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Implementation of Human Fall Activity Detection Systems

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Abstract

The elderly fall detection system has seen a rapid rise in medical devices due to the prediction of a 21.64% rise in the global population of elderly individuals over 65 by 2050. A significant challenge in researching elderly fall detection is the limited availability of data. The researcher cannot collect a large enough dataset on his own; access to care providers or medical institutions is extremely limited, and they typically reject ongoing research projects. However, such problems involving signal detection and recognition are a suitable area to use a machine learning approach. This paper address and provide a systematic review of contemporary issues in human fall detection systems, focusing on sensing technologies and machine learning approaches. The paper starts with a provision of a more focused introduction to the problem of falls in elderly populations. This is followed by description of sensing technologies, state of the art, and prototype design implementation. The accuracy of 91.8% obtained here shows high accuracy which indicate that the model is performing well. The result gave Sensitivity (%) = 92.3%. The significance of sensitivity in a fall detection system lies in its capacity to explicitly indicate the system's proficiency in accurately detecting falls. A high level of sensitivity in a fall detection system enables accurate identification of falls, therefore minimizing the likelihood of overlooked falls that can have serious health implications for elderly individuals.

Keywords: Machine Learning, Signal Sensing, Human Fall Dataset, Sensing Technologies, Fall Detection

Introduction

By 2050, there will be a predicted 21.64% rise in the global population of elderly individuals over 65 [1]. With aging came an exponential increase in the effect and risk of falls because of decreased leg strength, long-term drug side effects, visual impairments, and other factors that reduced strength. Fall rates differ between countries. For instance, according to a Southeast Asian study, Japan has 20% of its older population fall per year, compared to 6 to 31% in China. According to research conducted in the American region, the annual percentage of senior individuals who fall varies from 21.6% in Barbados to 34% in Chile. Still, a lot of old individuals fall at home. According to estimates from 2002, 28.6% (26-31%) of Italians 65 years of age and older fall within a year. Of these, 43% have several falls. Home is where 60% of falls happen [2]. When it comes to older adults living independently in their own homes, about half of the falls happen in the home and its immediate surroundings. These falls typically happen in areas that are used frequently, like the kitchen, bathroom, living room, and bedroom. The remaining falls happen in public places or in other people's homes [3]. The world has become quite concerned with fall detection and prediction in recent years [4]. Physiological reasons include age, a history of falls (for example, plantar phobia), mobility issues, sleep difficulties, and neurological illnesses are among the many factors that contribute to falls. Environmental factors also play a role. Dim light, smooth surfaces, and other environmental conditions are examples [5]. Though it doesn't stop falls from happening, fall prediction does necessitate taking into account all affecting circumstances. Health care providers are the only ones who should utilize fall risk assessment as a reference because fall prediction has a high likelihood of false alarms [6]. As such, the primary means of addressing the incidence of fall incidents is fall detection. Fall events and activities of daily living are the primary targets of fall detection systems now in use, which share a similar structure [7]. Sensing technologies play a crucial role in detecting and recognizing signals in healthcare. Over the past decade, a range of sensor technologies became available on the market. Unwanted outcomes and detrimental downstream impacts throughout the machine learning pipeline have been documented in recent research as a result of data problems [8,9]. Given that falls are the primary cause of fatal injuries in the elderly, such as fractures, early detection of falls is crucial in preventing loneliness, fractures, loss of consciousness, and other related consequences. Therefore, the risk of falls in today's ageing society is a critical concern. Consequently, the number

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of systems designed to detect falls has significantly increased in recent years. Furthermore, medical studies of the harm caused by falls have shown that this is greatly influenced by the speed of response and rescue. These falls constitute a minimum of 50% of the reasons for hospitalisation among the elderly, and around 40% of their non-natural causes of death. At a time when the identification and prevention of falls are vital for the welfare of older and susceptible persons, it is of paramount significance to get a high level of precision in detecting such occurrences [10].

