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# Fall Detection for Old Age Using Deep Learning Mechanism

Miss. Lagad P[1], Dighe Shreya[2], Dighe Sakshi[3], Badode Anjali[4], Shinde Sakshi[5]

[*1]Asst. prof. Department of Computer Technology, Padmashri Dr. Vitthalrao Vikhe Patil Institute of Technology & Engineering(Polytechnic), Loni, Maharashtra, India

[*2,3,4,5]Department of Computer Technology, Padmashri Dr. Vitthalrao Vikhe Patil Institute of Technology & Engineering (Polytechnic), Loni, Maharashtra, India

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## Abstract:

The rise of nuclear families has resulted in less care for the health of the elderly living in private residences. Because of this, they are forced to either abandon their lives of solitude or be admitted to an elderly care facility. This means they have to take care of themselves in every way, including taking their medication and doing their regular tasks. A fall at home or in a care facility could result from this. Serious health problems or even death could result from a fall for which assistance is unavailable. The good cause of assisting the elderly is always bolstered by the application of image processing to detect these falls. Using the idea of a convolutional neural network in image processing, the suggested system offers a reasonable and cost-effective solution to this problem. Frame by frame, the suggested model keeps an eye on the solitary person to make sure they don't fall. The YOLO V8 is being used to assess the region of interest and pixel displacement in data segmentation in order to measure the fall. In addition, the model sends a text message to the doctor, closest relative, and neighbor in an effort to rescue a life.

Keywords: Fall Detection, Image Normalization, YOLO V8, Region of Interest.

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## I. INTRODUCTION

A picture's "region of interest" (ROI) is the specific area that the user is most interested in focusing on. Most photos used for evaluation have diverse items and locations that are relevant to the process, thus this is very helpful in the field of image processing. Furthermore, it is necessary to eliminate numerous visible portions of the image that do not pertain to the specified procedure.

To minimize the likelihood of a false positive being identified as a result of an undesired area, it is very efficient to retain only the pertinent portions of the image for processing. Overall system accuracy is improved by using the Region of Interest to restrict the algorithm's field of vision. The elimination of superfluous data and the consequent reduction in processing time are two additional benefits of the Region of Interest application's exclusive nature that contribute to the system's enhanced efficiency. A crucial part of image processing, the region of interest allows for a much more optimized approach to processing images by focusing on what's really important and avoiding processing the rest of the image that isn't relevant. Images can be efficiently filtered using multiple Regions of Interest, provided that they are present in the image.

The acronym for "Convolutional Neural Networks" is CNN. They belong to the larger category of Artificial Neural Networks, which are algorithms that mimic the way the human brain functions. Because of their resemblance to the human brain, these networks are widely used and can mimic human behavior. Because the vast majority of our inventions originated in the human brain.

A.I. neural networks were designed with the human brain in mind. Consequently, it possesses traits that are intrinsic to it, such as the fact that the neuron is the fundamental computational unit in both the human brain and artificial neural networks. The sensory organs allow us to receive information that can be used to excite neurons in the brain. Neurons in Neural Networks are fine-tuned to only fire when a specific simulation threshold is met. Over a billion neurons comprise the functional human brain, allowing for thought and decision-making. Similarly, artificial neural networks use a plethora of stacked neurons that only activate in response to a stimulus that meets a predetermined threshold.

[1] An LIDAR-based fall detection system was introduced by Miguel Pineiro et al., who highlighted the system's non-intrusiveness, low cost, and respect for privacy. By staying away from cameras and other invasive or author-wearable gadgets, author not only safeguards user privacy but also keeps the everyday routines of the elderly unaffected. All of these considerations are critical for ensuring that the senior citizens' regular living conditions do not jeopardize their quality of life or health. This work is a first step in the continuous development of a system that can monitor and analyze additional parameters to improve the system's detection skills. This, in turn, might allow for a more comprehensive analysis to meet the varied needs of users. Automatic fine-tuning improves the system's accuracy and real-time effectiveness by first learning in controlled environments and then adapting to the unique circumstances of each home.Limitation\ Viewed as a first step, the authors intend to expand the system's capabilities in the future to track and analyze a broader array of commonplace actions and behaviors. In addition, the detection capabilities of the system could be enhanced by integrating LIDAR with various sensors, such as biometric and environmental sensors. This improvement has the potential to make analysis more thorough, which would help meet the different needs of users better.

