A Machine Learning Approach For Fall Detection and Daily Activity Recognition using KNN and QSVM Algorithm

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***Abstract*— The quantity of more established individuals in western nations is always expanding. A large portion of them like to live autonomously and are defenseless to fall occurrences. Falls frequently lead to genuine or even deadly wounds which are the main source of death for elderlies. To address this issue, it is basic to create hearty fall discovery frameworks. In this specific situation, we build up an AI structure for fall location and every day living action acknowledgment. We use speeding up and precise speed information from two open databases to perceive seven unique exercises including falls and exercises of everyday living. From the increasing speed and rakish speed information, we separate time and recurrence area include and give them to an order calculation. In this work, we test the exhibition of four calculations for arranging human exercises. These calculations are fake neural system (ANN), K-closest neighbors (KNN), quadratic help vector machine (SVM), and troupe sacked tree (EBT). New highlights that improve the presentation of the classifier are removed from the force otherworldly thickness of the speeding up. In an initial step, just the quickening information is utilized for movement acknowledgment.**

Keywords—Fall detection, activity recognition, machine learning, acceleration data, angular velocity data, feature extraction.

I. INTRODUCTION

Falls are the most widely recognized reason for incapacity and demise in more seasoned individuals around the globe. The danger of falling increments with age, yet it additionally depends on wellbeing status and natural components. Alongside preventive measures, there is likewise essential to have fall location arrangements to decrease the time wherein an individual who endured a fall gets help and treatment. Fall identification can improve the security and wellbeing of more seasoned individuals and ready when the fall happens. Studies in the field of programmed fall identification order fall recognition frameworks in three classes. Approaches dependent on wearable sensors, surrounding sensors, and vision. Every technique has ordinarily known points of interest and constraints. Wearable sensors are in some cases prominent and awkward; cell phones and savvy watches have battery impediments and restricted handling and capacity. Even though vision techniques are modest, unpretentious, and require less participation from the individual, they have protection issues and condition conditions can influence the memory. As of late, because of the expanding accessibility of various methodologies of information and more noteworthy office to gain them, there is a pattern to utilize multimodal information to consider diverse marvel or arrangement of intrigue [6]. The fundamental thought is that "Because of the rich qualities of regular procedures and conditions, it is uncommon that a solitary obtaining strategy gives total seeing thereof" [6]. Multimodal and information combination are additional patterns in wellbeing frameworks. The blend of various information sources, prepared for information combination is applied to improve unwavering quality and accuracy of fall recognition frameworks. Koshmak et al. [7] exhibited the difficulties and issues of fall recognition investigate with the center in multisensor combination. The creators depict frameworks of fall recognition of multifunction draws near, consequently, every one of them presents outcomes in their dataset making it difficult to look at. Igual et al. [8] present the need for an openly accessible dataset with an extraordinary decent variety of procurement modalities to empower correlation among frameworks and new calculation exhibitions.