Fall detection model performance relies directly on high-quality datasets combined with diverse representatives and extensive range of data points. The Authors in [8] explained that dataset development in machine learning research commonly faces problems with bias alongside incomplete data and insufficient transparency which results in unreliable models. The Researcher in [9] demonstrates through their research that machine learning operations succeed through data quality because inadequate datasets weaken fall detection system performance. In addition, [7] reviewed multimodal fall detection systems because they identify the shortage of standardized real-world datasets which hinders the development of generalizable models. Large-scale datasets available to the public are essential for algorithm training along with evaluation and benchmarking across different populations because they are unavailable. In addition, the detection of imaginary falls produces artificial alerts that result in increased distress for elderly patients together with their caregivers.

The identification of genuine falls from harmless movements remains difficult to separate. According to [3], improper alarms occur mainly due to uniqueness in each person's body motion combined with medical issues such as vision problems. The authors of [4] showed how machine learning models used for fall detection experience problems in distinguishing between actions that look similar (for example when someone sits down quickly or when there are many false alarms occur. However, timely response needs to be established because it helps reduce the effects of falls. Studies by the Health Quality and Safety Commission demonstrate that delayed medical care substantially raises mortality and health complications risks for senior citizens [1]. The review [5] showed that vision-based along with sensor-based detection techniques try to enhance real-time fall detection yet complications persist with respect to processing speed and messaging delays. The author in [6] support shifting fall detection systems from detection to prevention methodologies alongside predictive analytic models that identify fall risk factors beforehand. Local Binary Pattern (LBP) combined with transfer learning models represents [10] solution for improving predictive accuracy of falls while enabling proactive responses [10].

This paper performs a systematic review of sensing technologies and machine learning application for fall risk detection and identifies important areas for future work. The subsequent sections of this work are structured as follows: In Section 2, conceptual framework is presented. Section 3 present state of the art. Section 4 introduces the methodology and implementation of the proposed detection algorithm. Section 5 provides an overview of the conclusions drawn from the literature review and proposed fall detection algorithm.

Sensing Technologies

This section examined in detail the three primary kinds of fall detection sensor technologies-wearable, non-wearable, and hybrid along with their benefits and drawbacks.

Wearable Fall Detection Systems: As a result of their portability, simplicity of use, and capacity for real-time monitoring, wearable devices are among the most widely used fall detection systems. These devices are usually worn on the body, like on the wrist, waist, or chest, and are fitted with a variety of sensors to identify falls [11]. Applications for wearable devices have become incredibly popular in many spheres of daily life, including communication, entertainment, rehabilitation, education, and health [13] Patel et al., 2012; [14, 15]. The wearable and Internet of Things (IoT) patent conflicts of today are a direct result of these advancements in wearable technology and Internet infrastructure. In both academics and industry, wearable fall detection devices are one of the most popular disciplines. This is due to the fact that falls are a major and frequent cause of illness and death in the elderly [16]. Fall detection devices have the ability to produce fall alarms instantly and notify the appropriate parties for assistance. Prompt assistance after a fall minimizes treatment costs and hospital stays. If a person falls and is left unsupervised for an extended period of time, there may be physical and psychological complications that arise. Physical complications range from minor cuts and bruises to fatal brain damage and hip fractures [17, 11]. Psychological complications include fear of falling and other physical activities, which increases the risk of falling again. The length of time spent on the floor following a fall has a significant impact on physiological complications; staying there for an extended period of time has deeper effects on subjects, such as social isolation [12]. Figure 1 present images and schematic illustration of fall detection (Figure 1).

Types of Sensors in Wearable Technology are Triaxial Accelerometers, Gyroscopes, Barometers and Electrocardiogram (ECG) sensors are:

Triaxial Accelerometers: These sensors calculate the forces of acceleration applied to the body. An accelerometer can pick up on the abrupt change in acceleration that occurs during a fall. By capturing motion in three dimensions (x, y, and z) as indicated in Figure 1, the sensor enables the gadget to identify anomalous movements that could be signs of a fall [2]. This device has the ability to provide linear motion information on an individual's fall.

Gyroscopes: Gyroscopes measure the angular velocity of the body and are frequently used in conjunction with accelerometers. They aid in ascertaining the orientation and rotation and offer supplementary information to differentiate between typical activities and falls [18].

