate these all together make up a natural LSTM unit. The information flow into and out of the cell is controlled by the three gates, and the cell remembers values across arbitrary time periods. The reason we chose LSTM for our project is that it has an additional node in every neural network that stores the output and evaluates the data based on the current input and previous output. This will improve the model's accuracy

3.6.3 Bi-LSTM
Bidirectional recurrent neural networks (RNN) are made up of two independent RNNs that have been linked together. At each time step, both backward and forward knowledge about the sequence is knownto the network. When you use bidirectional, your inputs will go in two directions: one from the past to the future, and the other from the future to the past. This technique differs from unidirectional in that information from the future is maintained in the LSTM that runs backward. You may save knowledge from the past and future at any moment in time by combining the two concealed states. An LSTM layer learns long-term dependencies between time steps in time series and sequence data. When you want the network to learn from the entire time series at each time step, these dependencies might be advantageous. This is why Bi-LSTM works better and provides better accuracy in our project.

4. EXPERIMENTED SETUP
4.1. Training Methodology
The data to be trained is gathered by sensors installed around the house, and a class definition is developed using these sensor records. So, if any action is noticed, it is recorded as raw data. The acquired raw data includes information like as the sensor name, detected time and date, and the activity conducted We extract data such as activity change, sensor counts, the activity performed, last sensed hour, last sensed second, complexity, and so on from these data. These raw data are put into the deep learning training module. For example, suppose there is raw data for a house for 50 days. Using these data, a model definition is created, and the data acquired for the 51st day is immediately applied to this model, displaying the activity conducted. Because the name standards are diverse, we took data from 5 houses and did data prepossessing. There are ten million occurrences, which necessitates the use of additional resources. As a result, only typical activities are used to train.

We adopted a BiLSTM RNN architecture since we felt it would be better for HAR. Sequence input, Bidirectional long short-term memory (BiLSTM) layer, long short-term memory (LSTM), fully-connected, Softmax, and classification) layers comprised our BiLSTM RNN architecture. There are 64 layers in the input cell. The result layer of BiLSTM is 7 with 128 hidden units and a total of 75264 parameters. The output of the Bi-LSTM layer equals 128 with 128 hidden units and 270,600 parameters. The completely linked network has a 64-input and 7-output since there is 7 classes in the CASAS dataset. We utilised the validation subset to assess the accuracy of our design and correctly end the training, and the testing subset to compare the performance of our design to that of others while avoiding bias. Multiple trial and error processes were used to improve the model's performance and achieve the maximum degree of accuracy possible.

4.2. Training Analysis
We utilised the ANN algorithm to train the data in the first phase of the project. An artificial neural network (ANN) is a computer model in which on the basis of some activation function the output is produced. An input layer, many hidden layers, and an output layer make up an artificial neural network. The input layer takes data. All of the calculations to detect hidden features and patterns are done by hidden layers. The output layer is used to deliver data. The accuracy of this method was 60 percent, and there were several data imbalances. Then we switched to LSTM. The Long Short Term Memory(LSTM) is an nothing but advanced version of RNN (sequential network), that

allows the information to be stored for unlimited or unspecified period of time. It can deal with the vanishing gradient problem that RNN suffers from. For permanent memory, a recurrent neural network, also known as RNN, is utilised. A cell, an input gate, an output gate, and a forget gate make up a typical LSTM unit.
The flow of information in and out of the cell is controlled by these 3 gates, and for arbitrary time period cell remembers the value. The reason we chose LSTM for our project is that it has an additional node in every neural network where the output is kept, and it evaluates the data based on current input and prior output, increasing the model's accuracy. We obtained between 70 and 80\% accuracy with LSTM. We then used bi-directional and cascade LSTMs to try to improve the accuracy even further. After that, we landed on bi-directional LSTM. Our input runs in two directions in a bidirectional LSTM, which distinguishes it from a conventional LSTM. We obtained between 90 and 96\% accuracy with Bi-LSTM, which is better than the model employed in the basic study.