[2] in The attempt to automate caregiving duties for elderly people is becoming increasingly important in an aging world, according to Jesús Gutiérrez et al., if affordable, high-quality care is to be maintained. The automatic detection of falls is one of the jobs that may be automated in this field. Their extensive research into the development of automated fall detection systems has paid off with trustworthy devices. But the people who could really use these systems only think about them in specific situations. Falls in these situations often go unrecognized until the following morning, which delays the arrival of much-needed help. Here, the patient's comfort during nighttime slumber is of utmost importance, and the usual author arable systems' body-worn sensors aren't the way to go. The best course of action in this case may be an environmental system, preferably a visual one with cameras placed around the patient's surroundings. Nevertheless, due to the dim lighting, far-infrared (FIR) photographs must be processed. A fall detection system that utilizes FIR imaging is firstly developed and implemented in this paper. The technology combines the results of a neural network that estimates human poses with a detection method that looks at the relative motion of the body's key joints to see if a fall has happened.

The new fall injury prevention gadget can also give mobility support, and the methods for fall prediction described by Emily A. Kamienski et al. are discussed in their narrative. A baseline LSTM network predicts if the user would fall based on data from an IMU worn by the user. To improve performance over this network, three novel strategies were developed. One approach was to train models independently for fast and slow falls, using their own unique patterns. The second approach included combining the separated falls forecast with the time remaining prediction. This would postpone the prediction for slower falls, when instability is initially relatively mild and the signals could resemble activities of daily living movements. The third approach included supplementing the data with additional attributes to help differentiate the input space for fall trials that had comparable inputs but belonged to different target classes. The Lipschitz quotient test confirmed the usefulness of these data attributes. Compared to models trained using the initial set of six data attributes, all three architectures outperformed the competition.

## II. LITERATURE SURVEY

[4] Md. Impressive outcomes in identifying pre-fall, fall, and non-fall occurrences have been demonstrated by the ensemble CNN-LSTM-based fall detection system that Mohsin Kabir et al. suggested for use with older persons. The suggested system, which combines the advantages of long short-term memory models with convolutional neural networks, was able to detect falls with an accuracy of 97.34%, pre-fall events with a precision of 94.57%, and non-fall events with a precision of 96.56%, all using the author's famous SiS Fall as an example. A crucial concern for the health and safety of older persons, the device is non-invasive, cost-effective, and quickly deployable, making it a valuable tool for fall detection.

[5] In their paper, Chainarong Kittiyanpunya et al. describe a system that can detect falls in the elderly using data from z-axis point clouds and Doppler velocities. In order to detect falls, the system used the LSTM network, which is a smart classifier. In five separate rooms, the author ran experiments with ten individuals using a variety of continuous activity patterns. In the tests, mm Wave FMCW radar was used to capture radar scattering data, which were subsequently converted to point clouds and Doppler velocities. Doppler velocity and point clouds along the x, y, and z axes were used to create several input datasets.

[6] A potential lightweight model for human fall detection is ED-YOLO, as described by Guoxin Shen et al. [6]. To begin, we present the DBBC3 module. In order to replace the 3*3 conv on the C3 module in the backbone, the reparameterized DBBConv module is utilized. Secondly, DBBConv's pooling branch is eliminated. In order to create the efficient DBBConv (E-DBBConv) and DBBC3 module (E-DBBC3), a new conv group is integrated at the same time. In order to enhance the capability to extract detailed features, the DBBConv and DBBC3 modules take the place of the shallow Conv and C3 modules in the backbone, while the E-DBBConv and E-DBBC3 modules replace the deeper modules.

