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A NOVEL BASED HUMAN FALL DETECTION SYSTEM USING HYBRID APPROACH

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Abstract: *Our culture is experiencing a fast growing problem with falls, which has generated a lot of interest in the medical field. As we age or if we have pre-existing medical conditions, such as reduced muscle strength, the possibility of falling becomes more of a risk. The need for fall detection systems is growing as the world's population ages. A sudden slip or loss of stability while moving could be the cause of a fall. Several researches have been presented as a measure to alert people of a fall as a speedy post-fall remedy. As a result, numerous fall detection systems have been developed. We provide a Visual input-based fall detection system to address this issue. We have utilized the LR-CNN-PCA Hybrid approach in order to reach the maximum levels of accuracy and effectiveness. The system's robustness and generality were constrained by using wearable technology in the majority of earlier tests. Our method stands for a development in smart technology for older individuals who are single. The ability of our machine learning-based recognition system to identify falling behavior in the video further supports its viability and effectiveness.*

Keywords: *Fall detection, Linear Regression, Principal Component Analysis.*

INTRODUCTION

Falls are the second most common cause of death, according to a WHO report, with an estimated 646 000 incidents per year. Falling is a huge worry for seniors across the globe – it can have serious implications for their health and wellbeing. In 2030, the global population of people over 65 years old is predicted to reach 1 billion, with the percentage of people aged 20 to 64 years old increasing to 35% of the population. As people get older, the likelihood of having an accidental fall increases. It has been stated that the risk of falling in the elderly over the age of 65 is 28 percent to 35 percent, and the risk of falling over the age of 70 is 32 percent to 42 percent [1]. Falls are common in medical health care facilities, hospitals, and private residences and they can be dangerous. Falls in hospitals happen in patients' rooms and during transfers from one location to another. Furthermore, the vast majority of falls occur near seats and beds. Severe fall injuries can result in death. As a result, preventing fall-down-related injuries and "long lie" scenarios requires early diagnosis.

Due to significant health risks in the living room, most falls typically happen at home

[2]. Elderly people with neurological conditions like dementia and epilepsy are more likely than the average aged population to fall and sustain injuries from falls [3].

Visual object tracking has been vigorously researched because of its commercial potential in various computer vision applications. However, the issues of robustness in person tracking still remain as major difficulties despite numerous algorithms have been used. The robustness issues are usually created by cluttered background, appearance deformation, motion blur, occlusion, and illumination changes. Previous methods had difficulty recognizing falls in complicated situations where furniture was present. [4].

Several data collection tools are utilised to record information about events related to the fall and daily activities, including accelerometers, gyroscopes, RGB cameras, and radars. For the purpose of making the data useable in subsequent stages, data preparation, augmentation, feature extraction, etc. are performed during the step of processing data. The processed data is utilized to train a deep learning algorithm during the model development step. Data collected from sensors is analyzed and fed to a pre-trained model for precise categorization when performing the detection step. When a fall occurrence is discovered, emergency services are notified, and assistance is given by alerting nurses, doctors, and other skilled personnel [5].

Several approaches have been put out for automated activity recognition and fall detection [6–7]. Depending on the kind of sensor technology being used, these can be categorized into three main groups. Systems using sensors that are ambient, wearable, and hybrid are discussed [8-9].

Wearable technology requires routine maintenance, such as battery change or recharge, which the elderly frequently forget to do. Another drawback is that it interferes with daily tasks. The preference of elderly people for non-wearable devices over wearable technologies has been found in surveys [10].

As part of this research, we have suggested a method for detecting live falls based on machine learning. Our strategy might involve continuously monitoring the patient using a camera. The system ought to have the capability of instantly emailing for assistance in the event of a fall, enhancing the accuracy of fall detection and perhaps even fall avoidance. We have used LR-CNN and PCA algorithms for implementation of this work. We have trained machine to detect if any person has recorded a fall or not. If a person has fallen, we will generate an alarm and will give notification to the concerned person. The camera will be installed in any area of the house and continuous images will be captured. We recognize a human and start focusing on him as soon as he enters the field of view of the camera. We will notify the neighbors and caretaker if we see him fall.

LITERATURE REVIEW

A visual input-based system was suggested in a study on fall detection technologies by Nur Ayud Mohamed. To train object appearance models, they employed the Multiple-model Fully Convolutional Neural Network Tracker (MMCNN). Fall detection dataset (FDD) which is a public dataset has been used for model training. They trained their accuracy, robustness and efficiency with other trackers namely, TCNN and FCNN, but the accuracy result is not as impressive then other trackers. The reason for this was less use of dataset [11].