4.3. Accuracy and Training Time

4.3.1 Accuracy and Training Time Using ANN

Using ANN algorithm we got 40-60\% accuracy and training time of 1hr 30min (depends on dataset)

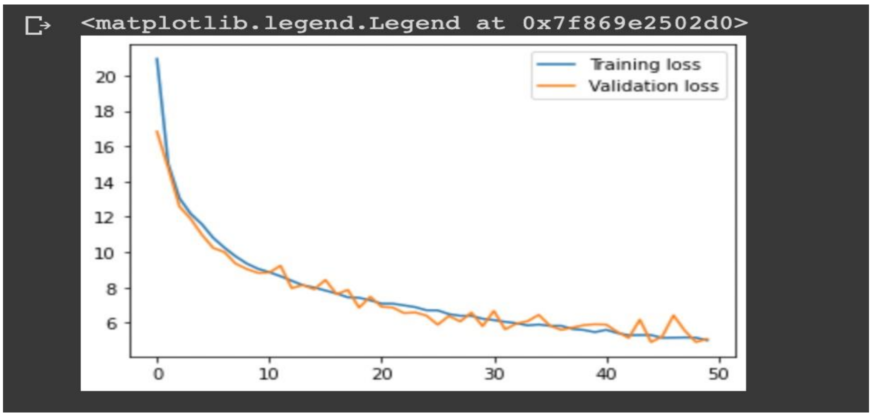

Figure 2: ANN Accuracy

4.3.2. Accuracy and Training Time Using LSTM

Using LSTM we got accuracy of 70-80\% and training time of 3-4hrs

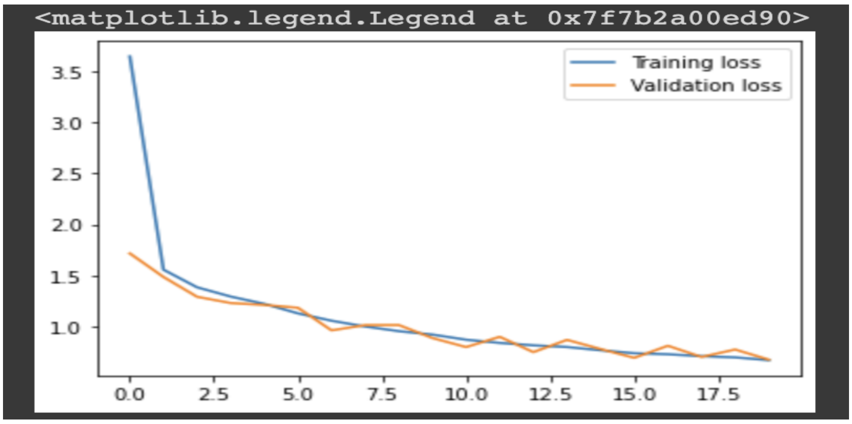

Figure 3: LSTM Accuracy

4.3.3. Accuracy and Training Time Using Bi-LSTM

Using Bi-LSTM we got accuracy of 90\% and training time of 5hrs for each house (5 houses)

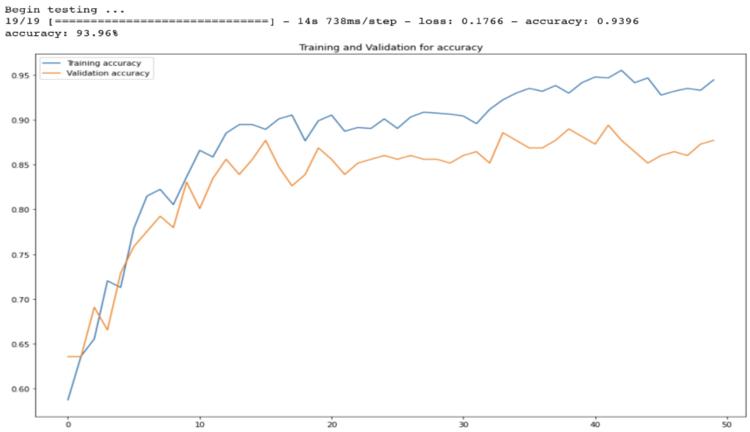

Figure 4: BiLSTM Accuracy for Cario Dataset

In the figure 4, graph x label was taken as epochs and y label was taken as a accuracy of the model. As we can see that the model training accuracy was higher than 95\% and validation accuracy was higher than 85\% for Cairo dataset.

