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HUMAN ACTIVITY RECOGNITION AND FALL DETECTION

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Abstract

Personalized monitoring ad its application is increasing with an advancement of technology. And during pandemic its become very essential to keep an eye on the prone area and one of the area to identify was old age home. Dizziness, unconsciousness and other are the common problems associated with elderly people due to weakness and this was also the symptoms of covid. So an unusual activity of falling of elderly people was very difficult to identify and also to monitor. The technology was updated till now to identify posture of normal activity such as running, walking, jumping and many but revert to that falling was an area need to explore. During fall of an elderly people the injuries are very fatal and to void this case a remedial solution is design to identify the fall and try to notify te system about its fall. Although we try to predict the fall so that it become easy to monitor and provide medical help as soon as possible. The main theme is to identify the posture activity and once identify we will compare the activity with trained datasets and if its normal in vision them no notification occurred and if the percentage of fall was high them we can predict the system as fall video.

Keywords—Elderly People, Activity Detection, Fall Detection, Predicted

1. INTRODUCTION

Many elderly are living alone during this lockdown and can have limited access to various facilities especially to medical help also. Various methods of technology has evolves to identify and monitor the activities related with it. And hence to monitor further about its fall it's very essential and important o predict the fall of a person. A surveillance camera will be available to capture the activity of elderly people and feed continuous video into the system for training part and for modeling purpose. There are two procedures to follow, first one is to feed those videos to the activity model and second step is to compare the activity frames with dataset and predict the fall. People above 65 age have the problem of weaker muscle and may lead to collapsing which affect critical injuries. An unusual activity model was creates to predict the fall with reference to the video feed. It will definitely help to resolve the issue of unusual activity and estimate the fall quickly and efficiently.

The past few years have seen a rapid increase in people using wearable devices. The use of connected wearable sensor devices is predicted to increase from 325 million in 2016 to 929 million in 2021 [1]. The wrist watch is one of the most popular forms of wearable devices. Sensors inside the device measure metrics like the steps taken, stairs climbed, sleep, heartbeat, and oxygen levels. Typically, the data from a wearable sensor device are sent to a cloud service for analysis and displayed on the dashboard of a connected mobile device. On the cloud, the data are synchronized with a data management environment, which is typically provided as a service by the manufacturer of the wearable device. A single accelerometer sensor at 200 Hz generates about 2.3 GB of data per day. The more the sensors or monitoring metrics are added, the more the data are generated by the sensors. There is a steady progression towards the era of the Internet of Things (IoT) where many such devices will be connected generating terabytes of data that must be analyzed possibly in real time to provide effective decision support. If all these data have to be uploaded to the cloud for analytics, it would result in a wastage of network bandwidth and a decrease in response time.

Wearable sensors can be used with edge computing devices that perform a bulk of data-processing tasks and then send out only a subset of the collected data to the cloud. This approach reduces the data transmission time and use of network bandwidth and enables edge devices to notify authorities faster about important analytical results. For example, data from wearable sensors can be received and analysed at an edge device to monitor patient health status and notify appropriate authorities in the event of a fall which can be critical for elderly patients.

According to the World Health Organization, a fall is defined as an event in which a person comes to rest onto the ground or any lower level [2]. An estimated 646,000 fatal falls occur each year, making it the second leading cause of death because of unintentional injury, after road traffic injuries [2]. Across the world, death rates are highest among adults over 60 years of age. More than 50% of injury-related hospitalizations are seen in people aged over 65 [2]. Consequently, almost 40% of the injury-related deaths are from falls in the elderly population [2]. In Canada, many retirement homes and long-term care facilities have a very high patient-to-nurse ratio, and falls do not get reported until after some time. Falls also cause hip fractures, another common problem in the elderly population. According to the Health Quality Ontario, the average time taken to treat a low-urgency condition in Kingston General Hospital (KGH) is 3.1 hours [3]. With the rising cost of healthcare and a growing elderly population having chronic diseases, there is an urgent need to shift elderly patient care from the hospital to other patient care facilities such as smart retirement homes. It would facilitate better patient monitoring and ensure the wellbeing of all the Canadians.

In the 1990s, Personal Emergency Response Systems (PERSs) were quite popular. One of the most common PERS devices is a pendant which is worn on the neck in the form of a chain. A person who needs help would press the pendant, and a notification is sent to the caregiver. This eliminates the problem of long waiting time before a person can rise and seek help. However, it is not an optimal solution as Roush et al. [4] pointed out that a fall often causes fatality in elderly people leaving them disoriented or not conscious enough to act logically such as pressing a button for help. There are also devices available nowadays which can detect falls automatically and send an alarm to the caregivers or ambulance services. But they are very expensive and require a subscription to a monthly service. An alternative solution is required for caregiving centres, which can detect a fall and generate a call for help when needed. A significant amount of research has been done on fall detection using sensors like accelerometers and gyroscopes, which are cheap and included in most of the smart mobile devices available today like smartphones and tablets.

