Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 44 No. 3 (2023)

Real-Time Posture Estimation-Based Human Fall Detection System

[1]Bharti Sahu, [2]Shreya Pawar, [3]Mansi Chaudhari, [4]Vaishnavi Kalal

[1]Assistant Professor, Department of Computer Engineering, Dr. D.Y. Patil Institute of Technology Pimpri, Pune, India
[2]UG Student, Department of Computer Engineering, Dr. D.Y. Patil Institute of Technology Pimpri, Pune, India
[3]UG Student, Department of Computer Engineering, Dr. D.Y. Patil Institute of Technology Pimpri, Pune, India
[4]UG Student, Department of Computer Engineering, Dr. D.Y. Patil Institute of Technology Pimpri, Pune, India

E-mail- sahubharti1430@gmail.com

Abstract— Special attention should be given to those in vulnerable age groups, such as children and the elderly, who live in solitary living arrangements and have an increased likelihood of experiencing falls. The primary objective of a fall detector is to minimize the duration of time an elderly person remains on the ground subsequent to experiencing a fall event. The length of time that an individual remains on the floor subsequent to a fall is a determining factor in assessing the severity of the incident. The act of engaging in prolonged deceit has been shown to elevate the likelihood of experiencing adverse health outcomes such as hypothermia, dehydration, and pressure ulcers. The ultimate objective of the detector system is to identify the occurrence of a fall and expeditiously notify a carer. The potential for individuals to inadvertently trigger a fall detector by engaging in rapid movements such as standing up and sitting down underscores the need for a dependable detector that can effectively differentiate between instances of falling and other related occurrences. The primary aim of this research is to enhance the understanding of fall-related mechanisms among medical technologists in the field of public health. The assessment of an individual's physique alteration potential relies on the calculation of the ratio between their height and width. To validate a human fall, it is necessary to measure the height and centre of the rectangle that encloses the individual, and thereafter compare these measurements to a specified threshold. An alert system has been developed to notify persons who are connected to the network in the event of a catastrophe, provided that a state of inactivity is maintained for 100 consecutive frames.

Keywords— Deep Learning, Transfer Learning, ResNet50, CNN.

1. Introduction

Statistics indicate that unintentional falls are a common occurrence among the elderly population [1, 2]. The occurrence of falls is prevalent even among those who possess the capability to live alone. Nevertheless, it is crucial to acknowledge that falls pose a significant threat to the well-being of older individuals, resulting in severe damage and even death. In fact, falls are the primary cause of mortality in the senior population [3]. The practise of manually monitoring for unexpected autumn activity is both labor-intensive and fatiguing. Hence, the implementation of a system capable of monitoring individuals' activity levels, detecting instances of falls or other irregularities, and promptly notifying users is of utmost importance.

In recent years, significant advancements have been achieved in the field of fall detection research [4, 5], which has a wide array of possible applications. Contemporary scholarly investigations largely depend on the utilization of wearable technology [6-8]. Consequently, this inclination has given rise to the advancement of intelligent environments outside residential settings, with the purpose of assisting the aged population. The majority of approaches often focus only on the detection of falling conduct, while giving little consideration to the direction of the fall and the extent of resulting injury. The direction in which an individual falls significantly influences the extent of their injuries, with different orientations during a fall leading to diverse levels of injury to the human body. When an individual has a forward fall, the likelihood of sustaining injuries is comparatively lower in comparison to a backward fall. Given the aforementioned considerations, an optimal and efficacious fall detection system should possess the characteristic of being inconspicuous to the subject under surveillance, while also demonstrating consistent proficiency in accurately detecting falls and effectively assessing the likelihood of fall occurrences.

2. Related Work

Extensive studies on the topic of fall detection have led to the development of various promising new methods. Based on different methodologies and experimental tools, there are two main types of fall detection systems: those that rely on wearable sensors and those that rely on the use of the human eye.

The wearable sensor-based system gathers information for mobility and other parameters from the right kinds of sensors. Afterwards, a computation technique is used to convert these signals into information that is reflective of the motion state, such as acceleration data [9]. The given data allows for an analysis of the current state of the target. Sensors are often worn at the torso, the lower extremities, or the neck. Accelerometers, three-axis gyroscopes, magnetometers, and barometers are common pieces of equipment. Using an accelerometer, Zerrouki et al. (2010) were able to detect falls in their research participants. Chen et al. (2011) detailed an innovative method for creating a fall detection system in their research. The system combined a Bluetooth module for wireless communication with a gyroscope and an accelerometer that each measured acceleration in three different directions. Using these parts, the researchers built a wearable fall detection system that could be attached to the waist. Device gathered information from gyroscope and accelerometer sensors to deduce human body locations via analysis of continuous signals. Based on the correlation between body language and communication, AI was used to build a very accurate model. Wearable sensor technology including a magnetometer, gyroscope, and accelerometer was used by Alarifi and Alwadain (2012) in their investigation. The gadget was attached to the subject at six different points throughout the body. The researchers then made use of the sophisticated AlexNet convolution network to detect instances of falls. The researchers unveiled a device worn around the waist that can detect falls in the elderly [13]. This gadget makes use of information gathered by its onboard three-axis accelerometer, gyroscope, magnetometer, and barometer sensors. Smartphones with in-built sensors may one day be able to detect falls [14]. In order to improve user experience, smart helmets include wearable sensors that can detect falls. It is usual practise to use machine learning or deep learning strategies for fall detection and evaluation once sensors acquire angular motion or trunk inclination data. Although the method that relies on wearable sensors achieves a high degree of identification accuracy, it comes at the expense of convenience since the person being watched must wear the equipment.