Barometers sensors: These sensors are sensors that can sense changes in altitude as well as atmospheric pressure. A barometer can pick up on the discernible shift in altitude that occurs during a fall due to the swift drop. The Authors in [19] state that a barometer and accelerometer are worn as a pendant to measure physiological and gait parameters, including walking adaptability, cadence, gait variability, gait endurance, visual contrast sensitivity, proprioception, quadriceps strength, reaction time, and postural sway.

Electrocardiogram (ECG) sensors: These sophisticated wearable gadgets track the electrical activity of the heart. Fall detection and subsequent medical assessment might benefit greatly from the important data that ECG sensors can provide, as a sudden fall may be linked to cardiac problems. Blood volume fluctuations and heart rate monitoring are accomplished by ECG sensors [20, 21, 19].

Non-Wearable Fall Detection Systems

This system relies on environmental sensors that are positioned

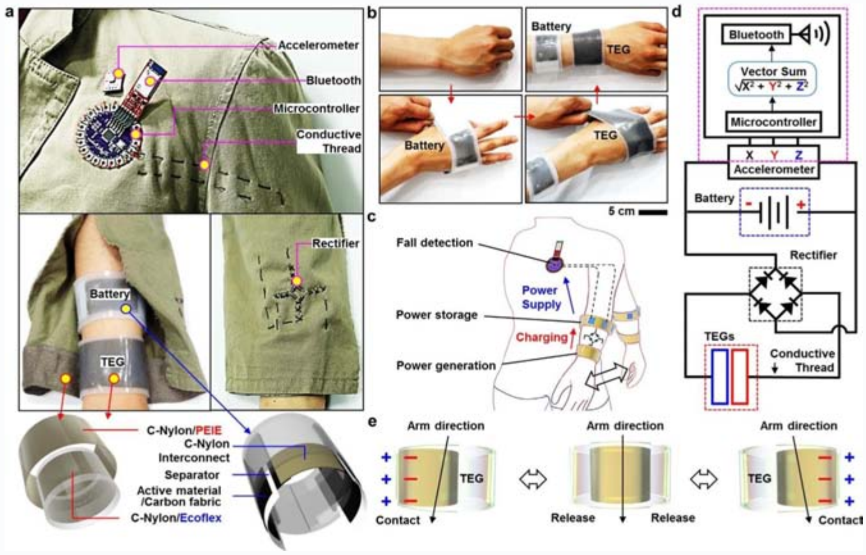

Figure 1: Images and schematic illustrations of the wearable fall detection system [97].

throughout the living area as opposed to the user. Without needing the user to wear a gadget, these systems are frequently employed in homes, hospitals, and care facilities to monitor the surroundings and identify falls [24]. Since these systems never shut off, there is never a need to remember to put anything on or charge gadgets. This eliminates compliance difficulties. Many types of sensing modalities have been studied: depth camera [25], depth camera with acoustic sensing [26], depth camera with wearable accelerometer [27] radar [28] and depth camera with wearable accelerometer [29]. Numerous of these studies show excellent outcomes; nonetheless, the majority had small testing datasets that were assembled from young, healthy volunteer subjects [24]. Numerous sensors are used by non-wearable devices to keep an eye on their surroundings, gather information, and communicate with the outside world. From industrial automation to smart home automation, these sensors can be incorporated into a wide range of devices [23]. Some of the commonly found sensors in non-wearable devices are the Environmental Sensors, Proximity Sensors, Motion sensor, optical sensor, Motion and Position Sensors, Acoustic and Vibration Sensors and Position Sensors Environmental Sensors are employed in smart homes, industrial monitoring, and environmental research, among other uses, to monitor the surrounding environment [2]. Optical sensors are used to measure and identify electromagnetic radiation, including light. Automation, security systems, and imaging applications all make extensive use of them [23]. Without coming into direct contact with an object, proximity sensors can identify its presence or absence. They are utilized in robotics, automation, and security systems [30]. Motion and Position Sensors monitor position and movement, sending data to applications in the gaming, automation, and security domains [31]. Through the use of sound, Acoustic and Vibration sensors identify falls. The characteristic sound that usually follows a fall can be heard by microphones placed throughout the space [24]. Non-wearable Fall Detection Systems offers benefit of continuous monitoring without the need for users to wear gadgets, which makes them more convenient for elderly or disabled people. Even when the user is not actively interacting with the device, they are still able to cover a greater area and identify falls [23, 22]. These systems can cause privacy problems, particularly when they use cameras or other invasive technology, and they might be less successful in detecting falls in places without sensor coverage. In addition, compared to wearable devices, installation and maintenance may be more difficult and expensive [22].