A remedial solution with an edge computing framework which is deployed in close proximity, i.e., within a maximum range of 100 ft from the wireless sensor devices, and collects and performs preprocessing of the data to only transfer the important data to the cloud. We develop machine learning models to analyse the data and generate notifications in real time to enable calls for assistance. We validate our framework for real-time fall detection use case scenario by analysing the accelerometer data collected from the wearable sensor devices. We are working with medical collaborators to deploy our framework at clinics and retirement homes to monitor patients in real time as a part of Kingston's Smart City initiative.

2. LITERATURE SURVEY

Sr.No.	Name of author	Title,Journal and year of publication	Description	Advantages	Disadvantages
[1]	Heilym Ramirez 1, Sergio A. Velastin2,3, (Senior Member, Ieee), Ignacio Meza1, Ernesto Fabregas 4, Dimitrios Makris5, And Gonzalo Farias 1	Fall Detection and Activity Recognition Using Human Skeleton Features IEEE Access VOLUME 9, 2021	These applications present solutions to recognize different kinds of activities such as if the person is walking, running, jumping, jogging, or falling, among others. Amongst all these activities, fall detection has special importance because it is a common dangerous event for people of all ages with a more negative impact on the elderly population. Usually, these applications use sensors to detect sudden changes in the movement of the person.	Pose estimation is proposed as a feature extraction mechanism that allows RGB images to be described by sets of human skeletons and considering the most prominent skeleton per image	It could also be adapted to multi person activity recognition.
[2]	Shobhanjana Kalita	Human Fall Detection during Activities of	For human activity recognition, Extended CORE9 has been used	Encoding the spatial information within a	It was noted that this approach is not always

	Arindam Karmakar Shyamanta M Hazarika	Daily Living using Extended CORE9 2019 Second International Conference on Advanced computational and Communication Paradigms (ICACCP)	for obtaining a qualitative spatial description of the video activity. The spatial description of an activity obtained using Extended CORE9 along with the temporal information can be encoded within a graph structure. Extended CORE9 has been applied for human-human and human object interactions. In this paper, they show how Extended CORE9 can be applied for single-person activities.	graph representation provides classification results that are comparable to the state-of-the-art for human-human or human object interactions	able to distinguish between a lying down activity and fall activity because the speed of the activity has not been taken into account
[3]	Ali Chelli, Member, IEEE, and Matthias P¨atzold, Senior Member, IEEE	A Machine Learning Approach for Fall Detection and Daily Living Activity Recognition DOI 10.1109/ ACCESS.2019.29066	**Two steps are followed in this system:** Only the acceleration data are used for activity recognition extract features from the autocorrelation function and the power spectral density of both the	It is worth to mention that the accuracy of fall detection for QSVM and EBT reaches 100% with no false alarm which is the best achievable	The process of finding the mean value was lengthy so as to find the accuracy but at the same time the processing time also increases

		93, IEEE Access	acceleration and the angular velocity data, which improves the classification accuracy	performance.	
[4]	Bharati Kaudki Anil Surve	IOT Enabled Human Fall Detection Using Accelerometer and RFID Technology, Proceedings of the Second International Conference on Intelligent Computing and Control Systems (ICICCS 2018), IEEE Xplore	The falls can be detected of the elder people who are living alone in the home and the person who is handicapped can have certain incidents like falling so to monitor the elder people activities this paper presents the accelerometer sensor and the RFID technology using this technology the activities of the elder people can identify.	KNN classifier to get much better performance and to recognize various activities. The future work will focus on a device free activity recognition system for elder people, by exploiting unobtrusive, low cost passive RFID tag.	The hardware complexity increases with sensor data
[5]	Hristijan Gjoreski, Simon Kozina, Matjaž Gams, Mitja Luštrek	RAReFall - Real-time Activity Recognition and Fall Detection System, 2014 IEEE International	The system consists of two wearable accelerometers sewn into elastic sports-wear, placed on the abdomen and the right thigh. The recognition of the user's	It was designed for robust performance in real life, so it uses a combination of relatively mature but	Real time activity recognition reduces some percentage of accuracy during image capturing part

		Conference on Pervasive Computing and Communications Demonstrations	activities and detection of falls is performed on a laptop using the raw sensors' data acquired through Bluetooth. The RAReFall system consists of two accelerometers into elastic sports-wear, placed on the abdomen and the right thigh. The AR and FD are performed on a laptop using the raw sensors data acquired through Bluetooth.	finely tuned methods. The competition setting is closer to real life than most AR evaluations, so our result at the competition is evidence of RAReFall's practical applicability.	

Fall monitoring has been an emerging field with new systems being introduced constantly. Several taxonomies on fall monitoring can be found in the research, but most of them are done for monitoring in general, i.e., for systems using video, audio, and ambient sensors. We present a literature review specifically for wearable sensor devices and the systems they use for monitoring as explained below.

2.1. Fall Detection Models

An efficient fall detection system detects a fall by analysing the raw sensor data. Threshold-based monitoring and machine learning-based predictive analytics approaches have been developed based on data collected from accelerometers and gyroscopes, the two most commonly used sensors for fall detection. In threshold-based techniques, a fall is detected when monitored data values exceed predefined threshold values. In contrast, machine learning techniques analyse data and try to learn hidden patterns to classify the data.

