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A Machine Learning Classification Paradigm for Automated Human Fall Detection

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Abstract—For elderly people, falls are a severe worry since they can result in serious injuries, loss of independence, and deterioration of general health. In fact, among older persons, falls constitute the main reason for injury-related hospitalisations and fatalities. There is an obvious demand for fall detection systems that can help avoid or lessen the negative effects of falls given the enormous impact of falls on the senior population. Systems for detecting falls are created to notify carers or emergency services when a person has fallen, enabling quicker responses and better results. Elderly people who live alone or have mobility or balance impairments that make them more likely to fall may find these systems to be especially helpful.

The difficulty of categorising various actions as part of a system created to meet the demand for a wearable device to collect data for fall and near-fall analysis is addressed in this study. Three common activities—standing, walking, and lying down—four distinct fall trajectories—forward, backward, left, and right—as well as near-fall circumstances are recognised and detected.

Overall, fall detection systems play a significant role in the care of elderly people by lowering the chance of falls and its unfavourable effects. In order to better meet the demands of this vulnerable group, it's expected that as the older population grows, there will be a greater demand for fall detection systems and ongoing technological developments.

I. INTRODUCTION

In today's world, technology has revolutionized the way we access healthcare. Remote health tracking, in particular, has emerged as a valuable tool for healthcare professionals to monitor patients' health status and provide timely interventions. With the advent of wearable technology and the Internet of Things (IoT), it is now possible to monitor key health indicators such as heart rate, blood pressure, and blood sugar levels remotely. In this context, the importance of remotely tracking the health and vitals of a person cannot be overstated. Falls are a major health concern, particularly for the elderly and those with disabilities.[1] Falls can result in serious injuries and even death, and they are a leading cause of hospitalization and long-term care. In many cases, falls occur when individuals are alone and unable to call for help.[2] Therefore, there is a need for automated fall detection systems that can quickly and accurately detect fall events and alert caregivers or emergency services. In this project, we use the open-source Fall Detection Dataset to train and evaluate the system. The dataset contains real-world falls, simulated falls, and activities of daily living, providing a diverse set of scenarios for training and testing the model. Our goal is to develop an accurate and reliable fall detection system that can improve the quality of life for elderly people, individuals with disabilities, and those prone to falls by providing an automated fall detection system that can quickly alert caregivers or emergency services. Type Style and Fonts

II. LITERATURE REVIEW

Yang, Allen Y. et.al [3] present a novel approach for recognizing human activities in smart environments named "Activity Recognition with Weighted Frequent Patterns Mining." To preserve sensor energy while achieving high accuracy, they propose the Distributed Sparsity Classifier (DSC). The proposed method is evaluated on the WARD dataset that involves 20 human subjects performing 13 action categories. While achieving high accuracy, the method has limitations since it relies on a set of training motion sequences as prior examples, which may restrict its capability to recognize new or unexpected actions.

Chereshnev, Roman et.al [4] propose a new method called RapidHARe for real-time human activity recognition using on-body sensors. Unlike other existing methods that use dynamic-programming-based algorithms or feature selection methods, RapidHARe utilises dynamic Bayesian networks to model the raw data distribution. This unique approach results in high accuracy and faster processing time compared to other methods, which makes it a feasible option for real-time recognition in mobile devices. This technology can be particularly beneficial for elder-care support and long-term health monitoring systems.

Ahmad.M Ahmad et al [5] suggested a model that can be used to detect and categorise falls in real-time using video data after being trained on a huge dataset of human events, including falls. RetinaNet and MobileNet are two deep learning models that the authors utilise to detect falls. While MobileNet is used for feature extraction and classification, RetinaNet is utilised for object identification and localization.The suggested method is precise and has the ability to increase the safety of those who are at fall risk.

Bulling et.al [6] advises categorising different eye movement patterns using machine learning techniques, which can then be used to infer the user's intended actions and activities from the context. The recommended system can detect if the user is reading, watching TV, or engaging in other activities and adjust the sensor values to optimise performance.

Jiahui wen et.al [7] proposes a new approach using weighted frequent pattern mining. The proposed approach is designed to be more efficient and accurate than previous methods, by taking into account the importance of each activity and the relationships between activities.

Ayokunle Olalekan Ige et.al [8] proposed unsupervised learning techniques for activity recognition using wearable sensors. The authors review various unsupervised learning methods such as clustering, density estimation, and subspace learning. The study's overall conclusion emphasises the potential of unsupervised learning as a promising method for activity recognition in wearable sensor-based systems.