The vision-based methodology captures the actions and movements of individuals inside the designated region by using various camera technologies, such as traditional cameras and depth cameras. Image processing and neural network techniques are used to examine persons by examining the temporal variations in their physical properties. Standard computer vision techniques, such as the frame difference approach, background removal, and foreground segmentation, may be used to extract human body silhouettes or bounding boxes. A variety of classifiers, including Gaussian mixture models (GMMs), support vector machines (SVMs), and multilayer perceptrons (MLPs), may use the aforementioned extracted properties as input in order to autonomously detect instances of falls. Sehairi et al. (2016) used a backdrop removal technique to derive the human silhouette from a sequence of video frames. The researchers made an estimation of the head's vertical velocity by using a finite state machine. They obtained the change in aspect ratio by analysing the variances in contours. By combining these determined features, they inferred the state of the target. In their study, Zerrouki et al. (2017) conducted calculations to determine the zones of occupancy around the gravitational centre of the human body. Once the suitable angles were determined, the aforementioned data was submitted to several classifiers. The Support Vector Machine (SVM) demonstrated superior performance in terms of accuracy compared to the other classifiers. The researchers in this study expanded upon prior research by including a hidden Markov model (HMM) to effectively characterise various body orientations, and by incorporating curvelet coefficients as additional characteristics [18]. The researchers Harrou et al. (19) used Multivariate Exponentially Weighted Moving Average (MEWMA) charts, a less often utilised approach. In their study, Rougier et al. (2020) devised a methodology for identifying instances of falls by monitoring the changes in individuals' bodily movements during the duration of a recorded video. The potential variability in camera angles used for capturing human body images may have an impact on the precision and reliability of detection outcomes produced by these systems. Furthermore, the detection results may be influenced by the presence of objects such as backpacks and crutches.

Individuals are ranked using a visual-based method that compiles data from posture estimation. With a high degree of precision, the posture estimate method can foretell the exact positions of specific body joints. In addition, it uses a set of 2D or 3D joint coordinates to accurately describe the abstract data relevant to the human body. Asif et al. [21] conducted a research that gave considerable attention to data about joints. To successfully extract human body features, they employed a layered hourglass network. The aforementioned characteristics were then used to train a convolutional neural network (CNN) model that included both modal-specific and multimodal embedding layers. To efficiently distinguish between fall and non-fall postures, it was necessary to establish a mechanism for training an embedding that captures high-level properties. Chen et al. (2022) accessed human joint point data for their research through the OpenPose framework (23). The pace at which the hip joint centre dropped, the angle established between the body's midline and the ground, and the width to height ratio of the rectangle surrounding the body were then analysed to establish whether or not falling behaviour was present. All of these factors were taken into account simultaneously, and so was the target's potential to recover on its own following a dip. When compared to using contour information, the utilisation of human bone joint characteristics for action recognition is more direct and less vulnerable to external effects. Therefore, a posture estimation method is used in this study to identify persona traits. The chance of injury from a fall is highly influenced by the direction in which a person's body is moving at the time of impact. Unfortunately, our plan is one of the few that takes into account the direction of the autumn, an important factor that has been neglected in most of the prior literature.

3. Software Requirement Specification

A. Project Scope

The use of a deep learning system called Convolutional Neural Network (CNN) is employed for the purpose of identifying the surrounding environment, including individuals, furniture, and the ground. The machine learning model is provided with input video frames by us. Continuous monitoring of the environment is being conducted. In the event of an emergency, immediate notification may be sent to any member of the family. A significant number of persons who live in solitary living arrangements might perhaps experience advantages and potentially be safeguarded by the widespread adoption and execution of this particular idea.

a. User Classes And Characteristics

- **Input**: Live video feed from the house. This is used to keep an eye on the position of the elderly or children.
- **Output**: The live video feed is continuously observed and detects if a person falls on the ground, furniture or floor.
- **Alert**: If a person falls on ground, this class sends a notification to the concerned authority asking for help.

b. Rules and Dependencies

- It is necessary to gather a large number of movies for use in training Machine Learning algorithms. The offered dataset aids the model in gathering data on human posture, with an emphasis on differentiating between safe postures like standing or sitting, and dangerous postures like when a person has fallen to the ground and sustained an injury.
- The elderly person's home must have a security camera installed, linked directly to the monitoring system.
- The old person must stay inside the camera's focus at all times.
- The member of the family who learns of the occurrence must have access to a cellular network on their mobile device.

c. Software Quality Attributes

- Users have the ability to modify this software according to their own requirements.
- Highly accessible: The application is readily available for download and use without any associated

costs. The programme is easily available to anybody who need its services.