Bourke et al. [5] presented a fall detection mechanism where sensors were placed on the thigh and trunk. By analysing the signals from these sensors, upper and lower fall thresholds were determined. If the resultant value exceeded the upper fall threshold at the trunk, a fall was detected. It was able to detect a fall with 100% specificity. But when tested against the real-time data, a lot of false positives were observed. So, Bourke et al. [6] in his next study monitored the patients after fall impact was detected. Though this decreased the number of fall positives, it still had problems with differentiating some fall-like activities. Kangas et al. [7] found similar results in his study where apart from monitoring the impact and posture, they tested the start of fall and the velocity before impact. While the start of a fall was clearly shown in the forward and sideward falls, it was not useful for detecting backward falls which are the major causes of hip fractures. Bourke et al. [8] calculated vertical velocity along with impact and posture for both scripted and unscripted activities which lead to fewer false positives.

He et al. [9] proposed a fall detection and alerting system using a smartphone. A median filter was used to smooth out raw accelerometer values. Features like signal magnitude area, signal magnitude vector, and tilt angle were analysed against the smoothed values. When the features exceeded a certain threshold, a fall was detected. Vo et al. [10] analysed falls with a smartphone in the hand, chest pocket, or pant pocket. Detection of fall was done in three steps: step 1—when the fall took place, step 2—when the person hit the ground, and step 3—when the person returned to normal activity or continued to lie down. The orientation was analysed in between two steps when monitoring data exceeded predefined threshold values. To monitor a subject after fall, the orientation data were analysed for movements in the third step. This mechanism was tested on five young people, which resulted in 85% accuracy.

Abbate et al. [11] proposed a mechanism to use both threshold and machine learning algorithms to detect falls. The system was implemented using a smartphone and a wearable sensor placed at the waist with a sampling frequency of 50 Hz. When a fall was detected using a threshold-based technique, it was sent to a classification model for further analysis. The mechanism also had a notification centre, using which the user could turn off the false alarms. The false-positive data were sent to the classification model again for training. A two-layer feed-forward neural network model was used for classification where features were generated from the input signals and fed into the model. In the case of continuous data acquisition, the model was able to distinguish between false positives and real falls with a specificity of 100%, but no fall occurred during the data collection. So only specificity could be calculated. The authors concluded by stating that small external sensing units will garner a more positive response because of low intrusiveness instead of forcing subjects to carry smartphones in their pockets.

Yuwono et al. [12] proposed a system to optimize the performance of fall detection using a neural network approach with a minimum amount of information from a triaxial accelerometer. The remedial solution constantly checks the magnitude of all the accelerometer values. If it exceeds some predefined threshold value, then the signals from 2.5 s before and after the impact are extracted and normalized. Using the discrete wavelet transformation (DWT), *K*-means seeded regrouping particle swarm optimization (RegPOS) and Gaussian distribution of clustered knowledge (GCK) refer each input signal to the cluster centroid and measure the statistical characteristics. Finally, the data are sent to a multilayer perceptron, augmented radial basis function neural network, and a voting ensemble of both. It is concluded that while the results were very promising, training and testing the data are difficult for this technique.

Khan and Hoey [13] surveyed different machine learning algorithms for fall detection. The authors concluded that recurrent neural networks (RNNs) were very well suited for this problem as the data are usually sequential time series data. Theodoridis et al. [14] built long short-term memory (LSTM) recurrent neural network models using a published dataset called the UR fall detection. When compared with support vector machine (SVM) and Bourke et al.'s [5] threshold-based approach, the LSTM model gave better results than the other approaches.

2.2. Fall Prevention Techniques

Besides fall detection, there is a dire need for fall prevention systems. External prevention can be done by installing handrails and teaching techniques to avoid falling, but internal fall prevention is trickier. It requires deep research on the neurological activities to analyse which part of the brain depletes their awareness and lowers the reaction time. Also, the gait and posture can be analysed to correct their balance in case of free fall. Cheng et al. [15] proposed that, by educating the elderly people on fall, teaching different types of exercises, and assessing and monitoring hazard situations, falls can be reduced. Some work has also been done on cushioning the fall so that any injuries can be avoided. Tamura et al. [16] built an innovative system where a wearable airbag inflates automatically when the system predicts a fall 300 ms before the fall occurs. Zhong et al. [17] conducted similar research on real-time falls. The airbag was able to inflate correctly for each fall with a sensitivity of 93.6%. Although systems such as these show great progress towards fall prevention, challenges still exist in handling situations like sideward and forward falls. More work is needed for expediting the inflation process of the airbag and avoiding false alarms.

2.3. Fall Detection Systems

Fall detection systems vary in the components they use. One of the most common sources for the sensor data is a smartphone. The data are collected, analysed, and stored on the smartphone itself. Most of the research studies we have discussed so far are performed through such a device. Because of their limited computational power and storage, advanced machine learning techniques are difficult to implement on smartphones.