II. LITERATURE SURVEY

In the writing, a few movement datasets are freely accessible which permit assessing fall location strategies and surveying their exhibition on true information. An ADL database which contains speeding up and precise speed information are given in [6], where a content depicting the arrangement of exercises to be done was given to the members. An aggregate of 30 members of various sexual orientations, ages, and loads added to this trial. The examination comprised performing ADL exercises including standing, sitting, strolling, strolling upstairs, strolling the first floor, and lying. To gather the speeding up and rakish speed information, a cell phone was joined to the midriff of every member. By and large, the all-out time of recording for every member was 192 seconds. It merits referencing that the dataset does exclude fall information, however just ADL exercises. Fall-related information can be found in some open databases. The creators of give a fall dataset that was performed by 42 members. Both increasing speed and rakish speed information were gathered during this trial. The members in this analysis were youthful sound grown-ups who performed arranged falls. This reality makes the gathered information not quite the same as that of genuine falls of older individuals. Because of the trouble of social event enough genuine fall information from more established individuals, the utilization of imitated fall information for testing the exhibition of fall location framework is a well-accepted approach by the analysts on this subject. In this paper, we propose an AI structure for fall discovery and movement acknowledgment. Our first primary commitment is identified with the highlights utilized for fall location. All the more explicitly, we utilize the mean estimation of the triaxial increasing speed and accomplish a fall location exactness and accuracy of 96.8% and 100%, separately. Even though, the mean estimation of the triaxial quickening isn't inherently another component since it was utilized in past work [6] to group ADLs, the mean an incentive for triaxial speeding up was not used as an element in the order of falls. Note that by extricating just the mean estimation of the triaxial quickening, we develop a component vector of size 3. A component vector of length 4 is utilized for fall location. This brought about a fall location exactness of 92% and an accuracy of 81%, while a component vector of length 23 is used prompting a fall identification precision of 93.5% and an accuracy of 94.2%. For our answer, we utilize an element vector of length 3 and accomplish a fall identification exactness and accuracy of 96.8% and 100%, separately. Consequently, we outflank the fall location frameworks as far as exactness and accuracy by utilizing fewer highlights. Our second principle commitment comprises in proposing new highlights that improve the arrangement precision of ADLs. For example, we have proposed new force ghastly thickness (PSD) highlights that improve the arrangement exactness, particularly, for the exercises strolling, strolling upstairs, and strolling the first floor. In the writing, a few highlights were separated from the PSD, for example, the biggest recurrence esteem [6] and the mean recurrence esteem. In any case, in this paper, we separate the principle pinnacles of the PSD and use them as an element for action grouping. As far as we could know, this component has never been used in action order. Besides, we remove extra novel highlights, for example, the pinnacles of the autocorrelation work (ACF), and the pinnacles of the cross-relationship work (CCF), which are extricated from the triaxial increasing speed and the triaxial precise speed signals. These proposed new highlights permit a progressively exact differentiation between various exercises. In this work, we consolidate the fall and ADL information from the datasets gave in [7] and [6]. This genuine information is then used to assess the presence of the proposed AI system in human action acknowledgment. The increasing speed and rakish speed signals are isolated into cushions of 2.56 s length. From each cradle, we separate a component vector of length 66, in an initial step. To improve the exactness of the arrangement, more highlights are removed from each cushion, with the end goal that the length of the element vector increments to 328. Note that the lengths of the considered element vectors (66 and 328) are littler than the number of highlights utilized in existing benchmark arrangements. We use 70% of the information to prepare the classifier, while 30% of the information is utilized to test the prepared classifier. For a component vector of length 66, we accomplish a comparative execution contrasted with existing arrangements, while for an element vector of length 328, our methodology beats existing arrangements. In this paper, we survey the presentation of four diverse grouping calculations, to be specific, the counterfeit neural system (ANN), K-closest neighbors (KNN), quadratic help vector machine (QSVM), and troupe sacked tree (EBT). In an initial step, just the increasing speed information is utilized for highlight extraction. A component vector of length 66 is fabricated and gave as a contribution to the order calculation. Our outcomes uncovered that the KNN calculation has the most noticeably terrible exhibition with a general exactness of 81.2%. The EBT calculation has the best execution with a general precision of 94.1%. The ANN and the QSVM calculations accomplish a general exactness of 87.8% and 93.2%, individually. The precision of fall recognition arrives at 97.2% and 99.1% for the QSVM and EBT calculations, individually, with no bogus caution. In a subsequent advance, we extricate highlights from both the increasing speed and the precise speed information and develop a component vector of length 328. This expansion in the number of highlights improves the exhibition of the four grouping calculations. The KNN, the ANN, the QSVM, and the EBT calculations accomplish a general precision of 85.8%, 91.8%, 96.1%, and 97.7%, individually. Also, the precision of the fall location arrives at 100% for both QSVM and EBT with no bogus alert, which is the best feasible exhibition.