- Maintainability: The modular architecture of the project facilitates quicker issue resolution for developers in the event of post-deployment problems.
- The output obtained by the software is very user-friendly due to the use of a graphical user interface application.

4. Analysis Model: SDLC Model To Be Applied

A. Waterfall Model

The waterfall model is a method for creating software that divides the development process into steps. According to this paradigm, the beginning of a new phase may not always coincide with the previous phase's completion. Each stage's output will be used as input in the next. Therefore, the development process inside the waterfall model may be seen as a linear trend. There is no overlapping between the stages here.

Smaller projects with well defined and well-understood requirements benefit greatly from the Waterfall approach. In fig 1 and 2 SDLC Model Diagram and System Architecture given.

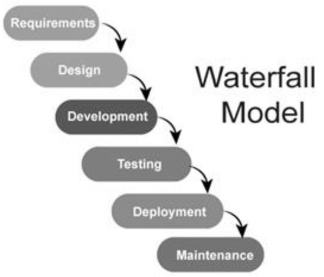


Fig 1: SDLC Model Diagram

B. System Implementation Plan

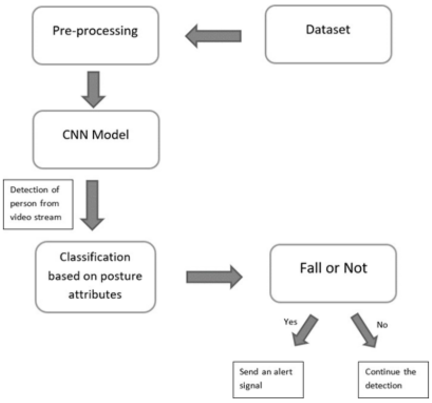
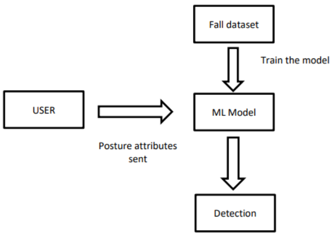


Fig 2: System Architecture

Fig 3: DFD Level 0



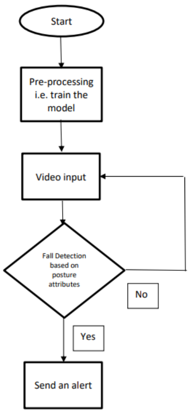


Fig 4: DFD Level 1 **Fig 5:** DFD Level 2

A Human Fall Detection System based on real-time posture estimation is a technology designed to automatically detect when a person falls or experiences a significant change in posture using sensors and algorithms. The primary goal of such a system is to promptly alert caregivers, medical personnel, or an automated response system in case of a fall or unusual posture, ensuring rapid assistance and potentially saving lives. Figures 3, 4, and 5 show DFD Level 0, DFD Level 1, and DFD Level 2. Here's how such a system typically works:

C. Components and Mechanism:

Sensors: The system utilizes various sensors to capture data related to an individual's posture and movements. Common sensors include accelerometers, gyroscopes, and sometimes depth sensors or cameras.

Data Acquisition: The sensors continuously collect data on the person's movements, acceleration, and orientation. This data is sent to a processing unit for analysis.

Data Processing: Algorithms and machine learning models process the sensor data in real-time to determine the person's posture and detect any abrupt changes that may indicate a fall or an unusual posture.

Fall Detection: The system compares the real-time posture data with predefined patterns or thresholds for normal postures. If the system detects a deviation from the expected posture, it may trigger an alert.

Alert Generation: When a fall or unusual posture is detected, the system generates an alert. The alert can take various forms, including notifications sent to caregivers or family members via smartphones, emails, or automated calls. In some cases, the system can also trigger alarms in healthcare facilities or emergency response centers.

User Interaction: Depending on the system's design, it may offer the option for the user to acknowledge or cancel the alert if it's a false alarm or if they don't require immediate assistance.

D. Key Features and Considerations:

Real-Time Monitoring: The system continuously monitors the person's posture and movements, ensuring that falls are detected promptly.

Customizable Alerts: Users and caregivers can configure the system to send alerts based on specific criteria, such as the angle of deviation, the duration of an unusual posture, or the user's response.

Privacy Considerations: Systems should prioritize user privacy by not capturing or storing sensitive visual data unless explicitly required. Privacy safeguards and data encryption should be in place.

Accuracy and False Positives: Reducing false alarms while maintaining high sensitivity is essential. Machine learning models and algorithms are continuously improved to enhance accuracy.

Integration: The system can be integrated with other healthcare or safety systems, such as medical records, emergency response systems, or smart home automation.

User-Friendly: To encourage user adoption, the system should be user-friendly and not interfere with daily activities. It should require minimal user interaction.

Battery Life: Battery-powered systems should be designed to have long-lasting battery life to ensure uninterrupted monitoring.

Human Fall Detection Systems based on real-time posture estimation have significant potential for improving safety, especially for seniors and individuals at risk of falling. They offer a proactive approach to reducing the risks associated with falls and ensuring that assistance is provided promptly when needed.