2.3.1. Cloud Computing

In fall detection systems, cloud computing is used to retrieve, preprocess, and analyse data remotely in a cloud, which provides a huge amount of computational power and storage. A mobile phone or a wearable device as intermediary devices can be used to send data to the cloud. The data stored in the cloud can be used for long-term analysis. Lai et al. [18] proposed such a cloud computing model for fall detection where the data are analysed using a MapReduce framework on the cloud. The analysed result is sent back to a mobile device to inform the user. The model was able to detect falls with an accuracy of 85% in the case of activities like running.

2.3.2. Edge and Fog Computing

Edge or fog computing applies the concept of cloud computing near the data source. In edge computing, data are retrieved, preprocessed, and analysed at the edge of the network enabling real-time decisions, and only the summary of the data to be uploaded to the cloud. Usually, the terms edge and fog are used interchangeably. Yacchirema et al. [19] used a decision tree-based big data model where if a fall was detected at the fog level, data were sent to the cloud for further analysis. In this case, fog represented a Raspberry Pi board which did the near node analytics. The data were collected at a frequency of 200 Hz. The decision tree model was trained using an existing historic dataset. The system performed with an accuracy of 91.67% and a precision of 0.937.

3. PROBLEM STATEMENT

- To create a system which will predict the fall
- To minimize the fatal accident happens to elderly people due to falling
- To overcome the problem associated with fall of elderly people which cause a critical injuries or other
- To track the activity of elderly people by continuous monitoring

4. OBJECTIVES

- To design an activity recognition model which will help to predict the system about the fall
- To design a remote-monitoring system in various organizational systems.
- To improve the detection method by comparing with large number of dataset

5. METHODOLOGY

To do the system more accurate the database need to gather of videos associated with falling pattern. Once the data was gathered we need to monitor the falling frames and divide them into fall and not falling posture. With the help of falling frames it become easy to identify the real view of falling of a person by comparing the real time or dataset falling video with the frames we classified.

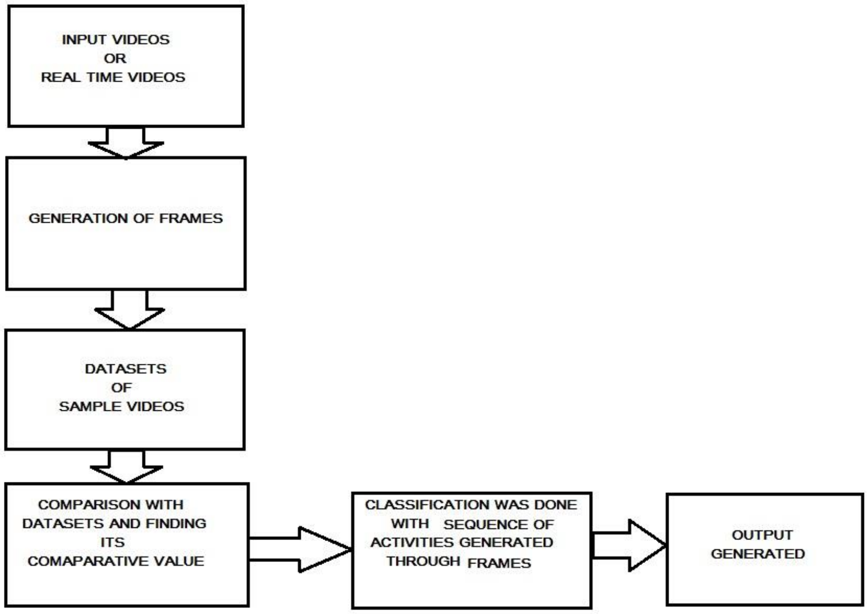

Fig.1. Depicting the flow of the system for fall detection

5.1 Data Store

The preprocessed data can either be stored on the edge device or sent to the cloud for storage and further processing. Different data storage systems can be used depending on the data type, flow rate, organization, and query requirements.

We used the local file system to store the data in the form of CSV files. A single wearable device generates up to 2.3 GB of data per day. In this study, we used a laptop as the edge device, and hence we performed the next level of processing on the same device to generate faster notifications. For future, the data can be sent to a cloud server for online training of the machine learning models.

5.2 Data Analytics Engine

The higher-level analytics and classification are done using the analytics engine. This can include training machine learning models, performing an analytic query on the stored preprocessed data, or using the data in decision support systems.

We used TensorFlow as the data analytic and machine learning component to classify the data as fall or nonfall for our use case scenario of fall detection. TensorFlow is an open source library which offers customizable training and layers for the machine learning models. It is one of the libraries that offers advanced machine learning techniques. We used TensorFlow as the data analytic component to build, train, and apply an LSTM neural network model to detect a fall from the human activity data ingested and processed by our framework. For this study, we developed and trained an LSTM model with an offline open source MobiAct dataset and then deployed the model in TensorFlow on the edge computing framework to score the real-time data as fall or nonfall.