[7]Yi Chu et al. presented a Wi-Fi CSI-based deep learning-based fall detection system. Specifically, the author created a deep learning classifier utilizing a cutting-edge image classification tool. In order to compile this exhaustive dataset, twenty-two volunteers underwent CSI on falls and other everyday activities in four separate indoor settings. In order to make the fall detection algorithm more versatile, the dataset also contained tasks done both on and off the dominating path. Achieving 99% accuracy with specific dataset combinations and maintaining over 96% accuracy when all gathered CSI from diverse contexts is included in the training dataset, the proposed fall detection technique surpasses two other fall detection systems.

[8] Fall detection is an important part of intelligent healthcare systems, according to Van-Ha Hoang et al, particularly for the elderly. A number of approaches have been developed by researchers to identify falls using skeleton data taken from RGB films. The author of this research thoroughly investigated fall detection algorithms that rely on skeletons. Data collecting, data preprocessing, feature extraction, and recognition methods were all part of the author's comprehensive examination of the system workflow. This work seeks to encourage researchers in this area to shift their focus from recognition accuracy to practical application factors, like detection speed and privacy concerns, of skeleton-based fall detection systems through in-depth analysis and debate. The author also compared the reviewed algorithms' performance on the common fall detection benchmark datasets, which is a limitation in terms of future scope. In addition, the author posed some important questions about the state of the discipline and suggested some avenues for further study.

  

[9] A multi-modal dataset for fall detection that takes real-world factors into account is presented by Stefan Denkovski et al. It takes into account ambient circumstances, a range of complicated tasks, and privacy concerns through its four physiological modalities and six vision-based modalities. The performance was evaluated using an anomaly detection framework across various visual modalities. The main emphasis of this work is to find instances of falls by analyzing the overall flow of images in the scene. Although pose estimation could be a promising avenue for future research, it is outside the scope of this paper. Future research can validate methods created on this dataset by applying them to other public domain recordings. After heat and depth modalities, IR modalities were the most effective, while conventional RGB was the least effective. Several reconstructive scoring approaches, including within-context and cross-context, preserved this sequence of outcomes. When the data were classified using a global threshold, this disparity became much more noticeable. Future research could build upon this analysis by incorporating multi-modal fusion, which is a limitation of the current work. It is possible to enhance overall performance with fewer false positives by combining several modalities and their strengths. To further enhance the auto encoder's reconstructive capability, one might modify the auto encoder's objective or loss functions. Additional deep learning techniques, such as visual transformer attention or contrastive learning, may be investigated in future studies.

[10] A fall detection system was suggested for AI-based edge computing by Bor-Shing Lin et al. [10] using neuromorphic computing hardware. The author's likeness was taken using a webcam and fed into a neural network model running on an edge computing platform. The object's features were detected, the SVM was employed for classification, and the manager was notified of the detection result using Wi-Fi. On the edge computing platform, this study's upgraded neural network model YOLO-LWon was successfully deployed. Unlike the model that employs a float-32 precision format on the computer side, YOLO-LW uses a deep divided convolutional layer to increase computational performance. In order to decrease model size and enhance FPS, YOLO-LW is converted to integer 8 precision format. To keep the model's correctness, an additional convolutional layer is added.

[11] Traditional fall detection methods are explained by Da-Min Ding et al. [11]; image recognition methods are not applicable to all illumination situations. However, multi-line LiDAR is pricey, and single-line LiDAR isn't good for outdoor settings. Not to mention that the smart walker isn't capable of running all of those complicated algorithms. By combining data from the smart walker's upper and lower limbs' multi-sensors, this study suggests a new fall detection system and algorithm based on the PLT-SPRT approach. A novel type of handle is constructed to gather signals from the upper limbs, completing this system. In order to identify the admittance control model of the walker system and create a kinematic model based on the user's lower limbs' swing states, a two-parameter model-based system identification approach is initially suggested for fall detection.