5. Single-person Pose Estimation

In this paper, we provide a comprehensive analysis of the subject matter. There are two possible approaches to developing a pose estimate: one for an individual and another for a collective group of individuals. Both technologies might be advantageous in different situations and need different levels of computational capacity. at situations where the focus of observation is limited to a single individual, such as an elderly person at their home or at a customised fitness facility, there is potential to reduce the amount of processing required in a multiple-person analysis method. This approach offers the possibility of achieving enhanced estimation accuracy. In the next section, we will outline the sequential actions required to execute this plan. In this novel approach to location estimation, the input may consist of either static or dynamic pictures. The use of deep neural networks (DNN) has rendered the provision of a basic human framework superfluous for the purpose of enhancing performance. Deep neural networks (DNNs) use a methodology whereby significant nodes are interconnected in a direct manner. The methods often used for detecting the posture of an individual are outlined below:

A. Direct Regression

Several distinct studies have been offered on the basis of the Direct regression paradigm. Alexander Toshev and Christian Szegedy proposed using a cascade of deep neural network (DNN) regressors, which may achieve decent accuracy in posture evaluation. It was suggested that a technique may be used to find the crucial regions directly from the characteristics. The carriers used an approach that includes continually supplying the computer with mistake data in an effort to improve its precision and efficiency. This was accomplished despite the model's many limitations that made it difficult to achieve the desired level of performance. Sun et al. employ a combination of the structure-aware technique and the compositional approach to posture recognition. The author of this study proposes a new technique for predicting pivot points that may be used instead of the regression-based strategies previously discussed. When compared to these other approaches, the suggested system prioritises bone identification above joint recognition. The previously mentioned technique, although carried out in a steady and basic manner, contained some aspects of a more fundamental approach. Luvizon et al. proposed yet another cutting-edge strategy. After mapping the heatmap's hotspots to coordinates, the analyst used a loss function that factored in the degree of error between each pair of points to determine the final outcome. The accuracy achieved with this technique was comparable to that of the heatmap-based method.

B. Heatmap

The presentation of a novel approach, Heat Map based regression, was motivated by the intricate nature, sensitivity, and volatility associated with the task of identifying the most favourable solution in key point regression. Heat maps, in their most basic manifestation, are visual representations of data that use color-coded graphs. In the given configuration, it is necessary to ascertain the probability of the existence of a key point for every individual pixel inside the image. The findings are shown in the format of a heatmap, whereby distinct probabilities are represented by varying colours. The sequential procedure for developing the heatmap approach is, as described. The estimation of posture is performed iteratively by using a neural pose machine framework that relies on heatmaps. Angjo, Michael Black, David Wjacobs, and Jitendra Malik proposed the use of heatmaps for the estimate of 3D human posture from a single colour image. Two primary concerns associated with heatmap-based regression are the difficulty in decoding and the accuracy of the ground truth. In summary, heatmaps have emerged as a prevalent and dependable technique for evaluating body positioning.

C. 3D Pose Estimation

The complexity of working with a three-dimensional (3D) model is greater in comparison to two-dimensional (2D) methods due to the need of less exact key point identification utilising regression techniques. There are essentially four main applications for its use [13]. The first component of the system is responsible for receiving data from the visual sources. Lee et al. parameterized several parts of the human body as truncated cones in their study. Subsequently, the individual proceeded to modify the orientation of the body segment in order to achieve a more accurate alignment with the model or, at the at least, approximate the authentic representation. The execution of the twofold 'backward/forward' flip by an individual introduces a level of ambiguity in the identification of physical components and joints, resulting in a significantly increased quantity of minima in an exponential manner. Upon recognising the presence of uncertainty, Rehg, Kanade, and Morris introduced a novel model known as the "2-dimensional scaled prismatic model" in order to address this issue. In contrast to the other models, this particular model exhibited little ambiguity. Triggs and Sminchisescu used inverse kinematics to examine the whole configuration and enhance performance compared to previous foundational research. Subsequently, their efforts were directed at mitigating the influence of indeterminate local minima. A pathway to the local minima is established by linking the data points with transition routes that are identified during the exploration for co-dimension saddle points. Now, let us transition to a discourse on the topic of modelling.

D. Kinematic Model

The skeleton model is another name for this framework. As its name suggests, this model requires the extraction of details like a set of joints and limbs and the body's position. This model makes it easier to see how different parts of the body connect to one another and how they should be oriented. However, it does a poor job of recognising shapes and identifying textures.

E. Planar Model

The term "contour model," abbreviated as such, is used in the estimation of two-dimensional postures. The aforementioned model has the capability to discern and recognise the outline or silhouette of an individual. Rectangles are used as visual representations to show the many anatomical constituents. The dynamic form concept is well recognised and often referenced in academic literature. Principal Component Analysis (PCA) is used in this study to capture a comprehensive representation of the whole human body, including the aforementioned distortions in silhouette.

F. Volumetric Model

As far as 3D posture estimate goes, the aforementioned model is as realistic as it gets. Named thus because it involves measuring the whole volume of a person, this technique is all-encompassing. The system is a deep learning framework. GHUM is only one of several readily available models. This training has included the examination of over 60,000 unique human body shapes, each with its own set of angles and characteristics.