Seyed Ali Rokni et.al [9] proposed using a Distributed Sparsity Classifier (DSC). This approach made use of Convolutional Neural Networks, which are proven to be very effective in tasks that require images and videos to be processed.

Enrique Garcia-Ceja et.al [10] proposed a Crowdsourcing approach for building personalised models for human activity recognition. This approach was designed to work with scarce labelled data since a large amount of labelled data can be tedious to produce.

Table 1. Literature Survey Table

Paper Title	Authors	Published in	Method Used	Used Dataset	Advantage	Drawback
Activity recognition with weighted frequent patterns mining in smart environments	Yang, Allen Y. et.al	Expert Systems with Applications	Distributed Sparsity Classifier (DSC)	WARD, (which consists of 20 human subjects performing 13 action categories)	The proposed method conserves sensor energy while preserving accurate classification.	The method relies on a set of training motion sequences as prior examples, which may limit its ability to recognize new or unexpected actions
A computationally inexpensive method for real-time human activity recognition from wearable sensors	Chereshnev, Roman et.al	Journal of Ambient Intelligence and Smart Environments	RapidHARe for real-time human activity recognition	collected data in two sessions, each lasting around 40 minutes, and used the data to train and evaluate their RapidHARe method	RapidHARe is a fast and accurate method for real-time human activity recognition.	The paper lacks information about the dataset used, which may limit reproducibility
: Fall Detection Based on RetinaNet and MobileNet Convolutional Neural Networks	Ahmad.M Ahmad, Hadir Abdo	IEEE 15th International Conference on Computer Engineering and Systems (ICCES)	Unsupervised IT plasticity model, Unsupervised IT plasticity model and Human psychophysics and analysis	IT population dataset [Majaj et al., 2015] and IT plasticity data [Li & DiCarlo, 2010]	The tolerant COR is instructed by naturally occurring unsupervised temporal contiguity experience that gradually reshapes the non-linear image processing of the ventral visual stream without the need for millions of explicit supervisory labels	Inability to observe behavioral changes for tasks with initial high d', this study cannot confirm or refute the hypothesized linkage between IT neural effects and behavioral effects in that particular regime.

4	Wearable EOG Goggles: Seamless Sensing and Context-awareness in Everyday Environments	Bulling et.al		Analysis of eye motion as a new input modality for activity recognition, context-awarenes s and mobile HCI applications.	string matching and two variants of Hidden Markov Models (HMMs), mixed Gaussian and discrete	It is an unobtrusive device that is applicable to different people and works in a wide range of applications.	It is Heavily dependent on the cognitive movements of the eyes' Motion and will take time to get used to the motion eventually to track even involuntary movements.
5	Activity recognition with weighted frequent patterns mining in smart environments	Jiahui wen et.al [5]	Source: Conversation with Bing, 4/20/2023(1) Fall Detection Based on RetinaNet and MobileNet Convolutional Neural .... https://www.semanticscholar.org/paper/Fall-Detection-Based-on-RetinaNet-and-MobileNet-Abdo-Amin/f0f1318af9ab10006b31699761632a0f226ee3ff Accessed 4/20/2023.	methods use are efficient association rule mining algorithm	CASAS research group	Achieves higher performance than traditional classifiers	Size of the model is small and could result in failure while handling big datasets
6	A survey on unsupervised learning for wearable sensor-based activity recognition	Ayokunle Olalekan Ige et.al [6]	(2) Fall Detection Based on RetinaNet and MobileNet Convolutional Neural https://www.researchgate.net/publication/353	state-of-the-art methods in addressing issues relating to data imbalance in wearable sensor-based HAR data through clustering and data augmentation	collate thirty-three wearable sensor-based HAR datasets based on Complex high-level activity	First attempt at a comprehensive review on the adoption of unsupervised learning in wearable sensor-based activity recognition	It is on a prototype stage
7	Personalized Human Activity Recognition Using Convolutional Neural Networks	Seyed Ali Rokni, Marjan Nourollahi, Hassan Ghasemzadeh	(4) [1704.04861] MobileNets: Efficient Convolutional Neural Networks for .... https://arxiv.org/abs/1704.04861 Accessed 4/20/2023.	Distributed Sparsity Classifier (DSC)	Sport and Daily Activity (SDA) (Altun, Barshan, and Tunc¸el 2010) and WISDM (Kwapisz, Weiss, and Moore 2011)	The approach uses CNNs, which are known to be highly effective for image and video processing tasks.	Dependence on labeled data
8	Building Personalized Activity Recognition Models with Scarce Labeled Data Based on Class Similarities	Enrique Garcia-Ceja & Ramon Brena	(5) Fall detection based on OpenPose and MobileNetV2 network. https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/ipr2.12667 Accessed 4/20/2023.	Crowdsourcing method for building personalized models for HAR by combining the advantages of both user-dependent and general models	Activity recognition from single chest-mounted accelerometer data set (2012), Dataset for adl recognition with wrist-worn accelerometer data set (2014), Activity prediction dataset (2012), Human activity recognition using smartphones data set (2012)	The proposed approach is designed to work with limited labeled data, which is a common challenge in many real-world scenarios.	The effectiveness of the proposed approach depends on the similarity between activity classes