Hybrid Fall Detection Systems

Wearable and non-wearable technology are combined in hybrid systems to capitalize on the advantages of each strategy. Through the use of numerous data sources, these systems seek to increase fall detection accuracy and dependability [32]. Information from wearable and non-wearable sensors is combined in hybrid systems via data fusion techniques. In order to identify falls with greater accuracy, the combined data is processed using machine learning techniques (Singh et al., 2020). The process of a hybrid fall detection system usually consists of integrating several sensors, such accelerometers, gyroscopes, and cameras, to keep an eye out for falls [32]. Abrupt changes in orientation and velocity are detected by the gyroscope and accelerometer, which may indicate an impending fall. Concurrently, the user's position or movement patterns are analysed by cameras or other environmental sensors, such as floor sensors. In order to verify whether a fall has occurred, the data from these sensors are cross-referenced and processed using algorithms (Singh et al., 2020). This reduces the possibility of false alarms by leveraging the advantages of many sensing modalities. The fall detection system's specificity and dependability may be enhanced by the multi-sensor fusion. A single sensor system struggles to deliver the required sensitivity and specificity because of the complexity of fall kinematics and the diversity of fall characteristics. In order to differentiate against the fall event, [33] proposed a novel system that combines audio sensors with floor vibration. In order to reduce any blind spots and increase the sensitivity of low impact fall detection, The Researcher in [34] used an infrared camera in conjunction with floor pressure. The benefit of Hybrid Fall Detection Systems lies in their capacity to decrease false positives and enhance the accuracy of detection, particularly in intricate settings [32]. However, when utilizing cameras or other invasive sensors, they may be more expensive to install and maintain, they demand more power, and they may cause privacy problems.

Machine Learning

Recently, there has been an increase in the desire to use machine learning to improve prediction accuracy in the healthcare sector in

Table 1: State of the art: Fall Detection System.