6. Multiple-Person Pose Estimation

Recognising individuals in a single image poses challenges because to variations in their positions and occlusion. The quantity of folks present in the scenario is only one of many factors that want consideration in this kind of model. These factors have significant importance when considering practical applications. Numerous methodologies were devised to estimate the poses of collective entities including individuals. This post will concentrate on a select selection of them.

A. Top Down Approach

Top-down object recognition begins with a comprehensive headcount of everyone in a given image, before moving on to any assessment of their posture. The open pose system, a popular method for predicting an individual's key-points, is employed by the system. The next step is to apply the greedy algorithm to divide the identifiers into groups representing different people or anatomical structures.

Multi-person pose estimation has been used in a wide variety of research projects. The authors of the aforementioned a top-down approach. According to their academic paper "A Basic Framework for Estimating Human Pose," Fang, Xie, and Tian (year) presented a top-down approach that makes use of faster RCNN for the purpose of recognising people, and then a two-stage network to estimate their postures. The mask RCNN model is used for persons identification, and a residual network is used for posture estimation in the academic work.

B. Bottom-Up Approach

It's possible to think of the bottom-up strategy as being the antithesis of the top-down approach. Identifying individual keypoints one at a time is a necessary step in the process of detecting picture keypoints. These keypoints are then aggregated or merged in order to construct poses. The strategy that is referred to as associative embedding is a method that can be broken down into two phases. To begin, it requires the acquisition of knowledge of a similarity matrix between the keypoints. Second, it necessitates the arrangement of these keypoints into postures in accordance with the matrix that was previously established. In point of fact, it employs an algorithm in order to classify graphs for the goal of doing so.The Bottom-Up Approach is shown here in the form of an illustration, which may be seen in Figure 6. Figure 5 is an illustration showing how bottom-up strategies are implemented. As was said in the introduction, the first step is to provide a picture to be used as the input. After that, in section 5b, the model is used to determine the essential aspects of the individual being modelled. In the last step, section 5c, all of the identified keypoints are combined in order to produce a human instance. A bottom-up methodology is often used in the research presented in academic publications that examine posture in groups of people.In their own pieces of published literature, famous scholars such as Zhe Cao, Thomas Simon, and Yaser Sheikh, amongst others, have provided a number of illustrations and explanations offer a deep grouping strategy that classifies postures according to specific keypoints. This technique makes use of a convolutional neural network. Both bottom-up and top-down cognitive processes are included into Bin Xiao's approach to strategic thinking. During the post-processing phase, a number of processes are carried out with the intention of improving the precision of the post-estimate by taking into account the interdependencies between the keypoints. The user did not provide any text for the system to modify. As a consequence of this, the bottom-up methodology has been used rather often in group pose evaluation.A large number of scholars have looked at different approaches to try to improve both productivity and accuracy.

C. Hybrid Approach

The hybrid strategy integrates elements from both the top-down and bottom-up methods. An illustration of this methodology may be seen in the use of the mask RCNN-based approach. This approach involves the use of object detection to identify human subjects, while using the bottom-up strategy for posture assessment. The use of the hybrid approach has the advantage of incorporating the robustness inherent in the top-down strategy for the estimation of postures and the localization of individuals inside pictures. The reason for this is because the hybrid strategy integrates elements from both techniques. The two-step procedure allows for the attainment of fine-grained accuracy similar to that of the bottom-up technique; nevertheless, it may incur significant computing expenses. Furthermore, it encompasses a variety of diverse networks.

D. Multi-stage Approach

The precision of posture predictions is refined by many iterations in the multi-stage method. One notable multi-stage approach used to improve the accuracy of keypoint localization and scale estimation is integral regression networks. Figures 6, 7, and 8 present the Deployment Diagram, ER Diagram, and State Machine Diagram, respectively.

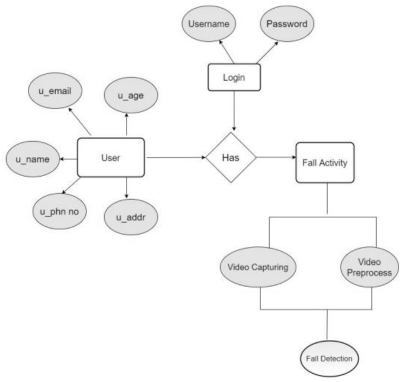


Fig 6: ER Diagram

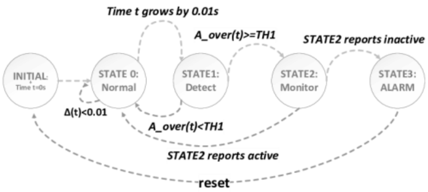


Fig 7: State Machine Diagram

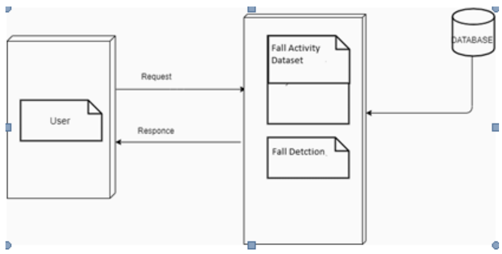


Fig 8: Deployment Diagram

E. Advantages

A Human Fall Detection System based on real-time posture estimation offers several advantages, particularly in the context of healthcare, elderly care, and safety monitoring. Here are some key advantages:

1 **Early Fall Detection:** Real-time posture estimation allows for the detection of falls as they occur or even before a fall happens. This early detection can be crucial for preventing serious injuries and providing immediate assistance to the individual.