[12] According to Kai-Chun Liu et al. [12], technical obstacles including degrading effects and mismatches of effective features necessitate additional research into how to improve the performance of LR-FD systems. The authors of this paper provide a deep learning (DL) ASE model that can learn the correlation and link between LR and HR signals in order to reconstruct HR signals from LR data. In order to overcome technological obstacles and improve performance, LR-FD systems use the improved accelerometer signals to anticipate fine-grained movement information. The outcomes demonstrate the efficacy of the ASE model in enhancing the performance of LR-FD systems.

[13] One of the most important things you can do for your older loved ones' health is to keep an eye out for signs of falls and injuries [13] according to Ahnryul Choi et al. Patients with impaired balancing ability could benefit greatly from near-

  

fall remote monitoring in their daily lives, as it could help them avoid future falls and offer valuable information on their rehabilitation progress. Using a single waist-mounted inertial measuring unit (IMU) device, the author of this work created a unique classification system based on deep learning to accurately classify three categories: falls, near-falls, and activities of daily living (ADLs). This study comprised a total of thirty-four young authors. A hyperparameter optimized directed acyclic graph-convolution neural network (DAG-CNN) design was suggested for the purpose of fall, near-fall, and ADL prediction. The author's predictions using the modified DAG-CNN structure were about 7% more accurate than those using the conventional CNN structure. By integrating gyroscope and accelerometer data, the updated DAG- CNN achieved an impressive prediction accuracy of more than 98% in the near-fall scenario.

[14] Activity recognition, which was introduced by YVES M. GALVÜO et al., is a significant area of research within the domain of machine learning. In the context of anomaly detection in particular, methods requiring explicit labeling pose difficulties and are often biased. It is more difficult to develop solutions with practical application when anomaly events are uncommon and no public datasets provide actual fall data. Therefore, a method that can train a model without labeled data is a viable option in this case. In this study, we offer a reconstruction-based, auto-encoder-using ST-GCN feature-based deep anomaly detection system for fall monitoring. The author primarily aimed to develop a strong solution that could be trained without prior knowledge of fall events. Therefore, it was believed that the model would generalize better if trained without simulated fall events. After reviewing the data, the author concludes that their suggested framework successfully identifies fall events in the majority of trials with a negligible amount of false positives and negatives. Future Scope Limitation: Additionally, the author's framework is not restricted to detecting falls but can potentially identify other health risk anomalies. To make it more robust and suitable to monitoring people in residence without requiring a health care professional, the author encourages future study to expand the framework to recognize other health risk problems in the setting of dwellings.

[15] According to Majd Saleh et al., most of the top-tier ML-based fall detection systems use simulated datasets for training [15]. These datasets often have an ADL type distribution that differs significantly from the real world. The author has demonstrated in this article that this occurrence leads to two significant issues. At the sacrifice of sensitivity, it first improves specificity. Additionally, it ensures that the specificity measure cannot be interrupted. In this study, we address these issues and offer a trustworthy architecture for a fall detection system that relies on machine learning. It is based on watching how elderly people go about their everyday lives. Because it is rotation invariant, the suggested method is compatible with fall detectors worn on the wrist as well as the neck. Both actual and simulated falls have demonstrated a sensitivity level of 100% for the system. Testing it on 303 days of recorded activity from seniors revealed a respectable level of specificity. Future research will address the computational complexity and embeddability problems with the suggested method.

[16] An innovative and thorough integration of the Hungarian job allocation system with the H-net neural network has produced a sequence to maintain the frames to evaluate fall detection. This study draws inspiration from the work of Shubham gade et al. This step of the process involves the author utilizing the sequence list to improve the slot allocation outcomes. Thanks to this vital information, the scheduling method used to find the closest electric vehicle charging station may be fine-tuned in real-time. The decision-tree approach is employed to determine whether the electric car charging station nearest to the user has any available slots based on the sorted list that was acquired in this stage of the choice tree procedure.