The LSTM network was built in Python using Keras with TensorFlow in the backend. It uses softmax activation function, Adam optimizer, mean squared error, and categorical cross entropy as the loss functions for binary and multiclass models, respectively. Each experiment was conducted using 58 feature values at the input layer and 30 LSTM units in the hidden layer. The number of expected outcome dictated the number of nodes at the output layer. Figure 5 depicts the performance of the system against the number of nodes in the LSTM layer. From Figure 5, we can observe that, at 30 nodes, the network gave the best results, and as the number of nodes increased further, performance degraded due to overfitting. Additionally, a dropout of 0.30 was used to avoid overtraining of the models. Each activity in the given dataset was recorded for 10 s. So, the data were fed into the LSTM accordingly; i.e., we used a time step of 10 for all the models. All the output labels were one-hot encoded. One-hot encoding converts the categorical data to a binary sequence for training purposes.

6 IMPLEMENTATION

6.1 Sequence of Execution

- Input data signals from dataset or real time camera
- Pre processing of input data to generate frames through segmentation
- Feature are extracted for specific activity
- Models for specific activity was created
- The generated values were compared with an ideal value and fall detection or not were justified.

6.2 To clarify the above diagram more clearly the following procedure was provided.

The input dataset video or a real time video was sent to justify the fall. This video was then broken down into frames which are then resized accordingly, converted into sequence of activities and sent to the models- Activity Recognition and fall detection Model. The activity recognition model recognizes the activities in the frames. This sequence of activities is then sent to the created model from datasets where the comparative values were generated. If these values are below the ideal value, then that sequence of activities is classified as abnormal. Fall activity need to identify so early so as to provide the help urgently.

7. ACTIVITIES FOR RECOGNITION

Usual activities which was identified of constant posture

- Working at Computer (working PC).
- Standing Up, Walking and Going up/down stairs.
- Standing.
- Walking
- Going Up/Down Stairs (stairs)
- Clapping
- Jumping
- Running
- Seating
- Bending

8. PREPROCESSING

- **Conversion of videos into frames**

This process was done after classifying the videos into various frames and that frames were stored for training with input sequence. The input will be either the stored video or from live camera. The patterns of the frames were resized for 300 * 300 pixels.

- **Frames Conversion**

This resized frames was converted into sequence of activity and extracted its features in comparison with the dataset model and helps to predict the fall. The intensity of frames was different with other frames surrounding