III. DATA PREPROCESSING

The process of cleaning, transforming, and preparing raw data before it can be used for analysis or modelling is known as data pre-processing. It consists of several steps to ensure that the data is correct, complete, and ready for analysis.

The main goal of data pre-processing is to make sure that the data is in a format that is suitable for analysis. This may involve removing or correcting missing or inaccurate data, converting data to a standard format, or scaling and normalising the data so that it can be compared or combined with other data sources.

Several typical data pre-processing methods encompass activities such as data cleansing, data conversion, data

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standardization, and data consolidation. These approaches are frequently employed in conjunction to guarantee the accuracy, comprehensiveness, and analysis readiness of the data [11].

Data pre-processing is a critical step in any data analysis or modelling project, as the accuracy and reliability of the results depend heavily on the quality of the data. By ensuring that the data is properly pre-processed, analysts can reduce the risk of errors and increase the likelihood of producing meaningful insights and actionable recommendations.

In our project, we start off by removing any records that are faulty or have NA values with the help of the dropna function of pandas.

MinMaxScaler is a data normalisation technique used in machine learning and data analysis. It scales the data to a specific range, typically between 0 and 1, by subtracting the minimum value and dividing the result obtained by the range of the values.

The formula used by MinMaxScaler is:

$$X\_scaled = (X - X\_min) / (X\_max - X\_min) \qquad (1)$$

In this equation, the original value is represented by X, the maximum X value is represented by X_min and X_max marks the maximum X value.

By using MinMaxScaler, we can ensure that all features in the dataset have the same scale and can be compared on the same basis. This technique is commonly used in distance measuring machine learning algorithms. For example, K-nearest neighbours (KNN) and Support Vector Machines (SVM).

We used the minmaxscaler function of scikit-learn to scale our heart rate data in the range of 33-208.

One of the most popular machine learning techniques for evaluating a model’s performance on new data is to split the data into two subsets. The model is trained using the training subset of the data and the other portion of the data, the testing subset is used to evaluate the performance of the model on unseen data. [12]

The main benefit of splitting data into training and testing subsets is that it prevents overfitting. Overfitting is a behaviour in machine learning that occurs when a model is very complex and the trained model is so used to the learning that it is unable to then correctly classify other data that is a little different to what is has been trained to do. This means that it predicts data for trained data very well but fails when it encounters new data. Therefore, by analysing the model's performance on a test data set that it has not encountered during training, we can get an estimate of how well the model generalises to new, unseen data. For our model, we used 95% of our data to train our model and 5% to test it.

StandardScaler is a pre-processing technique used to standardise the features in a dataset. It scales the features so that the features have a standard deviation of one and zero mean. StandardScaler is commonly used in machine learning algorithms that involve gradient descent optimization, such as linear regression, logistic regression, and neural networks.

The idea behind standardisation is to confirm that all features are on the same scale, which helps the algorithm converge more quickly and improves the overall performance of the model. StandardScaler transforms the data using the following formula:

$$z = (x - u) / s \qquad (2)$$

where x is the original feature, u denotes the mean of the feature, s denotes the standard deviation of the feature, and z represents the transformed feature.

IV. DATA VISUALISATION

The Dataset has six features: TIME, SL, EEG, BP, HR, and CIRCULATION.

Different parameters for fall detection are recorded in the dataset. While heart rate, blood pressure, brain activity, and blood flow throughout the body are all assessed by EEG, SL, and CIRCULATION, respectively, TIME is expressed in seconds. These variables provide informative information about a person's physiological state and can help with the early identification of potential falls or health problems.