Reference	Sensing Technology	Contribution
[2]	Wearable Sensors	The authors developed a deep learning model which utilizes LSTM neural networks with attention systems for fall detection purposes.
[3]	Vision-based	The framework evaluates conditions that endanger elderly adults through vision challenges leading to falls.
[4]	Multimodal	The paper evaluates modern approaches in fall detection and prevention technology that philtre through machine learning algorithms
[5]	Vision-based	This document evaluates systems that detect falls with image processing techniques.
[6]	Multimodal	The paper establishes two main fall-related system categories which encompass both detection and prevention strategies.
[7]	Multimodal	The article examines both performance aspects and difficulties and system restrictions regarding multimodal fall detection methods.
[8]	Data-Centric	The paper examines the use of Machine Learning datasets during research development.
[9]	Data-Centric	The research investigates MLOps while putting special emphasis on data quality aspects
[10]	Vision-based	Fall prediction technology receives performance enhancements through the combination of Local Binary Patterns (LBP) and transfer learning techniques.
[11]	Wearable Sensors	The research investigates what constitutes the most suitable position for wearable devices intended for fall detection functions.
[13]	Wearable Sensors	Reviews wearable health-monitoring systems
[14]	Wearable Sensors	Explores mobile wearable communication technologies
[18]	Wearable Sensors	The research project produced fundamental work toward the prototype design of wearable fall alert systems.
[19]	Wearable Sensors	Reviews wearable sensor systems for fall risk assessment
[20]	Wearable Sensors	It designs a detection technology for falls combined with heart rate tracking and body position recognition capabilities.
[21]	Wearable ECG	The paper evaluates wearable ECG devices which operate without physical contact for monitoring applications.
[22]	Wearable Sensors	Reviews wearable sensor devices for fall detection
[23]	Wearable & Non-Wearable	Reviews gait analysis methods for fall detection
[24]	Non-Wearable Sensors	Tests non-wearable fall detection methods in homes
[25]	Depth Sensors	The author introduces depth monitoring techniques for fall recognition that analyse body shapes.
[26]	Acoustic Sensors	The solution provides highly efficient methods to separate acoustic signals during fall detection
[27]	Vision-based	A particle philtre operates as the technology foundation for fall detection systems that use camera input.
[28]	RF Sensors	This system makes use of high-resolution time-frequency distributions when detecting falls.
[29]	Depth & Accelerometer	The device identifies falls through its integration of a 3-axis accelerometer with a depth sensor.
[30]	Capacitive Sensors	Reviews recent advances in capacitive proximity sensors
[31]	Motion Sensors	The paper reviews how position sensors as well as motion detection devices serve for fall detection purposes.
[32]	Wearable Sensors	The researcher develops a combined approach for detecting falls.
[33]	Floor Vibrations & Sound	The system detects falls through floor vibrations and recorded sound waves.
[34]	Floor Pressure & IR	The researcher has developed a combination of floor pressure analysis with infrared image technology for fall detection applications.
[35]	Big Data	It reviews progressive improvements and challenges within ML technology as they pertain to fall detection systems.
[36]	Data-Centric	Explores accountability in ML datasets
[37]	Data-Centric	Reviews responsible ML dataset practices
[38]	Data-Centric	The author presents an approach for describing datasets used in ML applications.
[42]	Healthcare Data	Reviews ML applications in healthcare
[54]	Wearable Sensors	The system utilises wearable sensors to create ML-based systems which detect human falls.
[55]	Decision Trees	The research depicts the employment of decision trees for maintaining responsible AI operation principles.
[56]	RF Sensors	The article enhances the Random Forest Algorithm design for classification purposes.
[58]	Unsupervised Learning	Reviews the K-Means clustering algorithm
[59]	Data-Driven	The researcher utilises KNN to make predictions about IT governance project outcomes.

order to improve patient care standards while boosting productivity and lowering costs. The primary goal of machine learning is to provide systems the capacity to continuously learn from data and perform better without the need for human involvement [35]. Data is becoming more and more crucial, especially in machine learning applications, which means that creating datasets requires increasingly sophisticated processes [36]. An assemblage of data used for model evaluation and training is called a dataset in machine learning. It usually consists of the matching output data (labels or targets) and the input data. The process of creating a dataset requires several teams and phases, including collection, labelling, and design. Unwanted outcomes and detrimental downstream impacts throughout the machine learning pipeline have been documented in recent research as a result of data problems [8,9] (Table 1).

Implementation of Prototype Design

Methodology

The simplified research methodology encompasses a thorough literature review on sensing technologies and machine learning, aiming to gain a comprehensive understanding of machine learning for signal sensing and the current limitations of existing systems. The methodology adopted begin with importing necessary libraries, loading the datasets, similarity measure and feature selection. The hardware requirements consist of a computer with at least 8GB of RAM and a modern multi-core processor. This is because some of the libraries used sometimes don't support the old machines due to need for GPU and more computational power. Internet Connection are put in place for downloading libraries, and dependencies. The software requirement consists Operating System (Windows, macOS, or Linux), Python 3.7 or higher and Jupyter Notebook: An interactive computing environment for writing and running code. Necessary Python Libraries are: pandas, matplotlib, seaborn, numpy, scikit-learn and google. colab (if running on Google Colab). The code for this work was run in a Jupyter Notebook environment, and follow a series of steps to ensure everything is set up correctly. The proposed system utilizes the University of Rzeszow fall detection (URFD) dataset. There are 70 videos in total, with 2,373 falling frames, 7,452 non-falling frames, and 1,719 transitional frames. A single person captured RGB and depth data types in this dataset using two Kinetic cameras in a laboratory setting. This section presents the implementation algorithm and flow chart.

Implementation

The fall algorithm is a crucial component of this review. The design and coding for this prototype algorithm is based on the architecture (Figure 2).