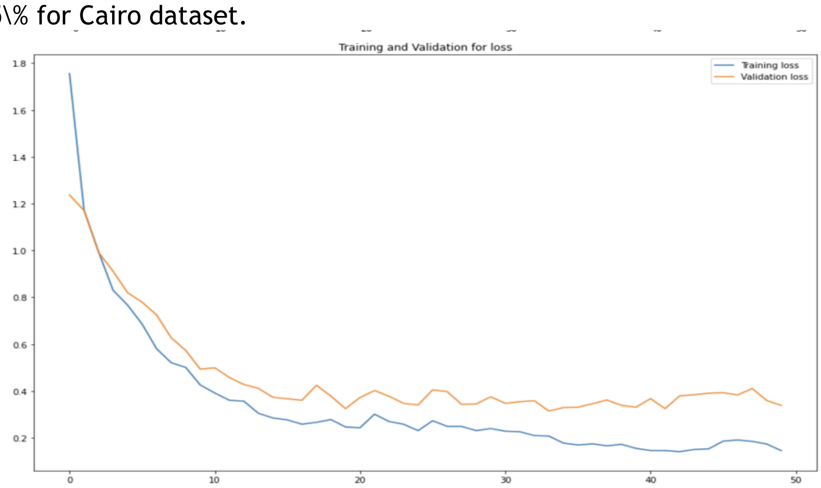

Figure 5: BiLSTM Accuracy Loss for Cario dataset

In Figure 5, the x label was taken as epochs and y label was taken as a loss of the model. For Cairo dataset, the loss for the training data set was lower than 0.2% and validation data set was about 0.4%

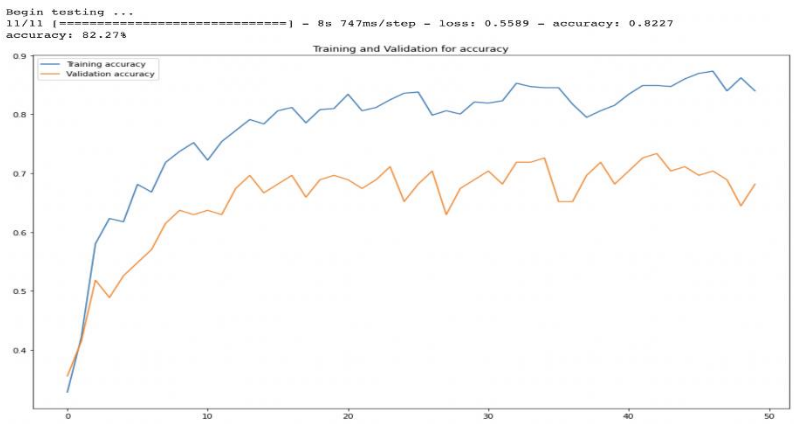

Figure 6: Bi-LSTM Accuracy for Kyoto dataset

In the figure 6, the x label was taken as epochs and y label was taken as a accuracy of the model. As we can see that the model training accuracy was higher than 85\% and validation accuracy was higher than 70\% for Kyoto dataset.

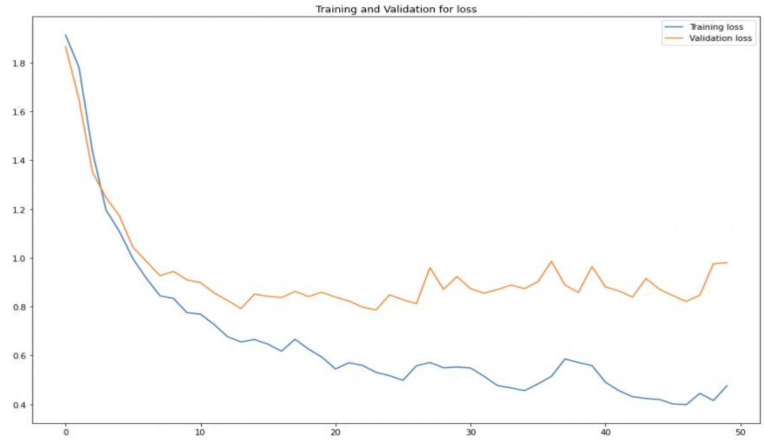

Figure 7: Bi-LSTM loss graph for Kyoto dataset

In figure 7, the x label was taken as epochs and y label was taken as a loss of the model. For Cairo dataset, the loss for the training data set was lower than 0.4\% and validation data set was about 0.8\%