III. Problem Definition

To structure the framework utilizing AI for fall discovery and the everyday movement acknowledgment of the human exercises. we build up an AI system for fall identification and day by day living movement acknowledgment. We use speeding up and rakish speed information from two open databases to perceive seven distinct exercises including falls and exercises of day by day living. From the quickening and rakish speed information, we remove time and the recurrence space includes and gives them to a characterization calculation. In this work.

IV. Algorithm Used in Machine Learning

1. Qualitative Support Vector Machine:-

The Support Vector Machine Algorithm is utilized for arrangement or relapse issues. In this, the information is partitioned into various classes by finding a specific line (hyperplane) which isolates the informational collection into numerous classes. The Support Vector Machine Algorithm attempts to discover the hyperplane that boosts the separation between the classes (known as edge augmentation) as this expands the likelihood of ordering the information all the more precisely.

A case of the Support Vector Machine Algorithm utilization is for the examination of stock execution for stocks in a similar part. This aide in overseeing speculation settling on choices by the money related foundations.

As compare to other algorithm like KNN, ANN, EBT the QSVM algorithm achieve 100 % accuracy.

2. K Nearest Neighbours Algorithm –

The K Nearest Neighbors Algorithm partitions the information that focuses on various classes dependent on a comparable measure, for example, the separation work. At that point, a forecast is made for another information point via looking through the whole informational collection for the K most comparative occurrences (the neighbors) and condensing the yield variable for these K examples. For relapse issues, this may be the mean of the results and for characterization issues, this may be the mode (most continuous class). The K Nearest Neighbors Algorithm can require a ton of memory or space to store the entirety of the information, yet just plays out a figuring (or realizes) when an expectation is required, in the nick of time.

As compare with other algorithm like QSVM, ANN and EBT the KNN achieve worst performance with an overall accuracy.

3. Artificial Neural Networks Algorithm

Compare ANN with other algorithm like KNN, QSVM and EBT the ANN achieve very less accuracy. Result achieve from ANN algorithm is not good.

Artificial Neural Networks are pieces of computing system used to designed and simulate the way of the human brain analyzes and process information.

4. EBT

EBT algorithm is used to enhance classification accuracy for activities walking, walking upstairs, walking downstairs, sitting, standing and falling etc.

As compare to other algorithm like KNN, QSVM, ANN the EBT algorithm achieve 100 % accuracy.

V. Proposed System

Our objective is to determine the users activity based on the measured acceleration and angular velocity data. In this section, we provide an overview of the framework used for classifying ADLs as well as fall events and explain the activity recognition strategy. Fig. 1 illustrates the activity recognition framework which encompasses:

(i) the input acceleration and angular velocity data obtained from the smartphone,

(ii) the feature extraction block, and

(iii) the classification algorithm. In the following, we discuss each component of this framework.