  

## III PROPOSED METHODOLOGY

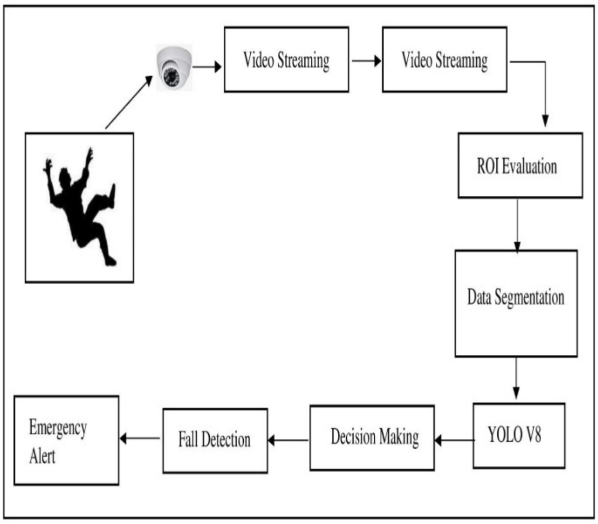


Figure 1: Proposed methodology diagram

The method that has been suggested to establish a Fall Detection system depicted in the system overview in Figure 1 up top. The suggested method was based in part on the execution of the procedures detailed below.

*Step 1: Training the Fall images for YOLO V8:* The system successfully identifies the fall in the image by utilizing the image. In order to generate an alert to the mix, the first step of the approach is to identify the fall in the image. human being. For accurate person recognition in the event of a fall, the fall identification module employs the Yolov8 method. Training this model is a prerequisite to using it for fall detection. In order to begin training, you must first download the roboflow dataset and install the ultralytics for the Yolov8 model. Download the fall detection dataset from https://universe.roboflow.com/roboflow-universe projects/fall-detection-ca3o8. Then, link the robotflow with an API key. In order to retrieve the directory's file list, the downloaded dataset is thoroughly examined. The number of files in the directory can then be extracted using the file list. For training, there are 3148 files, and for testing, there are 450 images. To begin the yolov8 model for the yolo job of person recognition, it is necessary to successfully integrate the roboflow data and effectively shuffle the fall dataset. The detection model is being started with the trained weights. The dataset was trained for 200 epochs with a batch size of 32 and an image size of 640 X 640. After training the yolov8 model, the project runs are saved as a zip file in the provided directory. The details of the Yolov8 model can be found in the table 8.2 provided below.

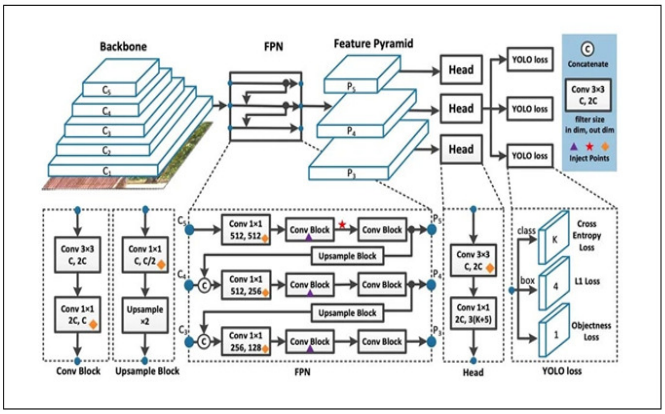


Figure 1: Model Summary for YOLOv8

From the Convolutional Neural Network comes the YOLOv8. To improve the accuracy of person recognition, it employs the CNN approach's components in a novel and efficient way. To regularize the model and prevent overfitting, the Yolo architecture uses a combination of methods, including 24 convolutional layers with variable parameters, 4 max pooling layers, and several dropout and batch normalizations. Two fully connected layers constitute the model's apex. With a stride of 2 and a kernel size of 2x2, the channels are max-pooled after the first convolutional layers deconstruct and reduce them. All of the model's layers use the same max pooling algorithm. To handle the increase in data, the kernel sizes of the succeeding convolutional layers get progressively larger. Specifically, these layers make use of the RELU activation function. For the purpose of creating the.pt file, which serves as Yolo8's trained data file, every layer has the same activation function; however, the completely connected layers use a linear activation function.