In [12], authors suggested a novel method for detecting falls that integrates a sensor for depth and a three-axis acceleromete. Feature extraction and classification are the two components of the suggested methodology. The test subjects' attempts to quickly get on the mattress created an experience so similar to falling that it caused the fall detection system to malfunction, so the proposed classification model is used with low-performance platforms and has a high degree of generalization.

Based on information about floor tremors caused by falls, the authors of this work [13] detailed an intelligent real-time fall detection, location, and alerting system. A sophisticated seismic sensor system that is mounted on the floor and can detect floor vibrations is used by the system. They then use the floor vibrations as a source of recognition to identify the person's footsteps and let them know who they are. In order to increase the precision of person identification, they also developed a voting system among sensor nodes. The system's limitation to smart homes is a drawback, and optimization methods could improve the feature selection.

The authors describe a system for identify falls in this article, in which they used a photo manipulation technique to extract moving features using an optical flow method. They created a dataset for fall recognition using CNN for classification and proof-of-concept implementation. To increase the accuracy, they also used a majority voting method. The system is not applied in the actual world. Additionally, they do not consider some routine activities that do not contribute to accidents. [14].

In this paper [15], they used a real-time method to identify falls using a grouping of MHI with human figure deformation. To identify falls in real-time, they used image processing and a video monitoring system. This structure supports family members or other carers who are taking charge of elderly people. Fall detection is helped by computing a ratio of the human body to its rate of change since a human shape changes quickly after a fall.

In this paper [16], the information set is being gathered in preparation for migration knowledge to improve the model's exactness based on the detection of human key coordinates in OpenPose, combined with the SSD-Mobile Net object detection framework. This is done because there is a severe lack of fall-related data in the available dataset. This system's accuracy, which is lower than many previous proposed systems, was only 74.3%.

The authors of this paper [17] introduced a system that is divided into two categories: Fallen state and falling state both refer to the same event, albeit from different perspectives. For the preprocessing phase, the Yolo object detection model with Open Pose model for detecting human posture are both utilized. A dual-channel sliding window model is used to extract dynamic properties of the human body.The dynamic and static features are categorized using random forest. UR and Le2i fall detection datasets are used to test the dataset. The system has the drawback that it is not concentrating on real-world applications when it ought to be.

Convolution neural networks with a spatial temporal graph (STGCN) were used by researchers in [18]. They have demonstrated that the model is adaptable to new data without having to repeatedly retrain it. The datasets used are TST Fall Detection V2, the RGB-D Data set, and fall free detection. People frequently move around furniture and other objects in an interior phase, especially in a home, leading to partial or complete occlusion issues. They haven't tested this with the presence of items that obscure skeleton data because the public datasets don't include occlusion scenarios.

A new fall detection pipeline based on data from wearable accelerometers was proposed in this work [19]. By applying a variety of feature reduction techniques, including mutual information, the Boruta method, and the removal of Pearson correlation coefficient is used to identify features that are highly correlated, they identified leading characteristics for each dataset. Many conventional machine learning (ML) techniques were employed to recognize falls depending on the information obtained. The proposed technology was not tested under actual fall conditions, which was the biggest drawback.

MECHANISM THAT DETECTS FALLS

Fall prevention systems are in desperate need in addition to fall detection. Installing handrails and training fall prevention practices can help with external fall prevention, but internal fall prevention is more difficult. To identify the brain region that affects awareness and reaction time, extensive research on neurological processes is needed. Moreover, Examining the posture and gait can help correct balance in the event of a free fall. According to [20], falls can be decreased by educating the elderly about falls, introducing various exercise routines, and analyzing and monitoring hazard conditions.

Different components are used by different fall detection systems. One of the most popular places to get sensor data is from a smartphone. The data are collected, processed, and saved directly on the smartphone. The majority of the research investigations described so far is carried out using this apparatus. The implementation of advanced machine learning techniques on smart phones is challenging due to their constrained processing and storage capabilities [21]. Cloud computing is utilized in fall detection systems to remotely obtain, preprocess, and analyze data using the large amount of computing and storage capacity provided by the cloud. To send data to the cloud, a wearable gadget or a mobile phone might be utilized as an intermediary device. Long-term analysis can be performed on the data kept in the cloud. Such a cloud computing paradigm for fall detection was put forth by [22], in which MapReduce, a cloud-based framework, is used to analyze the data.

The cloud computing principle is used close to the data source through edge or fog computing. With edge computing, only the summary of the data is uploaded toward the cloud; instead, Real-time decisions are made possible by the edge of the network's data retrieval, preprocessing, and analysis. Edge and fog are frequently used interchangeably. Using a decision tree-based big data model, [23] forwarded data to the cloud for additional analysis if a fall was observed when there was a light fog.