2 **Improved Safety for the Elderly:** Elderly individuals are more prone to falls and their associated injuries. This system can provide an extra layer of safety and peace of mind for both the elderly person and their caregivers.

3 **Reduced Response Time:** When a fall is detected, the system can automatically trigger an alert to caregivers, healthcare professionals, or emergency services. This reduces response times, which is critical in case of injuries or emergencies.

4 **Non-Intrusive:** Unlike wearable devices or traditional fall detection systems that require individuals to wear sensors or pendants, a posture-based system is non-intrusive. It doesn't require the person to wear any additional equipment, promoting greater user compliance.

5 **Continuous Monitoring:** The system can provide continuous monitoring, offering real-time feedback on a person's posture and movements. This continuous data can be valuable for healthcare providers to assess the person's overall health and mobility.

6 **Privacy and Dignity:** Since the system doesn't rely on cameras or invasive sensors, it respects the privacy and dignity of the individual being monitored. This is especially important in healthcare settings and senior care facilities.

7 **Customizable Alerts:** Users and caregivers can customize the system to send alerts based on specific criteria, such as detecting a fall or identifying certain posture changes. This flexibility ensures that alerts are relevant and not triggered unnecessarily.

8 **Cost-Effective:** Compared to some other fall detection systems that may require expensive hardware or subscriptions, a posture-based system can be cost-effective, especially if it utilizes existing sensors or technology.

9 **Machine Learning and AI:** Posture estimation systems can leverage machine learning and AI algorithms to continuously improve their accuracy and adapt to individual user's movements over time.

10 **Integration with Healthcare Systems:** These systems can be integrated with electronic health records (EHR) and healthcare management systems, allowing healthcare providers to access valuable data for better patient care and assessment.

11 **Home-Based Care:** Posture-based fall detection systems can be used in home-based care settings, making it easier for individuals to age in place while still receiving necessary care and monitoring.

12 **Research and Data Analysis:** The data collected by these systems can be used for research purposes, helping researchers gain insights into the causes and patterns of falls, which can inform strategies for fall prevention.

Overall, a Human Fall Detection System based on real-time posture estimation offers a proactive and unobtrusive approach to ensuring the safety and well-being of individuals, particularly those at risk of falling. It has the potential to save lives, reduce healthcare costs, and improve the quality of care for vulnerable populations.

F. Applications

A Human Fall Detection System based on real-time posture estimation has a wide range of applications across various industries and domains, primarily focused on enhancing safety, healthcare, and monitoring. Here are some key applications:

1. **Elderly Care:** In-home monitoring: Ensuring the safety of elderly individuals living alone by detecting falls and sending alerts to caregivers or medical professionals.
   Nursing homes and assisted living facilities: Providing an additional layer of safety for residents and reducing response times in case of falls.
2. **Healthcare Settings:** Hospitals and clinics: Monitoring patients, especially those at risk of falling due to medical conditions or post-surgery, to prevent falls and related injuries.
   Rehabilitation centers: Assisting therapists in monitoring patients' movements during rehabilitation exercises and ensuring proper posture.
3. **Emergency Response:** Rapid response teams: Aiding first responders and emergency medical teams by automatically alerting them when a fall occurs, which can be vital in emergencies.
4. **Occupational Safety:** Industrial and construction sites: Enhancing worker safety by detecting falls and alerting supervisors to provide immediate assistance.
   Manufacturing facilities: Monitoring workers in high-risk environments to prevent accidents.
5. **Sports and Fitness:** Athlete training: Assisting coaches and trainers in analyzing athletes' movements and postures to improve performance and reduce the risk of injuries.
   Fitness tracking: Ensuring correct form during exercises and alerting users if they are at risk of injuring themselves.
6. **Smart Homes:** General safety: Integrating fall detection systems into smart home setups to ensure the safety of all household members, including children and the elderly.
   Home automation: Triggering automated responses, such as turning on lights or sending notifications, in the event of a fall.
7. **Public Spaces:** Public transportation: Installing fall detection systems on buses, trains, and subways to detect accidents and improve passenger safety.

Shopping malls and airports: Ensuring the safety of visitors by monitoring for falls and providing timely assistance.

8. **Security and Surveillance:** Intrusion detection: Integrating fall detection into security systems to identify unauthorized access or security breaches.
   Monitoring sensitive areas: Protecting valuable assets or critical infrastructure by detecting unauthorized access or falls.
9. **Rehabilitation and Physical Therapy:** Physical therapy clinics: Monitoring patients' movements and posture during therapy sessions to track progress and adjust treatment plans.
   Home-based therapy: Assisting patients with remote rehabilitation exercises and providing feedback on their posture and movements.
10. **Research and Data Analysis:** Fall prevention research: Collecting data on falls and near-falls to study patterns, causes, and preventive measures.