5. RESULT ANALYSIS

5.1. PERFORMANCE EVALUATION

Three different metrics were used for evaluation of F1 score, Recall and precision and F1 score can be calculated by taking a harmonic mean of precision and recall.

$$\text{Precision} = \frac{\sum TP}{\sum TP + \sum FP} \quad \text{Recall} = \frac{\sum TP}{\sum TP + \sum FN} \quad \text{F1} = 2\frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (1)$$

Our dataset is skewed and consists of time series data frames; utilising ANN, we were able to achieve an accuracy of 40-60%. As a result, time series data frames were inappropriate for the Naive Artificial Neural Network. We obtained an accuracy of 70-80\% with LSTM because to the link, and LSTM is best suited for time series data frames. With BI-LSTM, we reached 90-percentage accuracy because input flows from left to right and right to left considerably boosted the quantity of information available to the network, raising the context available to the algorithm.

Table 2: Accuracy and performance table for Activity Monitoring

Methodology	Epochs	Accuracy	Precision	Recall	F1 Score
ANN	50	33%	0.32	0.26	0.28
	200	60%	0.54	0.46	0.49
RNN LSTM	100	65%	0.62	0.56	0.58
	200	72.36%	0.68	0.63	0.66
RNN Bi-LSTM	50	92.4%	0.92	0.81	0.84
	100	96.3%	0.94	0.83	0.87
	200	**97.15%**	**0.92**	**0.83**	**0.88**
	250	97.13%	0.94	0.80	0.84

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5.2. Comparing with Existing Approaches

As the need and importance for surveillance is realized there are many people and organization coming up with different approaches to efficiently detect and monitor the activity of a person. Some of the most commonly used are Wearable sensor-based activity detection, Activity detection based on skeleton joints identification. The majority of data recorded from visual sensors in activity detection based on skeleton joints is in the form of depth maps, RGB data, nodal points as skeletal joints, and so on. Wearable sensor-based activity recognition, as the name suggest it requires the user to wear a sensor in his body. Wearable sensors overcome the environmental constraints and and sensor idle constraints that cameras often suffer from in other approaches. Activity detection based on skeleton joints detects activity uses 2D and 3D body representation, upper body action recognition etc. This type of activity recognition have certain drawbacks like large number of degree freedoms are required, skeleton tracking inaccuracies, sensitivity to illumination changes and human clothing styles, difficulties in mapping image feature space to pose space, view point an lot more. This make this approach not consistent with the accuracy in detecting the activity performed.

Wearable sensor based requires a sensor attached to the person to be monitored. This is not suited for home surveillance. The drawbacks are it is difficult to wear due to the nature of the elderly and battery life is limited, the battery should charged by third party. This type of activity detection is limited to single person and not for home surveillance and has a physical burden of wearing sensor on body this makes the activity monitoring difficult. In our project we use data collected by a sensor to find the activity performed by the human being. Then the collected data is fed into our training model were we used Bi-LSTM which is best suited for time series dataset. this provides us with 90-97\% of accuracy for activity detection unlike wearable sensors and skeleton based approach were they get 80-90\% accuracy because of the environmental factors and other factors being a block for activity recognition.

5.3. Performance Analysis

```
{'Other': 0, 'Bed_to_toilet': 6, 'Take_medicine': 2, 'Eat': 5, 'Leave_Home': 4, 'Sleep': 3, 'Work': 1}
19/19 [==============================] - 17s 915ms/step - loss: 0.1766 - accuracy: 0.9396
accuracy: 93.96%
               precision    recall  f1-score   support

        Other       0.66      0.75      0.70       570
         Work       0.10      0.12      0.11        34
Take_medicine       0.00      0.00      0.00        35
        Sleep       0.14      0.11      0.13        80
   Leave_Home       0.09      0.10      0.10        58
          Eat       0.17      0.10      0.12       102
Bed_to_toilet       0.00      0.00      0.00        17

     accuracy                           0.51       896
    macro avg       0.16      0.17      0.16       896
 weighted avg       0.46      0.51      0.48       896
```