9. RESULT

9.1 Selecting the input

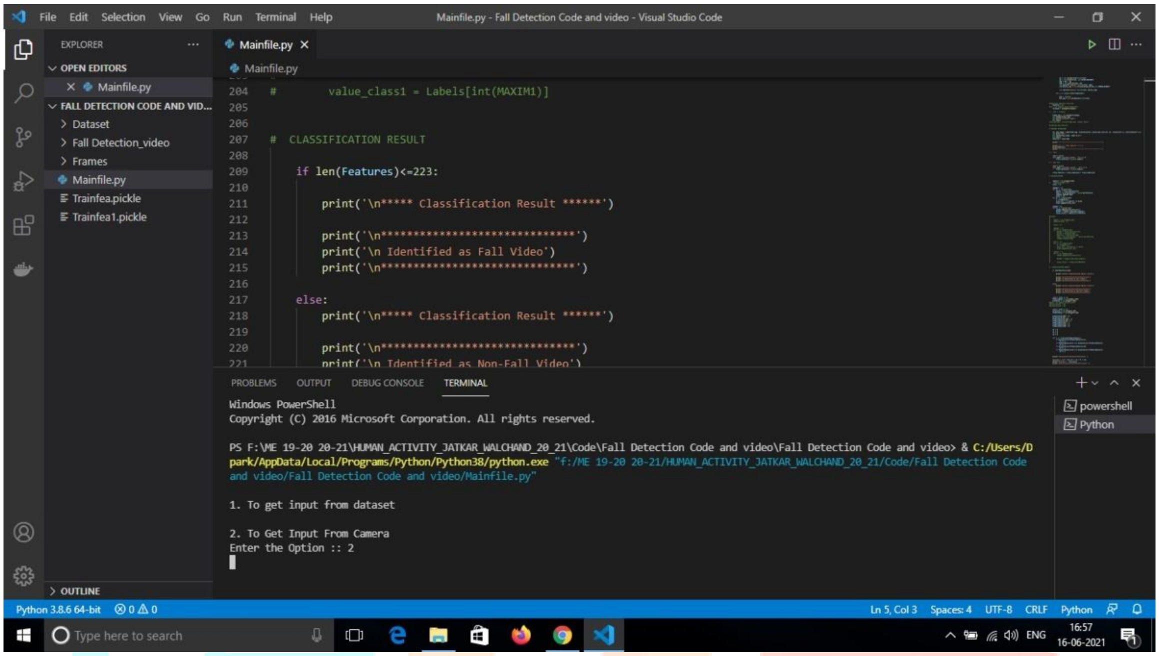

Fig.2 Selecting the input

9.2 Selection of video

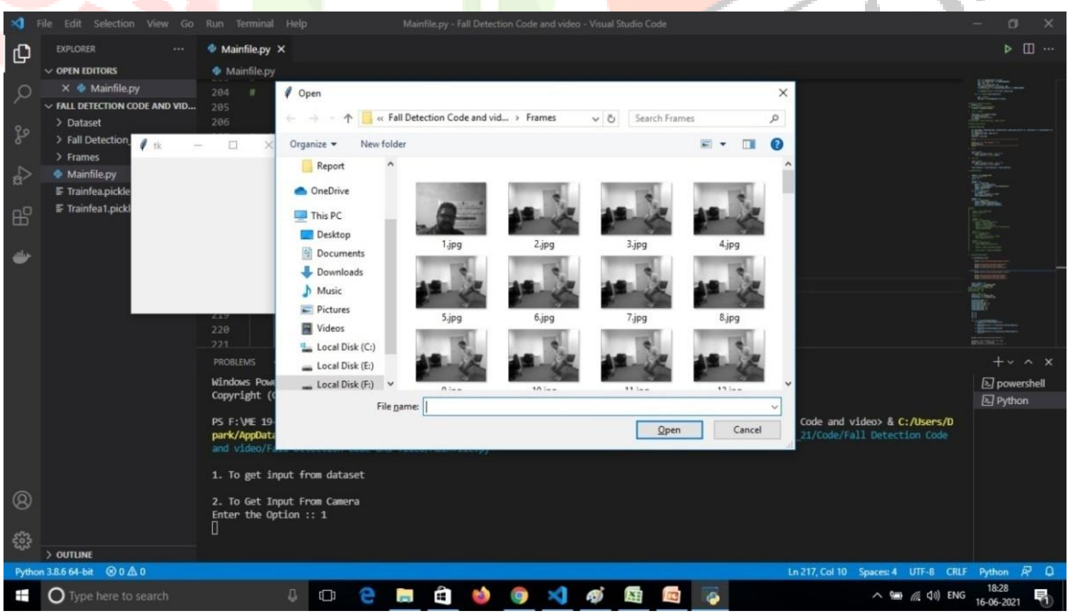

Fig.3 Selection of video

9.3 Frames generation

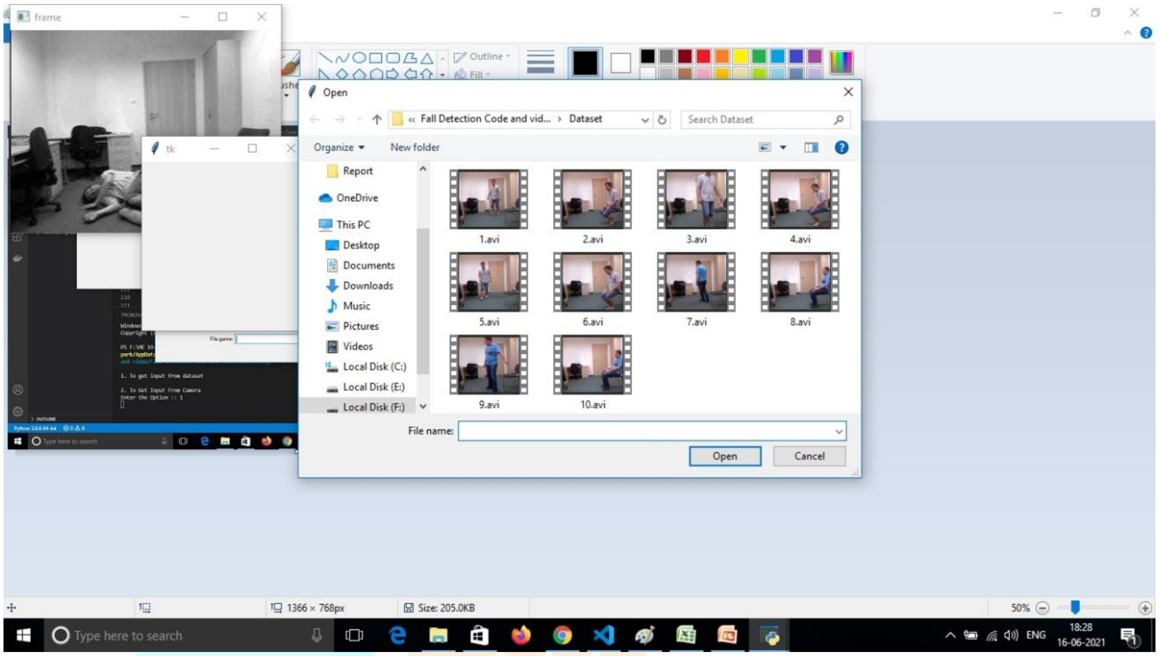

Fig. 4 Frames generation

9.4 Selected Frame

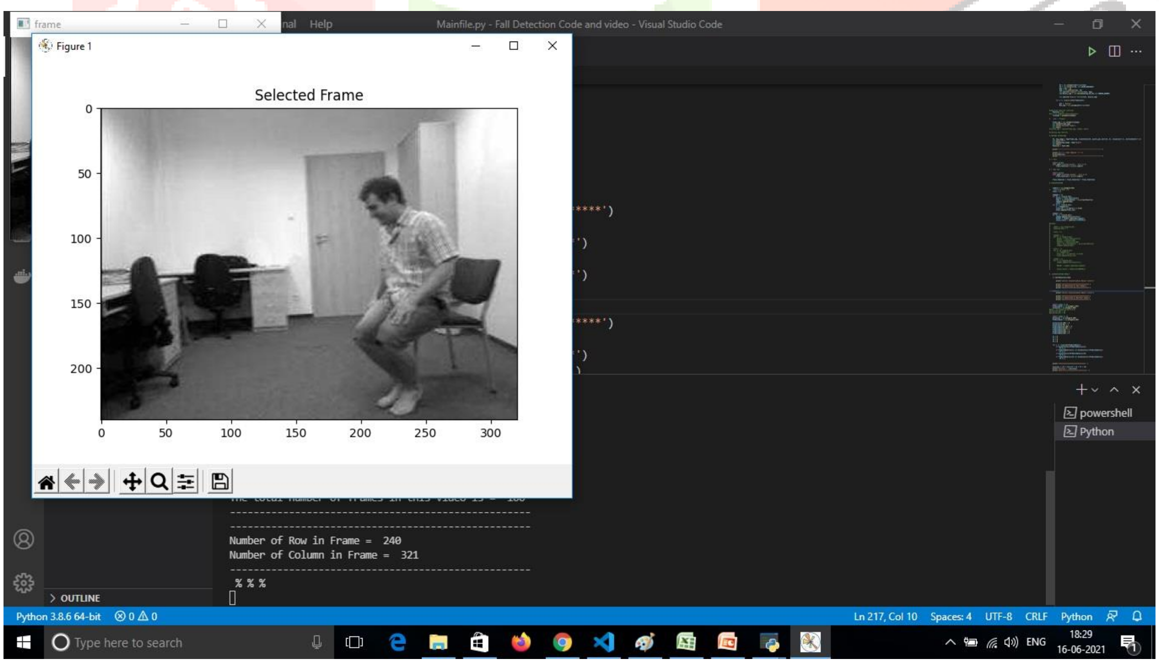

Fig. 5 Selected Frames

9.5 Feature Extraction

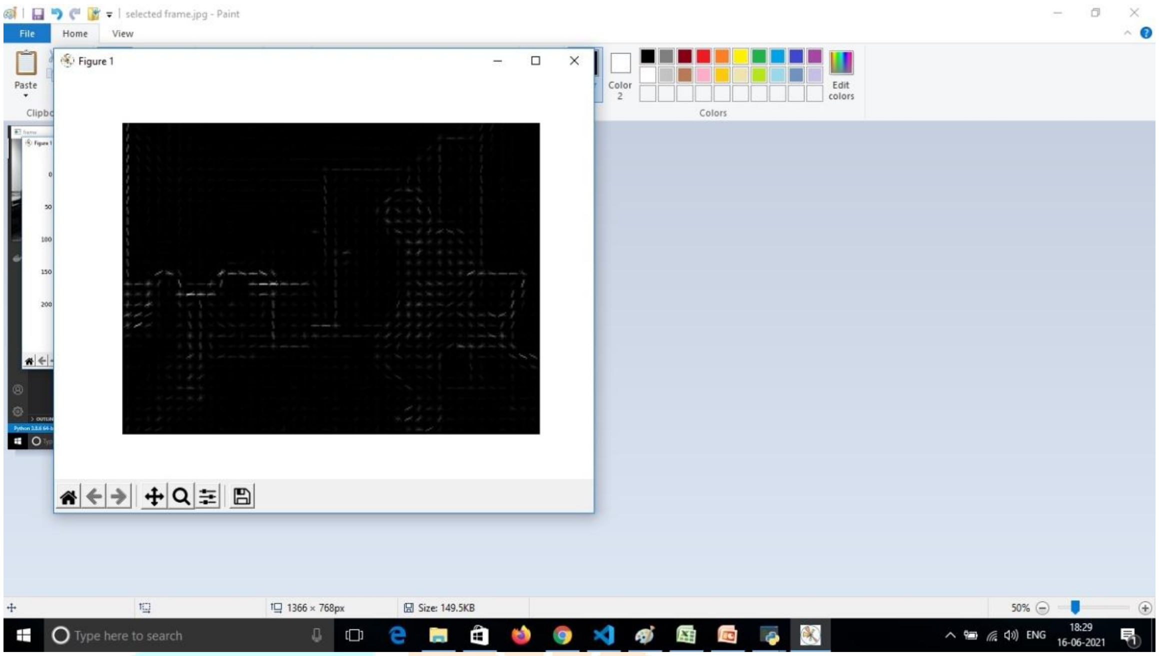

Fig. 6 Feature Extraction

9.6 Performance Estimation

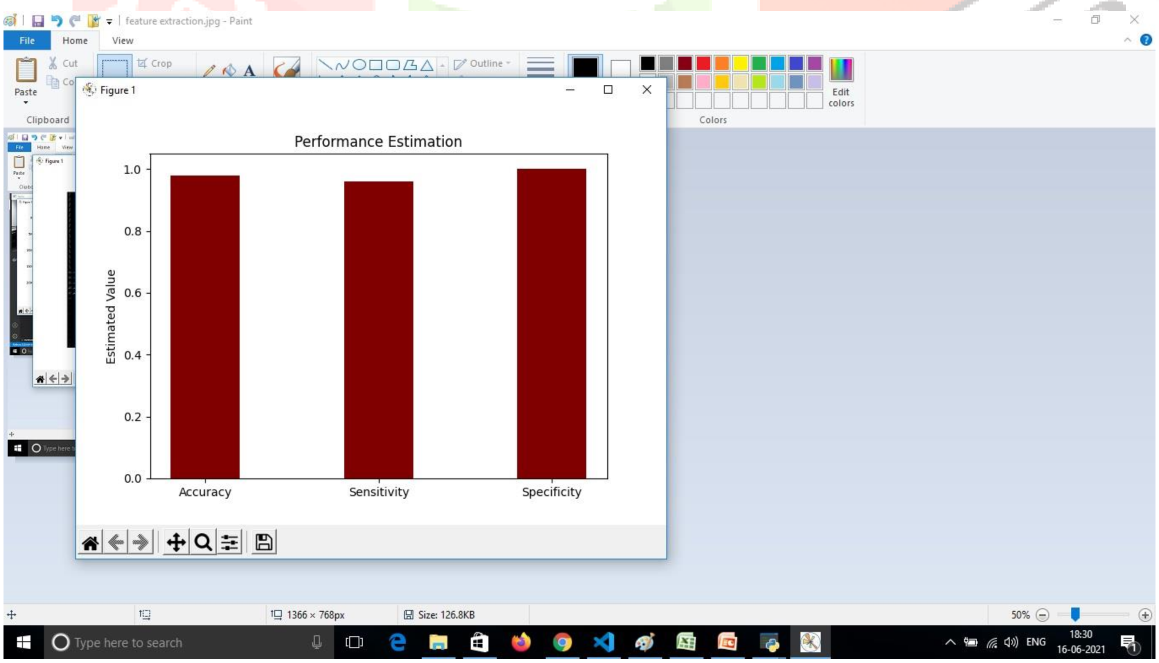

Fig. 7 Performance Estimation