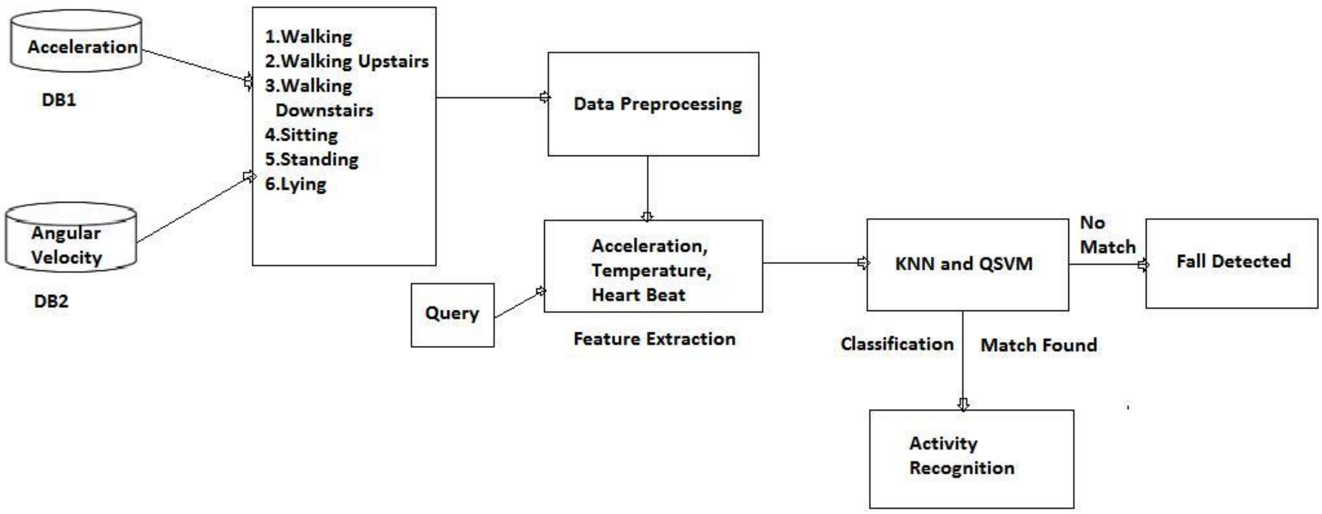


Fig. Machine Learning Architecture

Modules Identification: -

The various modules of the project would be divided into the segments as described.

1. Raw Data Fetch:-

This module consist of the fetching process from the database which is in raw format. This data may contains the data which is not useful for the proposed system. The database contains the triaxial angular velocity and acceleration data are obtained from two public databases.

2. Data Preprocessing:-

The data fetched from the database may contains the noise data. So we need to remove the noise i.e. unwanted data from the raw data. This process will provides the data to system in its intended format.

3. Feature Extraction:-

This module offers an overview of the concept of feature extraction and highlights its importance in obtaining an accurate classification. The acceleration and angular velocity signals are provided as input to the feature extraction blocks.

4. Classification:-

This section classify the features extracted by the previous module. This will calculate the probability of each class in the system. We have 5 classes for classification. This will assign the class to the result which is having the highest probability among the other classes.

5. Activity Recognition:-

This module will represent the class assigned to the data or system. The highest probability class is displayed as the result of the activities. The activities are walking, walking upstairs, walking downstairs, lying, sitting.

VI. Mathematical Model

Let S represent from system as a set of components as follows:

S: - F, A, DB, I,H, C, R,F, where,

I:- Input

O:- Output

H:- Human

A:- Actions

C:- Classification

DB:-Database

F:- Feature Extraction

R:- Results

Input: -

I1:- set of input data from data set {h1,h2,h3,h4… hn}

I2:- set of input data from feature extraction {c1,c2,c3,c4…cn}
I3:- set of input to System {a1,a2,a3,a4…an}

$$a_x(t) = a_x^g(t) + a_x^b(t) \quad (1)$$
$$a_y(t) = a_y^g(t) + a_y^b(t) \quad (2)$$
$$a_z(t) = a_z^g(t) + a_z^b(t) \quad (3)$$

$$\|a^b(t)\| = \sqrt{[a_x^b(t)]^2 + [a_y^b(t)]^2 + [a_z^b(t)]^2}. \quad (4)$$

$$a_i^{b,\mathrm{RMS}} = \sqrt{\frac{1}{T}\int_0^T \left[a_i^b(t)\right]^2 dt} \quad \text{for } i = x, y, z \quad (5)$$

Output: -
O1:- set of output data from System {s1,s2,s3,..sn}
O2:- set of output data from feature extraction Module {r1,r2,r3….rn}
O3:- set of output data from Database{d1,d2,d3.dn}

Functions: -
F1:- set of functions on the data from datasets.
F2:- set of functions for data preprocessing.
F3:- set of the functions of feature extractions.
F4:- set of the functions classification.