Figure 8: Classification Report for each activity

Result of the project is shown in Table 2 and this results show that the accuracy of the dataset will be more in terms of Bi-LSTM then the other two modules ANN and LSTM.The accuracy of the model also depends on the number of epochs used too train the model because more the number of epochs more training to the model and accuracy increases. The precision, recall, F1 score and support for each activity is also given in Figure 8. In the previously existing approach, they were only using the LSTM module due to which the accuracy was very low. We are using a bi-directional LSTM which means that there are two separate RNNs joined together and it allows the network to have both the forward and backward knowledge of the sequence because of which the accuracy of the system is increased.

Figure 9: Confusion matrix

In the above figure 9 we can see the confusion matrix of the results obtained. In the figure we have different activities listed in rows and columns, In the rows the values displayed are the actual value and column are the predicted value by the model.

6. CONCLUSIONS AND FUTURE WORK

To deliver effective services to its people, the IoT ecosystem need sophisticated activity learning technology. By giving information on transitions on activity and hence information on activity start/end timings and duration, activity segmentation increases the resilience of these systems. Increased data and improved activity learning might be utilized in a number of applications to track human behavior patterns and offer activity-aware services. We proposed a human daily activity segmentation based on CPD algorithms in an online or streaming format based on unscripted data from smart homes. Different segmentation and window-based activity detection methods were evaluated using pre-defined metrics.The tests using real-world smart home datasets show that activity detection may be improved by identifying activity transitions and using segment attributes. In this project, we proposed a method to detect the activity inside a home using sensors for the HAR task using a deep learning algorithm which is achieved using Bi-LSTM.

Some ideas for future work emerge from this project. They include enhancing the model's ability to detect extremely brief behaviours such as Enter house and Leave home, as well as investigating real-time methods based on wall clock time and the quantity of sensor events. Implementing new unsupervised algorithms to time series segmentation in order to adapt them for application to real-time activity segmentation in smart home settings is another avenue of future study. In home surveillance system is model is very helpful but for that to happen some activities should be added such as climbing the wall, breaking the lock and so on if we are able to add those activities then we can also use AI to secure the premises as well. Similarly it can be used in other places as well. As a part of our future work, we intend to write an implementation to alert or send an SOS signal if the sensors detect any suspicious activity or abnormal activity which can be used as surveillance in home and in hospital premises. The demand for used parts of vehicles has been suggested as one of the factor associated with the stealing of older motor vehicles. The probability of arrest appears as a crucial factor in explaining demand and supply in the stolen motor vehicle market. An increased probability of arrest of motor vehicle thieves is not necessarily related with increases in the size of the police force, there shall need of police force and new technologies in preventing this crime.

APPENDIX

Limitation

One of the issues with these models is that whether someone is asleep, sitting on the bed, or lying on the floor, the trained model will recognise it as a fall.to remove such an issue we can separate the zones in which the bed is so for example if we separate the zone where the bed is then if we sleep it wont be recognized as fall. Another problem with the model is that it will just give the data for the activity but not the location like which part of the room he/her fell down etc.therefore localization is not there in the data. In our project we are using already sensed data to detect activity detection, but in real environment we require sensors which is to be placed in rooms of the house. high amount of resources required for activity detection in multiple houses.

Scope

Continuous research is going on in this field of Activity detection detection using deep learning and the systems are getting better every year. Using smartphone sensors conducting a HAR is very time consuming process and a hectic one. These systems are not restricted to single house, Around the world number of violent acts such as shooting,theft, terrorist attacks have been increased so HAR helps us to know what is happening in public places and minimize those as much as possible, thus research is going around to practically implement these systems. Main goal is to limit the number of mistakes done by human error, which might have serious repercussions. This job is not just limited to home monitoring; it can also be used in hospitals, schools, restaurants, factories, and large-scale industries to ensure the security and safety of employees because the accidents in large scale factories are common and we can help reduce it or take action immediately if it happens.

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