PROPOSED SYSTEM ARCHITECTURE

A hybrid CNN-based LR-PCA approach is suggested in the paper for fall detection, as shown in the figure 1. Unrecoverable consequences, including fractures and even death, may happen if someone loses consciousness and does not seek quick medical help. To avoid such consequences, we will use video recording to teach a machine how to recognize when someone falls. If person fall, we will generate an alarm and an email notification will be send to specific person.

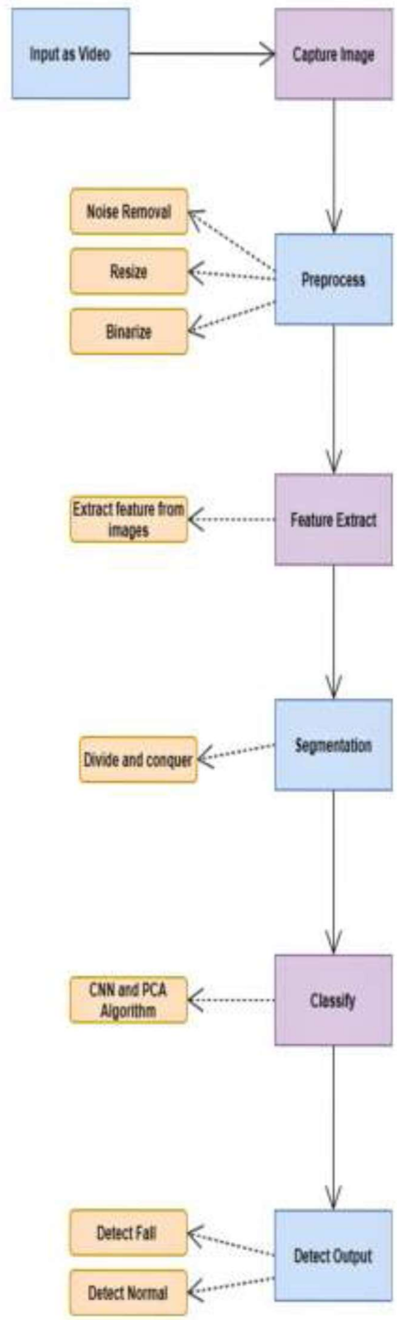


Figure 1. Proposed system for fall detection

We created a live fall detection dataset utilizing several fall scenarios, and the entire dataset was produced using a single camera. To do so, we will first record a live video from a single angle while doing a specified action, and then we will store the coordinates (x, y, and z) in the file. As a result, we will record a person's movement from various angles and under various illumination circumstances and all of the coordinates (x, y, and z) will be saved in the same file.

The dataset file will be copied into the main dataset file, and our training file will then be generated. Again, the camera will open, and this time live fall detection will be tested. The person's coordinates will be recorded by the camera and added to a different file. The testing file's coordinates will be compared to those in the training file.

A subset of frames from the dataset has been preprocessed. A new label has been assigned to designate the group that includes the fall event as 'fall,' and the other groups as non-fall. Learning rate, number of epochs, and other deterministic aspects are some of the options we have. We chose the best performance indicators, such as sensitivity and specificity, for a better evaluation of the fall detection system. Specificity is the true negative rate, whereas sensitivity is often known as recall value or true positive rate.

Preprocessing involves scaling and resizing the video and removing noise from the data. By minimizing the inherent flaws in the image, it enhances the signal on the image. Feature extraction is a method for transforming raw data into numerical data that can be processed while still preserving the original database's contents. By directly applying the machine learning algorithm to the raw data, it produces the best results. We have taken dataset properties like edges, size, etc. and included them into this system.

When inputs is broken down into parts or segments that can be defined, accessed, taken advantage of, profitable, and have potential for growth in the market, segmentation comes into play. For instance, due to limitations on time, money, and effort as well as confusion, a corporation can find it challenging to assess against the market as a whole. It must possess a "definable" characteristic, such as a sizable population that can be identified and targeted with a reasonable amount of work, price, and time.

Principal components (PCs) that are significant and extracted from the PCA are chosen using logistic regression (LR). We used the LR-PCA method and CNN for classification. CNN uses input in the form of an image; the various objects in the image are biased and weighted based on their importance and ability to distinguish between them. PCA is a method for finding patterns in data and highlighting similarities and differences in the data. Because high dimensionality refers to a data set with a lot of features, it can be challenging to find patterns in data. In this case, PCA is advantageous to us because we cannot analyze the data using graphical presentation. Figure 2 illustrates how a dependent set of features is converted into a set of independent features using an analytical technique called PCA.