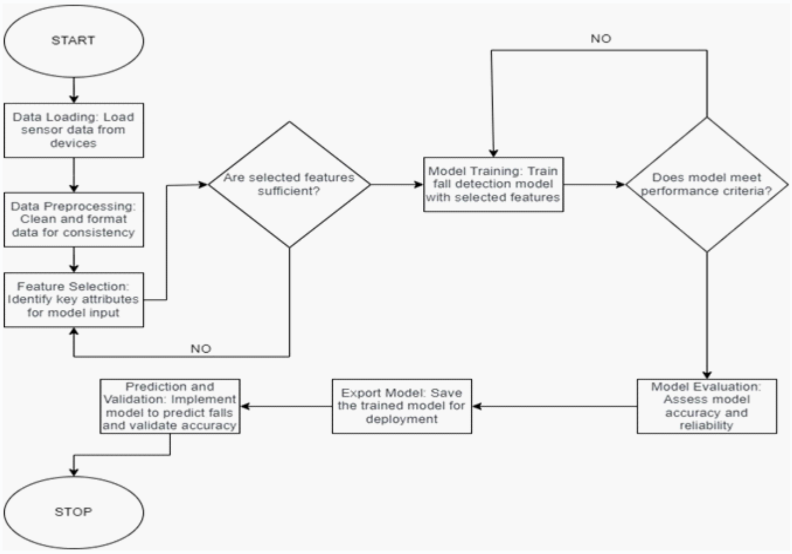

Figure 2: Flowchart of prototype system.

In the project, the dataset is an image-based dataset hosted on Google Drive. The dataset contains images which is categorized into two classes: Fall and Non-fall. They represent different scenarios.

Since the dataset is stored in Google Drive, it's necessary we mount Google Drive to the Colab environment. *from google.colab import drive drive.mount ('/content/drive')*. The dataset is located in the directory */content/drive/MyDrive/fall-detection/fall_dataset*. This path is passed to torchvision.datasets.ImageFolder to load the dataset. The dataset is loaded using PyTorch's ImageFolder method, which organizes the data according to the directory structure, where subfolders represent different classes (e.g., "fall" and "non-fall"): dataset = datasets.ImageFolder(root=image_path, transform=data_transforms).This method automatically labels the images based on their directory names (classes). The dataset is split into training and validation sets in an 80/20 ratio using random_split():

*train_size = int(0.8 * len(dataset)) validation_size = len(dataset) - train_size*

train_dataset, validation_dataset = random_split(dataset, [train_size, validation_size])

The image data undergoes several transformations and feature extraction processes before being passed into the machine learning model: A series of transformations are applied to the dataset to preprocess it for training. These transformations are vital to ensure that the images are in a format suitable for deep learning models. Images are resized to a fixed size of (224, 224) pixels to fit the input requirement of the model:

transforms.Resize((224, 224)).The pixel values are normalized with the standard mean and standard deviation of the ImageNet dataset to enhance convergence during training:

transforms. Normalize([0.485, 0.456, 0.406], [0.229, 0.224, 0.225]). The image is converted into a tensor, a PyTorch data format suitable for deep learning computations.The dataset consists of two classes: fall and non-fall. The class labels are automatically assigned based on the folder structure. This dataset contains slightly more images of falls than non-falls, as observed in the class distribution analysis.

] count = Counter(labels)

The project employs EfficientNet-B0, a pre-trained deep learning model, fine-tuned for binary classification (fall vs. non-fall).The model is pre-trained on ImageNet, which helps it start with learned weights from a broader image domain.

model = models.efficientnet_b0(pretrained=True)

Since the model is pre-trained to classify 1000 classes, the final classifier layer is modified to match the number of classes in this project (2: fall and non-fall):

num_ftrs = model.classifier[1].in_features

model.classifier[1] = nn.Linear(num_ftrs, len(dataset.classes))

The training and validation datasets are loaded into the model using DataLoader for batch processing. Both the training and validation data are processed in batches of 32 images:

train_loader = DataLoader(train_dataset, batch_size=32, shuffle=True)

validation_loader = DataLoader(validation_dataset, batch_size=32, shuffle=True)

The model is trained for 5 epochs. In each epoch:The training data is passed through the model to compute loss and update weights using back propagation. The training and validation accuracy and loss are recorded after each epoch, helping to track the model's performance.