VII. Algorithm

Step 1: Fetch data contain angular velocity and acceleration Data from public database.
Step 2: Apply Data Preprocessing.

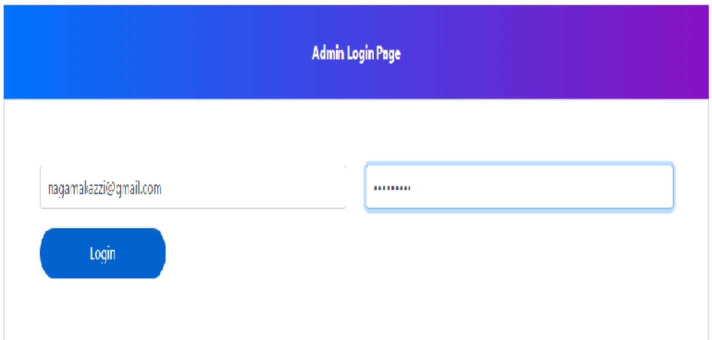
Step 3: Apply Feature Extraction

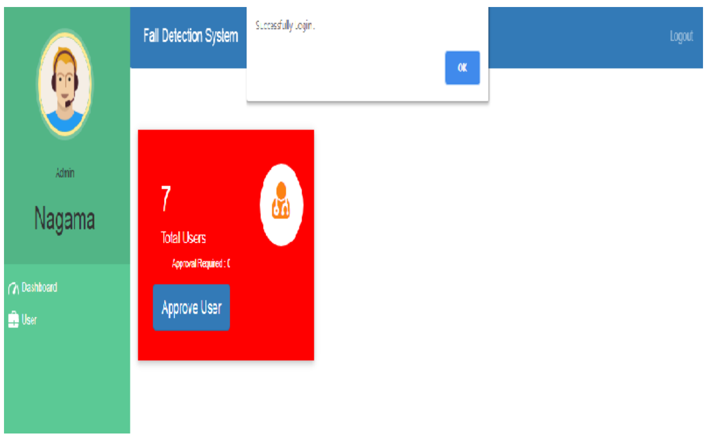
Step 4: Classify the data
If perfect match of activity is found then Activity is recognised Else Fall is Detected.

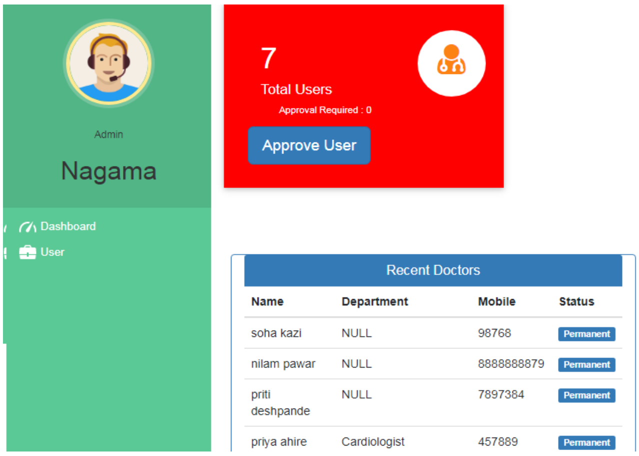
VII. Result Analysis

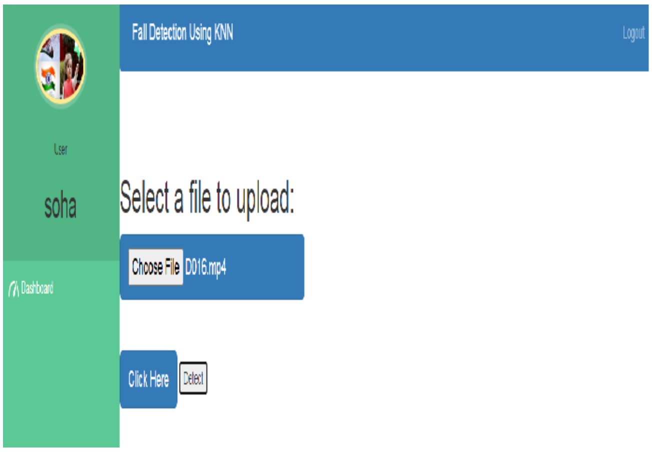
We have implemented the system using KNN algorithm which has the lowest accuracy in existing system. We consider the proposed system on the following parameters for graph generation.
1. Efficiency
2. Latency time
3. Accuracy
4. Classification time.