Healthcare analytics: Using fall data to assess patient risk factors and improve healthcare strategies.

These applications highlight the versatility and potential impact of Human Fall Detection Systems based on real-time posture estimation. They play a critical role in improving safety, healthcare outcomes, and overall quality of life for individuals in various contexts.

7. RESULT

We tried using this posture estimation network and discovered that it only detects keypoints when the body is in a nearly upright position, but not when it is laying on the floor. Our solution was to provide the network with the original picture as well as two rotated versions of it, one turned by -90 degrees and the other by 90 degrees. The network was able to locate the body's major landmarks while it was laying on the floor, and it did so effectively and precisely.

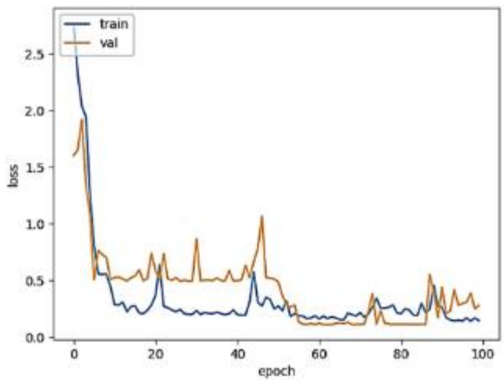


Fig 9: MLP Network Loss Diagram

After the posture estimation network successfully detects the keypoints of the human body, the discovered points are next used as input for a Multilayer Perceptron (MLP) network that has been trained to distinguish between instances of falls and other types of occurrences.The Multilayer Perceptron (MLP) network consists of two interconnected layers, each using the Rectified Linear Unit (ReLU) activation function. Additionally, the network includes a classifier layer that use the sigmoid activation function. The Adam optimizer was used to train the network, with binary cross entropy as the chosen loss function. The custom dataset that was just introduced was used for a total of 100 epochs throughout the training process. Figures 9 and 10 depict the diagrams representing the loss and accuracy, respectively.

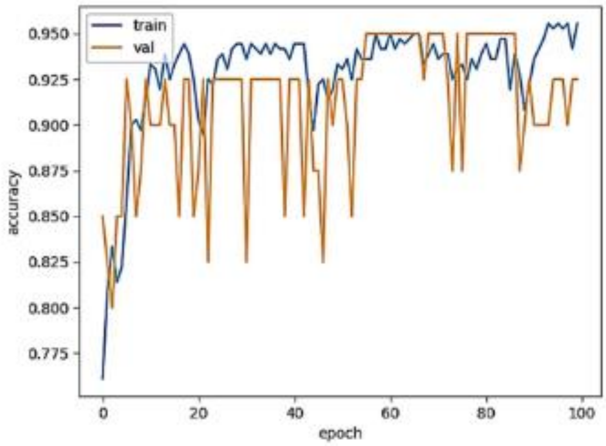


Fig 10: MLP Network Accuracy Diagram

8. CONCLUSION

In summary, the Real-Time Posture Estimation-Based Human Fall Detection System represents a significant breakthrough in the domain of healthcare and assistive technology. Its ability to continuously monitor an individual's posture and promptly detect potential falls in real-time holds tremendous promise for improving the safety and quality of life for vulnerable populations. This system not only offers an extra layer of security for the elderly and individuals with mobility issues but also provides a sense of independence by enabling them to live more confidently in their own environments. Moreover, as technology continues to evolve, we can anticipate further advancements in accuracy and reliability, making this system an invaluable tool in healthcare settings, residential homes, and caregiving facilities.

Nevertheless, it's important to acknowledge the ongoing challenges associated with the Real-Time Posture Estimation-Based Human Fall Detection System. These challenges include refining the system's robustness to minimize false alarms, addressing privacy concerns related to continuous monitoring, and optimizing its cost-effectiveness for widespread adoption. As research and development in this field progress, addressing these issues will be essential to ensure that this technology becomes a ubiquitous and accessible solution for safeguarding individuals prone to falls, thereby enhancing their safety and well-being in an increasingly aging society.

With growing age, people get diseases such as arthritis, this makes difficult for them to walk . If they are alone at home and they fall prey to a situation in which they cannot get up or ask for help, this can cause severe damage or also cost lives. In this paper built a system in which there is a surveillance camera which records the movements of the human present in it's camera range. If there is a sudden change in posture of the person, the system measures if the person is safe or has fallen on the ground. If the person is safe, then the detection continues. But if the system detects that the person has fallen, an alert is sent to the caretaker or acquaintance of the elderly. Due to this, emergency medical service can be provided, which helps in saving lives.

Our methodology encompasses two neural networks, namely posture estimation and MLP classifier, which are used to categorize the positions of the landmarks in order to ascertain if they pertain to a fallen individual or not. The trials demonstrated the high reliability and robustness of the overall system. Furthermore, it was found that the sensitivity of the fall detection region and the threshold for fall length may be adjusted to suit the specific environment and the needs of older individuals.

REFERENCES

[1] D. Mrozek, A. Koczur, and B. Maysiak-Mrozek, "Fall detection in older adults with mobile IoT devices and machine learning in the cloud and on the edge," Information Sciences, vol. 537, no. 5, 2020.