The training Steps encompasses Forward pass to compute the model's output for a batch of images.

Loss calculation using Cross Entropy Loss:

criterion = nn.CrossEntropyLoss()

pass to compute gradients and update weights using the Adam optimizer:

optimizer = optim.Adam(model.parameters(), lr=0.001).

After each epoch, the model is evaluated on the validation set.

The accuracy and loss are computed to assess how well the model

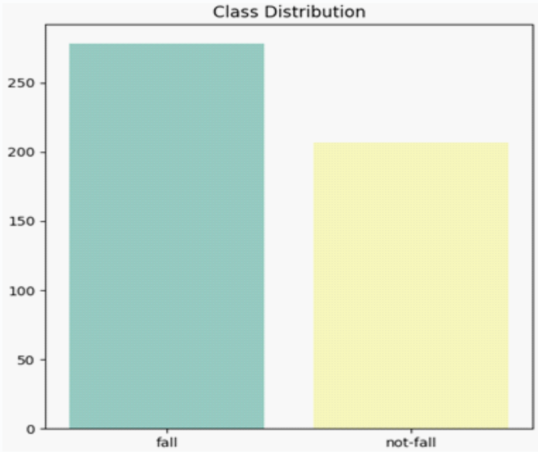

Figure 3: Class boundary graph.

generalizes to unseen data.

In addition to training the model on images, a video-based simulation is implemented to detect falls in real-time using a pre-trained model. The implementation is as follows:

A video is loaded using OpenCV (cv2.VideoCapture) to process each frame: cap = cv2.VideoCapture(video_source).

Every second frame is captured and processed by resizing and normalizing it, as was done with the images: image_tensor = transform(frame).

For each frame, the model predicts whether it shows a fall or non-fall, and a confidence threshold (e.g., 0.8 or 80%) is applied to the predictions: confidence, prediction = torch.max(probabilities, 1).

The percentage of frames classified as "fall" is computed. If more than 80% of the processed frames are classified as falls, the system triggers a fall detection: if fall_percentage >= 80: print("Fall detected!").

A class distribution chart is generated to visualize the distribution of fall and non-fall images in the dataset. The class distribution chart shows that the dataset has slightly greater fall cases than non-fall cases (about 260 falls and 210 non-falls). Although the elegance distribution is really balanced, the distinction might also nonetheless make contributions to a moderate bias inside the version's predictions. Techniques like resampling, cost-sensitive studying, or data augmentation should help deal with this potential imbalance (Figure 3).

Result and Discussion

Confusion matrix

A confusion matrix displays classification performance through its depiction of actual labels on the y-axis and predicted labels on the x-axis. The confusion matrix contains cells which present the number of predicted samples that fall under specific labels. Model performance analysis starts with the confusion matrix because it reveals vital information regarding which classes have better or worse prediction results. The graphical display provides insights into specific performance areas of individual classes to help developers improve modeling effectiveness (for example through weight modifications or increased training examples for specific classes). The matrix helps analysts understand both false categorization percentages and

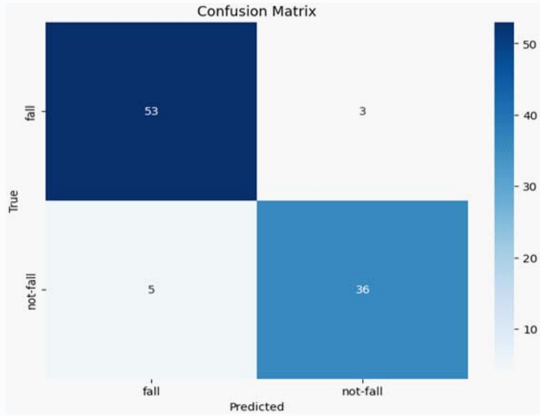

Figure 4: Confusion matrix.