In results we provide login for admin and user.admin allow access to user. Admin approve or deny request of user. After successfully login of user, user select the fall detection video and detect the fall. In base Paper KNN accuracy is worst than ANN, EBT and QSVM algorithm . In this paper improve the accuracy of KNN. Compare accuracy of KNN , ANN , EBT and QSVM algorithm. KNN. Show the confusion matrix for KNN, EBT, ANN and QSVM algorithm etc.






Admin
Nagama
Dashboard
User
7
Total Users
Approval Required : 0
Approve User
Recent Doctors
Name Department Mobile Status
soha kazi NULL 98768 Permanent
nilam pawar NULL 8888888879 Permanent
priti deshpande NULL 7897384 Permanent
priya ahire Cardiologist 457889 Permanent


Fall Detection Using KNN
Logout
User
soha
Dashboard
Select a file to upload:
Choose File D016.mp4
Click Here
Detect

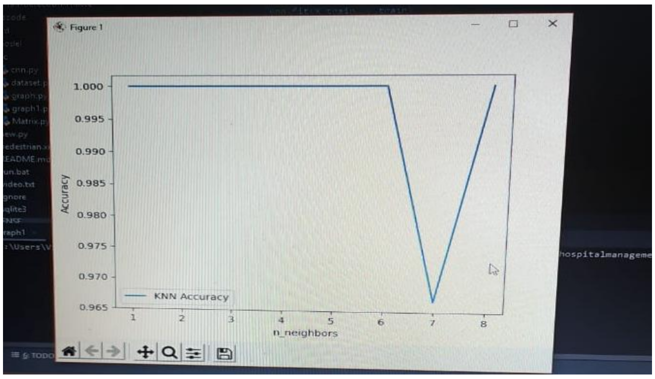
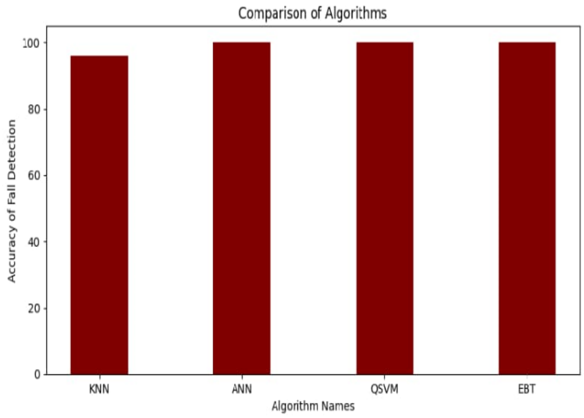
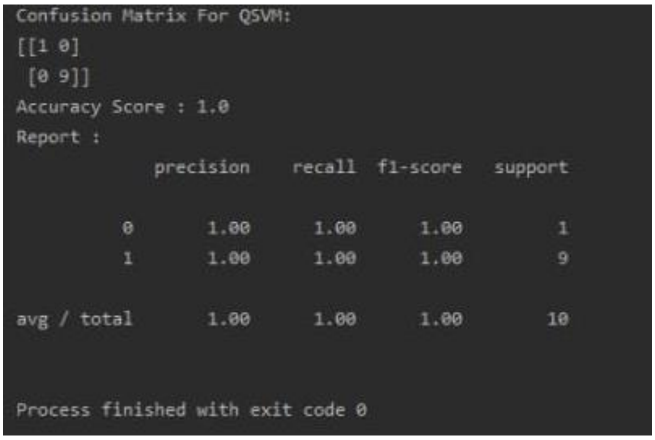
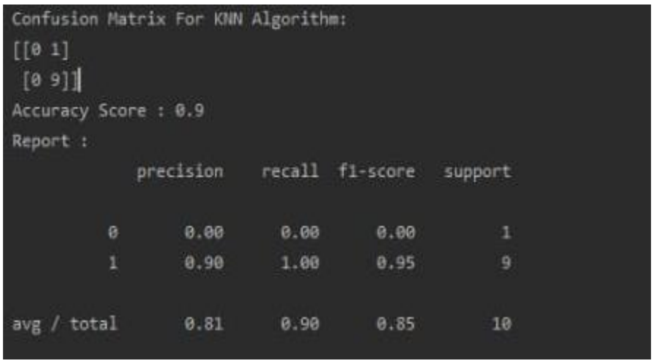
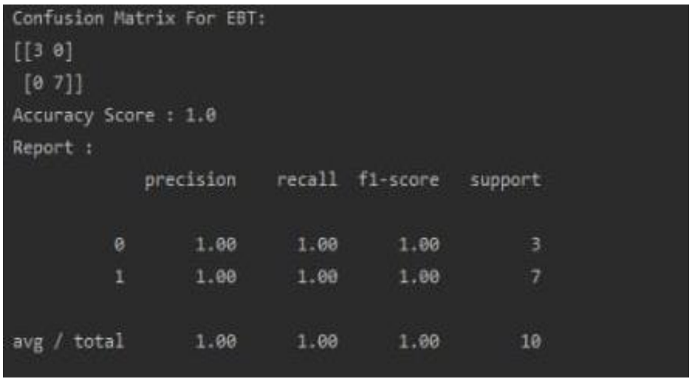