9.7 Detection of Fall or not

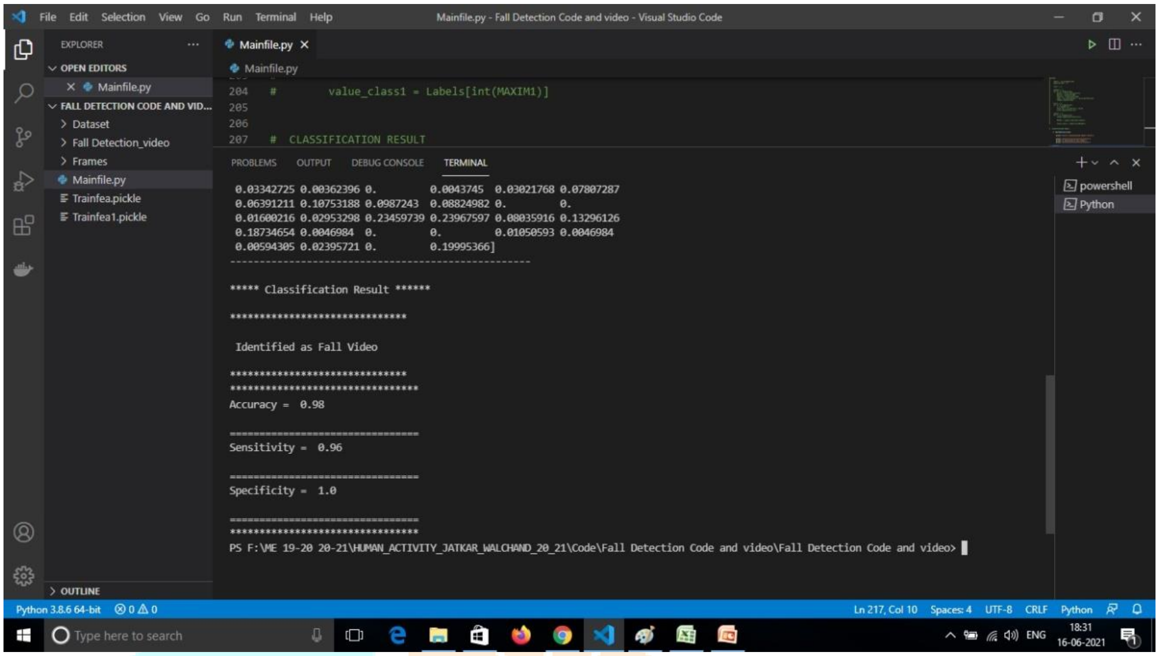

Fig. 8 Detection of fall or not

10. CONCLUSION

The way of living of an elderly people alone during this lockdown and can have limited access to various facilities especially to medical help also. This method is helpful to identify and monitor the activities about falling of an elderly person. The use of surveillance camera will be available to capture the activity of elderly people and feed continuous video into the system for training part and for modeling purpose. Two procedures that was proposed and design of which first one is to feed those videos to the activity model and second one is to compare the activity frames with dataset and predict the fall. People above 65 age have the problem of weaker muscle and may lead to collapsing which affect critical injuries. An unusual activity model was creates to predict the fall with reference to the video feed. It will definitely help to resolve the issue of unusual activity and estimate the fall quickly and efficiently. Further it will extended as a part of research

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