A. Distribution Plot

For our fall detection system, a distplot is a useful tool for exploring and visualising the distribution of data in a single variable. The distribution of data for each feature in the dataset, such as sugar level, EEG, blood pressure, circulation and heart rate can be examined using a distplot.[13] Using this data, it is possible to spot trends or anomalies that could be useful for spotting falls. An individual may have fainted, which could be a symptom of a fall, if there is a cluster of data points with high blood pressure and low heart rate, for instance.[14] We can learn about the qualities of the data that can be helpful in creating a fall detection system by dissecting the data with distplots.

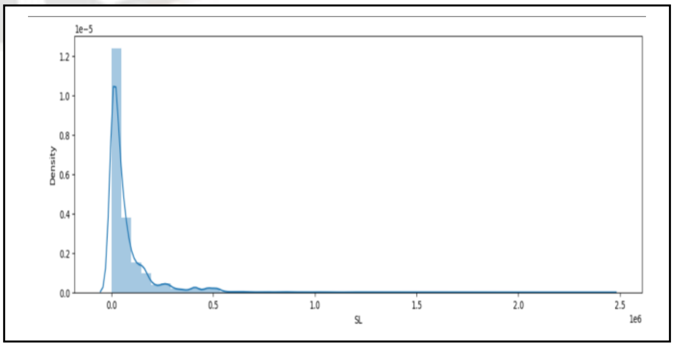

Figure 1. Distribution Plot of feature SL.

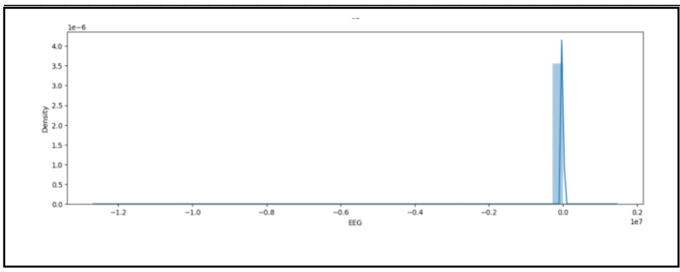

Figure 2. Distribution Plot of feature EEG.

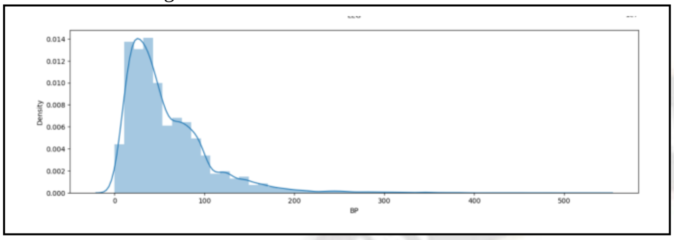

Figure 3. Distribution Plot of feature BP.

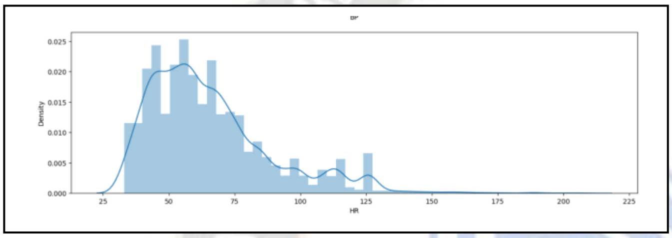

Figure 4. Distribution Plot of feature HR.

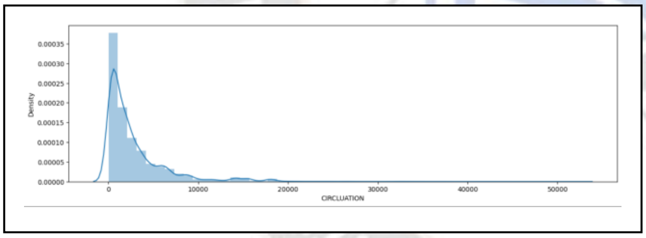

Figure 5. Distribution Plot of feature CIRCULATION.

B. *Correlation Matrix*

We use a correlation matrix to visualise the connections between various attribute pairs. A correlation matrix shows the pairwise correlations between each dataset characteristic. We can determine which features are most useful for detecting falls by using a correlation matrix.[15]

To create the correlation matrix, we created a new dataframe called test_df which contains a subset of the original dataset's columns, including SL, EEG, BP, HR, and CIRCULATION. We then created a correlation matrix by computing the correlation coefficients between these columns using the corr() function of seaborn.