Figure 1
Accuracy
KNN Accuracy
n_neighbors


Comparison of Algorithms
Accuracy of Fall Detection
Algorithm Names
KNN
ANN
QSVM
EBT


Confusion Matrix For QSVM:
[[1 0]
[0 9]]
Accuracy Score : 1.0
Report :
precision recall f1-score support
0 1.00 1.00 1.00 1
1 1.00 1.00 1.00 9
avg / total 1.00 1.00 1.00 10
Process finished with exit code 0


Confusion Matrix For KNN Algorithm:
[[0 1]
[0 9]]
Accuracy Score : 0.9
Report :
precision recall f1-score support
0 0.00 0.00 0.00 1
1 0.90 1.00 0.95 9
avg / total 0.81 0.90 0.85 10


Confusion Matrix For EBT:
[[3 0]
[0 7]]
Accuracy Score : 1.0
Report :
precision recall f1-score support
0 1.00 1.00 1.00 3
1 1.00 1.00 1.00 7
avg / total 1.00 1.00 1.00 10

```
Python Console
Confusion Matrix For ANN :
[[10]]
Accuracy Score : 1.0
Report :
             precision    recall  f1-score   support

          1       1.00      1.00      1.00        10

avg / total       1.00      1.00      1.00        10
```

VIII. Conclusion

A strong fall discovery framework is basic to help the autonomous living of elderlies. In this paper, we have proposed an AI approach for fall location and ADL acknowledgment. We will test the exhibition of four calculations in perceiving the exercises falling, strolling, strolling upstairs, strolling ground floor, sitting, standing, and lying dependently on the speeding up and the precise speed information. We have proposed a new time and the recurrence space includes and has exhibited the significance of these highlights and their positive effect on improving the exactness and accuracy of the classifier. Also, we will test the presence of the KNN, QSVM arrangement calculations on real-world quickening information got from open databases. The interior parameters of these calculations have been streamlined utilizing the preparation information. A while later, the exhibition of the prepared calculations might be evaluated utilizing the test information. In an initial step, just the increasing speed information has been utilized for movement acknowledgment.

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