The machine will create a model when the training phase is complete. The model will then proceed to the testing phase, after which the user will receive the output. If the person is fall it will detect the output as person is fallen and if not is will detect that the person is not fallen. A fall detection alarm will sound, and the specific person will receive an email notification.

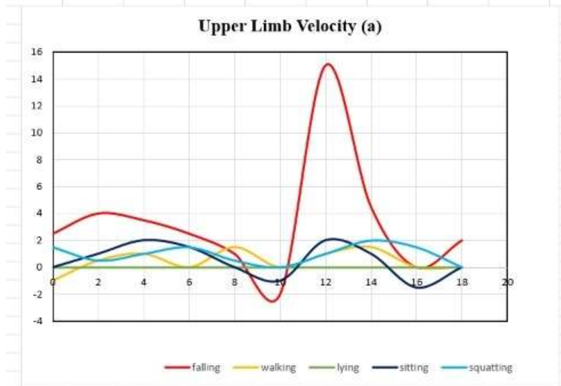


Figure. 2. Upper Limb Velocity

EXPERIMENTAL SETUP

Table 1 displays the primary configuration of the system used in the experiment. The operating system was Windows 10, and the code language utilized was Python with spyder as the constraint tool. Sklearn, Tkinter, NumPy, Pandas, Python 3.8, Tensor Flow, OpenCV, and other components of the primary software package are required.

Hardware	Hardware Type
CPU	Acer Nitro 5
GPU	NVIDIA GeForce GTX1060
Graphic Card	6 GB
RAM	16 GB
System	Windows 10

Table 1: Configuration of a system

EXPERIMENTAL RESULTS

The fall detection system implemented using CNN, LR and PCA has given better performance as compared to existing systems of fall detection. . The figure 3 and 4 shows the accuracy, sensitivity, specificity, precision, and F-score measurements represent the fall detection system's performance. The results have shown that our hybrid system gives better values as compared to other systems. We've reviewed the expected outcomes of our fall detection system laboratory tests. Standing, sitting, and laying positions from the camera were used for cross validation. The result was also cross-validated with a volunteer-reported fall and a system-detected fall.

Figure 5 shows the classification accuracy of each algorithm. In this study, we chose a deep learning algorithm for fall detection after accurately classifying test data using a variety of techniques. There were many algorithms used, including CNN, linear regression, linear discriminant analysis, K neighbours classifier, SVM, Naive Bayes, AdaBoost, Random Forest, and more.