This way, we got a heatmap of the correlation matrix with annotations indicating the correlation coefficients using the heatmap() function from the Seaborn library. The correlation coefficients are colour-coded on the heatmap, with red denoting positive correlations and blue denoting negative correlations.[16] The annotations display the precise correlation coefficient values, with stronger connections denoted by darker colours. The produced heatmap can be used to determine the connections between the various fall detection dataset parameters.[17]

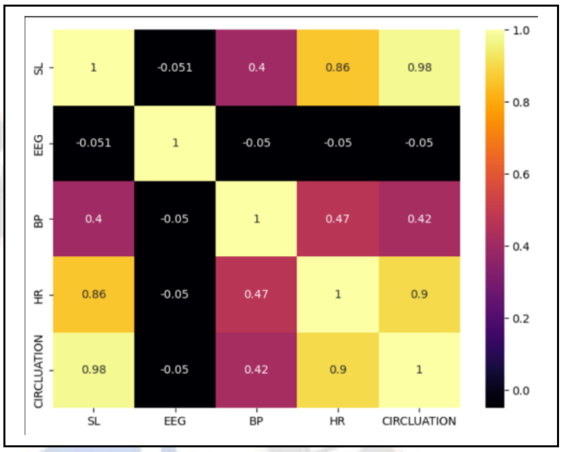

Figure 6. Correlation Matrix Developed.

V. CLASSIFICATION MODELS

A. *Support Vector Machine*

Our project involves utilising classification models to identify cases of falling incidents. Among the models we have implemented is the Support Vector Machine (SVM), a highly effective and commonly used classification algorithm. SVM operates as a supervised learning algorithm and is applicable to both classification and regression analysis.

To begin, we divided our data into two subsets: training and testing sets, using the “sklearn”’s "train_test_split" method [18].

For our implementation of SVM, we opted to utilise the Radial Basis Function (RBF) kernel, a frequently used method for solving non-linear classification issues. To create our SVM model, we utilised the "svm.SVC" function, setting the gamma parameter to 'auto'. The model was subsequently trained on our training data utilising the "fit" method. Once the model was trained, we applied it to predict the classes of our test data utilising the "predict" method. Lastly, we utilised the "accuracy_score" function provided by "sklearn.metrics" to compute the accuracy of our SVM model.

B. *K Nearest Neighbours Distplot*

The K-Nearest Neighbors (KNN) algorithm is a powerful yet easy-to-understand classification method that determines the class of a data point by identifying the k-nearest data points in the training set and assigning the most frequent class amongst those k-neighbors.[19]

In our fall detection project, we have implemented the KNN algorithm by creating a KNeighborsClassifier object and training it on the scaled training data using the fit method. The predict method of the trained KNN model is then used to predict the classes of the test data[24]. Finally, we have evaluated the performance of the KNN model using the accuracy_score function from the sklearn.metrics module, which calculates the proportion of correctly classified instances.

C. Naïve Bayes

Naive Bayes is a fast and efficient probabilistic machine learning algorithm that is well-suited for high-dimensional domains and large datasets[26].

Using Naive Bayes, it is clear that the model is trained on the x_train and y_train data, predictions are made using the trained model on the x_test data, and the accuracy_score() function is used to print the precision score of the model's predictions on the test data.[20]

The precision score for Naive Bayes is 0.11585365853658537, which is a relatively low score. The accuracy scores obtained from the Naive Bayes model indicate that it has a relatively low accuracy rate. This suggests that the Naive Bayes algorithm may not be the best choice for this particular dataset, or that the model may not accurately capture the underlying patterns in the data.

D. Random Forest

Random Forest is a highly favored and extensively employed algorithm in the field of Data Science. It falls under the category of Supervised Machine Learning Algorithms and finds wide application in tasks involving classification and regression. The algorithm constructs decision trees using diverse samples and leverages their collective majority vote for classification and average for regression [21]. A notable attribute of the Random Forest Algorithm is its ability to effectively handle data sets comprising both continuous variables (as observed in regression) and categorical variables (as encountered in classification). It demonstrates exceptional performance in classification and regression endeavors. [25].
In our case, we used the random forest classifier with the number of trees to build (n_estimators) as 100, the maximum depth that the tree should grow (max_depth) as 100 and to control the randomness of the algorithm, we used the random_state hyperparameter as 2. This way, we were able to achieve an accuracy of 77.80% which implies that the algorithm is capable of detecting 3 out of 4 falls correctly.