[2] V. Kumar, N. Badal, and R. Mishra, "Elderly Fall Due to Drowsiness: Detection and Prevention Using Machine Learning and IOT," Modern Physics Letters B, vol. 35, 2021.

[3] M. Suh and I. Cho, "Effectiveness of Nursing Care provided for Fall Prevention: Survival Analysis of Nursing Records in a Tertiary hospital," Japan Journal of Nursing Science, vol. 18, 2021.

[4] S. Usmani, A. Saboor, and M. Haris, "Latest research trends in fall detection and prevention using machine learning: a systematic review," Sensors, vol. 21, no. 15, p. 5134, 2021.

[5] N. Mozaffari, J. Rezazadeh, and R. Farahbakhsh, "Practical fall detection based on IoT technologies: a survey," Internet of Things, vol. 8, Article ID 100124, 2019.

[6] Y. Nizam and M. Jamil, "Classification of Daily Life Activities for Human Fall Detection: A Systematic Review of the Techniques and Approaches," Studies in Systems, Decision and Control, vol. 273, 2020.

[7] V. R. Xefteris, A. Tsanousa, G. Meditskos, S. Vrochidis, and I. Kompatsiaris, "Performance, challenges, and limitations in multimodal fall detection systems: a review," IEEE Sensors Journal, no. 99, p. 1, 2021.

[8] P. Bet, P. C. Castro, and M. A. Ponti, "Fall detection and fall risk assessment in older person using wearable sensors: a systematic review," International Journal of Medical Informatics, vol. 130, Article ID 103946, 2019.

[9] A. Ramachandran and A. Karuppiah, "A survey on recent advances in wearable fall detection systems," BioMed Research International, vol. 2020, pp. 1–17, 2020.

[10] N. Zerrouki, F. Harrou, Y. Sun, and A. Houacine, "Accelerometer and camera-based strategy for improved human fall detection," Journal of Medical Systems, vol. 40, p. 284, 2016.

[11] M. C. Chen, Y. T. Cheng, and R. W. Chen, "Improve the accuracy of fall detection based on artificial intelligence algorithm," Computer Modeling in Engineering and Sciences, vol. 128, no. 3, pp. 1103–1119, 2021.

[12] A. Alarifi and A. Alwadain, "Killer heuristic optimized convolution neural network-based fall detection with wearable IoT sensor devices," Measurement, vol. 167, Article ID 108258, 2020.

[13] P. Pierleoni, A. Belli, L. Maurizi, and S. Valenti, "A wearable fall detector for elderly people based on AHRS and barometric sensor," IEEE Sensors Journal, vol. 16, no. 17, pp. 6733–6744, 2016.

[14] X. Li, L. Nie, H. Xu, and W. Xianzhi, "Collaborative Fall Detection Using Smart Phone and Kinect," Mobile Networks & Applications, vol. 23, pp. 4775–788, 2018.

[15] K. M. Shahiduzzaman, X. Hei, C. Guo, and W. Cheng, "Enhancing fall detection for elderly with smart helmet in a cloud-network-edge architecture," in Proceedings of the 2019 IEEE International Conference on Consumer Electronics - Taiwan (ICCE-TW), IEEE, Yilan Taiwan, May 2020.

[16] K. Sehairi, F. Chouireb, and J. Meunier, "Elderly Fall Detection System Based on Multiple Shape Features and Motion analysis," in Proceedings of the 2018 International Conference on Intelligent Systems and Computer Vision (ISCV), pp. 1–8, IEEE, Fez, Morocco, May 2018.

[17] Zerrouki, N. Harrou, and F. Houacine, "Fall Detection Using Supervised Machine Learning Algorithms: A Comparative study," in Proceedings of the 2016 8th International Conference on Modelling, Identification and Control (ICMIC), IEEE, Algiers Algeria, Nov 2017.

[18] N. Zerrouki and A. Houacine, "Combined curvelets and hidden Markov models for human fall detection," Multimedia Tools and Applications, vol. 77, no. 5, pp. 6405–6424, 2017.

[19] F. Harrou, N. Zerrouki, S. Ying, and A. Houacine, "A simple strategy for fall events detection," in Proceedings of the 2016 IEEE 14th International Conference on Industrial Informatics (INDIN), IEEE, Poitiers, France, July 2017.

[20] C. Rougier, J. Meunier, A. St-Arnaud, and J. Rousseau, "Robust video surveillance for fall detection based on human shape deformation," IEEE Transactions on Circuits and Systems for Video Technology, vol. 21, no. 5, pp. 611–622, 2011.

[21] U. Asif, B. Mashford, and S. Von Cavallar, "Privacy Preserving Human Fall Detection Using Video Data," Machine Learning for Health Workshop, vol. 116, pp. 39–51, 2020.

[22] W. Chen, Z. Jiang, and H. Guo, "Fall detection based on key points of human-skeleton using OpenPose," Symmetry, vol. 12, no. 5, p. 744, 2020.

[23] Z. Cao, T. Simon, and S. E. Wei, “Realtime multi-person 2d pose estimation using part affinity fields,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 7291–7299, IEE, San Juan, PR, USA, June 2017.