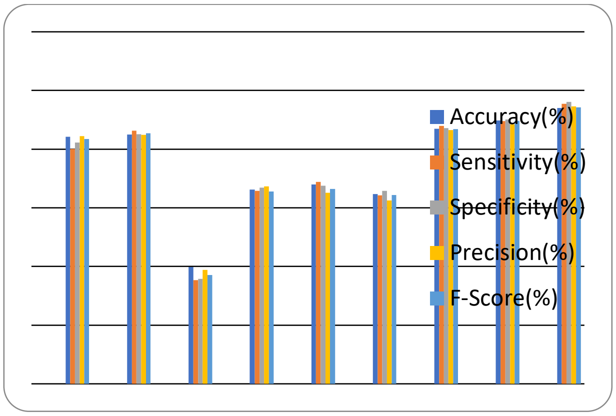


Figure 3. The precision of different classifiers in falling-state detection

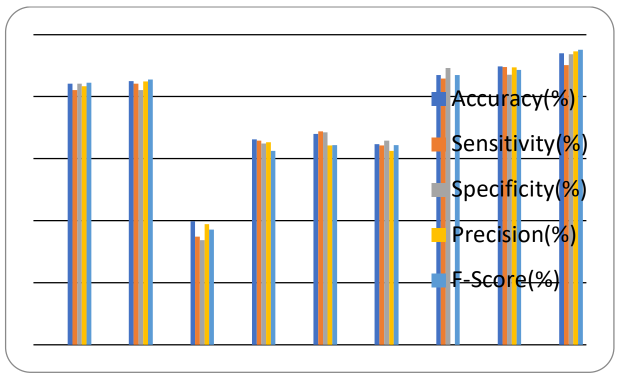


Figure 4. The precision of different classifiers in identifying fallen states

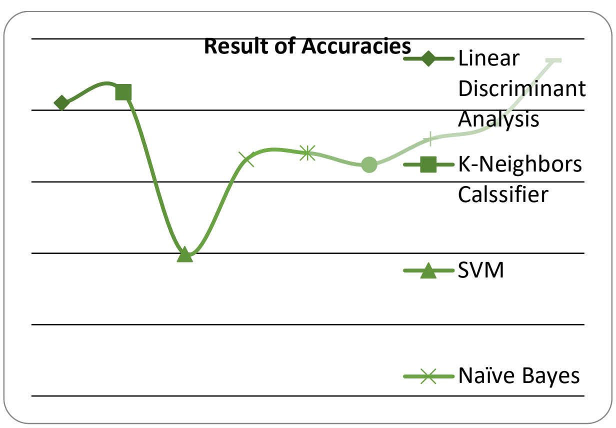


Figure 5. Result of accuracies

We used the 5-fold cross validation method to assess the accuracy of each algorithm. There are 1600 learning data (4 actions x 400) and 400 verification data (4 actions x 100). According to the findings, linear discrimination had an accuracy of 82%, K Neighbors Classifier had an accuracy of 85.0%, SVM had an accuracy of 39.75%, Naive Bays had an accuracy of 66.25%, Ada Boost had an accuracy of 68.0%, and random forests had an accuracy of 64.75 percent. Bagging was at 72%, voting was at 76%, linear regression was at 88%, and CNN had the highest

rate at 94%. LR-CNN-LR has a 94% accuracy rating as its maximum. Therefore, it is thought that a classifier with an accuracy of 94% will be adequate for detecting falls.
Some qualitative outcomes of sample images are shown in figure 6(a) and 6(b).

Figure 6(a): Qualitative outcomes of a few sample images

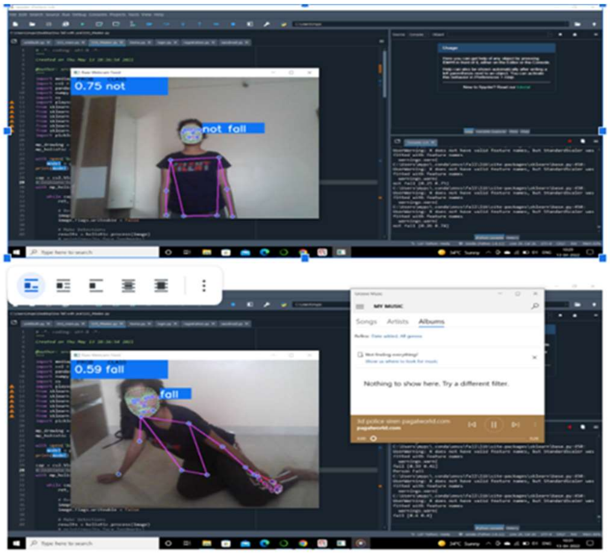
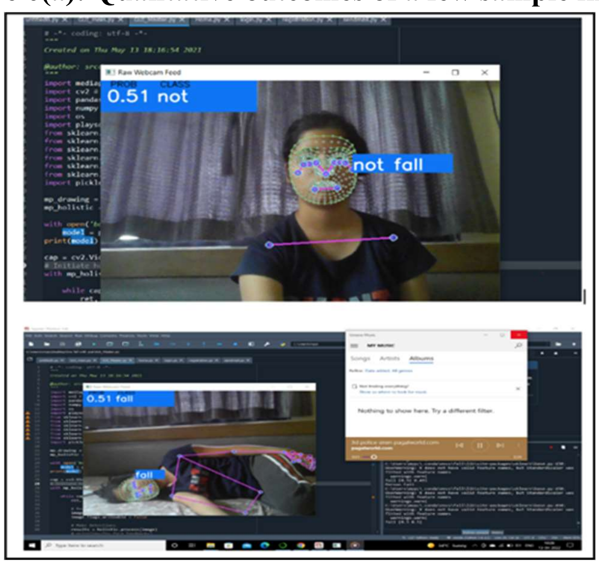


Figure 6(a): Qualitative outcomes of a few sample images



CONCLUSION

In this study, we proposed a hybrid fall detection system based on deep learning algorithms with an effective method of output delivery. The dataset was built using the live camera with different standing positions as well as sitting positions. In a complicated setting, experiments demonstrate that this strategy can reduce the false detection rate and increase robustness. Experimental findings demonstrate the universality of the suggested strategy. Our approach also successfully strikes a balance between sensitivity and specificity. The combination of falling-state and falling-state features is significant, as evidenced by the results. The falling-state characteristics help to recognise abrupt changes in the shape of the human body. The fallen-state features can be used to recognise a human body that is lying on the ground and help prevent mistakes when performing similar actions, like bending over. The evaluation of falls is more reasonable and accurate thanks to the fusion of several features. Our system can distinguish between actual falls and non-falls like bending over with greater accuracy.

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