E. Decision Tree

This algorithm is used to analyze the majority of classifications and regressions problems. In our fall detection project, we employed the decision tree algorithm to create a classification model. Initially, we divided the data into training and testing sets. Subsequently, we employed the StandardScaler() function to scale the data, thereby enhancing the performance of the classifiers.[22]

We built the decision tree classifier with the DecisionTreeClassifier() function of the sklearn.tree library. The code specified the maximum depth of the decision tree as 20, and the random state was set to 2. We used the fit() function to fit the classifier to the training data[25]. Afterward, we used the predict() function to make predictions on the testing data.

Finally, we used the accuracy_score() function of the sklearn.metrics library to evaluate the accuracy of the decision tree classifier[23]. The accuracy score provided an insight into how well the classifier could predict the correct label for each instance in the testing data.[26]

VI. RESULTS

Table 2. Table Defining the Accuracy of Each Classifier

SR NO	CLASSIFIER	ACCURACY
1	Support Vector Machine	45.12
2	K-Nearest Neighbors	68.65
3	Naïve Bayes	12.68
4	Random Forest	78.78
5	Decision Tree	72.19

We can clearly see from the table that the Random Forest Classifier works best for this job.
We can further see which features contributed the most to the random forest classifier.

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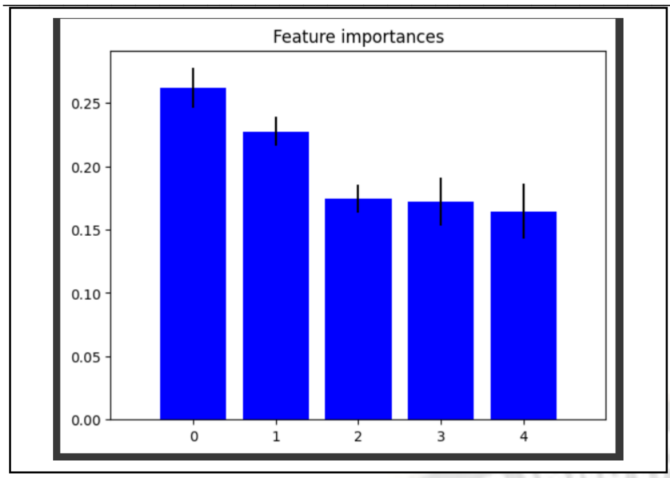

Figure 7. Feature Importance Graph

We can see from the graph that the features with the most influence are in the order SL, EEG, BP, HR and lastly CIRCULATION.

VII. CONCLUSION

Fall detections systems are an absolute necessity to enable elderly people, especially those who have mobility or balance impairments to live independently. In this research, we employed various classification models to accurately identify a fall including support vector machine, K-Nearest Neighbours, Decision Trees, Random Forest and Naive Bayes using attributes such as Sugar Level, EEG, Heart Rate, Blood Pressure and Circulation. We can safely conclude that random forest classifier worked the best and that it can detect 3 out of every 4 falls correctly. Inexpensive solutions to monitor these vitals can assist in moving our project into execution and further improving our solution to achieve even better results.

VIII.APPLICATIONS

Homecare for the elderly: A fall detection system can be integrated into the homes of elderly individuals, providing them with a sense of security and enabling them to live independently while knowing that help will be summoned in the event of a fall.

Assisted living facilities: Fall detection systems can be deployed in assisted living facilities to monitor residents and ensure prompt assistance in case of falls. This can enhance the safety and well-being of residents and provide peace of mind to their families.

Hospitals and healthcare institutions: Fall detection systems can be utilized in hospitals and healthcare institutions to monitor patients who are at a higher risk of falling, such as those with mobility impairments or post-surgery. This helps healthcare professionals respond quickly to potential falls and mitigate the risk of injuries.

Occupational safety: Fall detection systems can be implemented in workplaces, particularly in industries with elevated risks of falls, such as construction or manufacturing. The system can alert supervisors or safety personnel in real-time to provide immediate aid to workers in case of falls.

IX. FUTURE SCOPE

Refining and improving the accuracy of fall detection algorithms to minimize false positives and negatives.

Incorporating machine learning and artificial intelligence techniques to continuously learn and adapt the system's fall detection capabilities based on user-specific patterns and behaviors.

Exploring the use of wearable devices with integrated sensors, such as accelerometers and gyroscopes, to gather more precise data for fall detection.

Developing a mobile application or web-based interface to provide real-time notifications and alerts to caregivers, emergency services, or designated contacts.

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