  

The next steps will involve using this.pt file to notify the blind individual of the impending collapse.

Step 2: *Testing the model for Fall* : Here, the Python software uses the mobile phone's camera to record video and, by extension, the frames. It does this by utilizing the Droid Cam app, which is compatible with both laptops and mobile phones. By referencing the.pt file, which contains the trained model, we can determine where in the live streaming frames the falls occurred; specifically, we can find their upper left rectangular coordinates. This role is responsible for checking the frames' stability; if anything goes wrong, an alert will be raised and a WhatsApp message with map directions will be sent to the relevant individual.

## IV RESULTS AND DISCUSSIONS

The Anaconda framework, Python, and the Spyder IDE were utilized in the development of the proposed technique for fall detection for old age. The development computer comes with 8 GB of primary RAM and 1 TB of auxiliary memory. In order to establish the plan's practicability, many things have been thought about. We describe the study's experimental findings here. The RMSE is employed to evaluate the efficacy of the suggested model. Absolute difference between the two continuously connected variables is shown by root-mean-squared error (RMSE). The real fall and the system-detected fall are two continuously associated entities in this experiment. The suggested model runs five trails, with ten experimental sets each trail, to quantify this. Table 1 and picture 2 display the recorded results.

The RMSE can be shown in the equation 3.

$$RMSE_{fo} = [\sum_{i=1}^{N} (z_{f_i} - z_{o_i})^2 / N]^{1/2} \qquad \_(3)$$

Where

$\sum$ - Summation

$(Z_{fi} - Z_{oi})^2$ - Differences Squared for Actual no of falls and detected number of falls

N - Number of samples or Trails

| Trail no | No of Experiments | Actual number of fall | Detected number of fall | MSE |
|---|---|---|---|---|
| 1 | 10 | 6 | 5 | 1 |
| 2 | 10 | 4 | 2 | 4 |
| 3 | 10 | 3 | 3 | 0 |
| 4 | 10 | 5 | 5 | 0 |
| 5 | 10 | 4 | 3 | 1 |

Table 1: Recorded Mean Square Error Rate ( MSE)

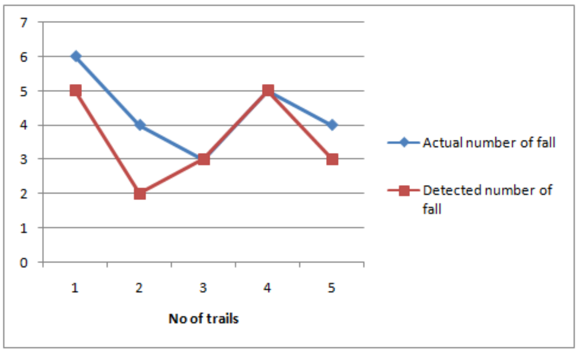


Figure 2: MSE Difference between the No of actual fall v/s detected fall

Based on the data in the table, we can calculate an average RMSE of around 1.1 and an MSE of about 1.2. In reality, such a little margin of error shows that the suggested model performs admirably under limited conditions for fall detection.

## V. CONCLUSION AND FUTURE SCOPE

With only 1.3 megapixels of depth, the webcam on a laptop provides an inadequate setting for the suggested model of fall detection utilizing video surveillance. A solitary person residing in their home faces the risk of catastrophic injury or death in the event of an unexpected fall if they do not receive prompt medical attention, as depicted in the model. By standardizing the frames acquired in the one-second time slice, the model maintains a watch on the subject. In order to identify the fall, these normalized frames are processed using data segmentation using the YOLO V8. The suggested device immediately notifies loved ones, the hospital, and neighbors through text message when it detects a fall, allowing for the prompt summons of life-saving assistance. The device has the potential to be integrated into real-time CCTV surveillance and to detect falls even at night in the future.

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