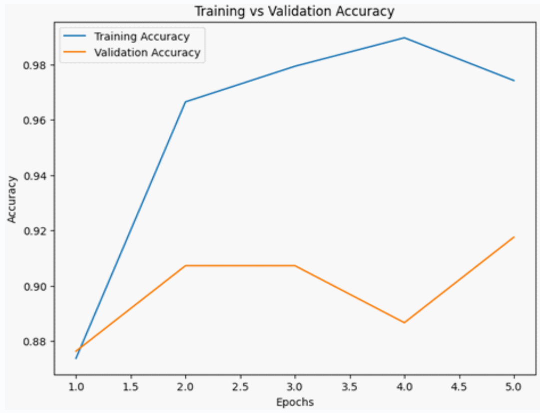

Figure 5: Training versus accuracy graph.

measures for model quality enhancement. In Figure 4, we plotted confusion matrix of proposed system for the subject (Figure 4).

From the implementation, the components of a Confusion Matrix are:

True Positives (TP) = 53

True Negatives (TN) = 36

False Positives (FP) = 5

False Negatives (FN) = 3

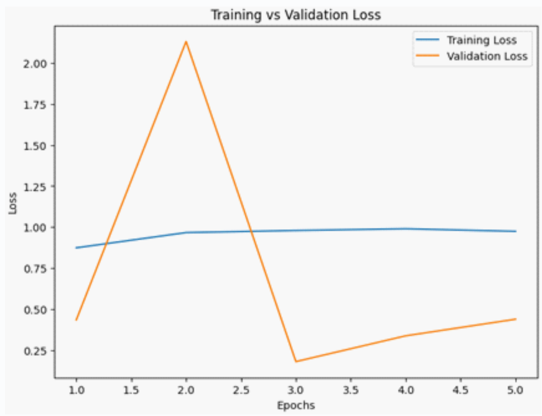

Figure 6: Loss versus validation loss graph.

Figure 7: Predicted fall and non-fall.

Accuracy

Accuracy (%) = (TP+TN)/(TP+FP+TN+FN)*100

Accuracy (%) = (53+36)/(53+5+36+3)*100

Accuracy (%) = (89/97)*100

Accuracy (%) = 91.8%

Figure 5 depicts Training versus Validation Accuracy graph.

In addition, figure 6 depicts loss versus validation loss graph. Training versus validation loss graph shows that the training loss decreases regularly, while the validation loss fluctuates, spiking at epoch 4 earlier than dropping once more. This indicates that the model starts off evolving to overfit around the middle of the schooling procedure (epoch three), earlier than enhancing. The model may be gaining knowledge of some noise from the training facts, however regularization strategies (like dropout) or extra statistics may also help improve generalization to lessen the fluctuations in validation loss (Figure 6).

Precision

Precision (%) = 100*(TP)/(TP+FP)

Precision (%) = 100*(53)/(53+5)

Precision (%) = 100

Precision (%) = 91.4%

The sensitivity

Sensitivity (%) = 100*(36)/(36+3)

Sensitivity (%) = 100*(36/39)

Sensitivity (%) = 92.3%

The overall implementation predicted fall and non-fall image is presented in Figure 7.

Conclusion

The presented fall detection system survey attempts to address and provide a systematic review of contemporary issues in human fall detection systems, focusing on sensing technologies and machine learning approaches. The paper starts with a provision of a more focused introduction to the problem of falls in elderly populations. This is followed by description of sensing technologies, machine learning, Fall detection challenges and suggestions, elderly people event accident model performance indicator, state of the art, and prototype design implementation. Concerning wearables, Non-wearables and Hybrid sensing system each technologies have its advantages and disadvantages. As a result of their portability, simplicity of use, and capacity for real-time monitoring, wearable devices are among the most widely used fall detection systems. Non-Wearable Fall Detection system relies on environmental sensors that are positioned throughout the living area as opposed to the user. Wearable and non-wearable technology are combined in hybrid systems to capitalize on the advantages of each strategy. The benefit of Hybrid Fall Detection Systems lies in their capacity to decrease false positives and enhance the accuracy of detection, particularly in intricate settings. Based on the description and review of relevant machine learning methods, the authors deduced that the functionality of fall detection algorithms through machine learning depends heavily on three significant elements: sensor choice between wearables, cameras and radar, dataset quality standards and data balance requirements and the extraction of relevant features and the selected processing algorithms. Therefore, the author concluded that such outcome of a thorough analysis of machine learning for a few chosen studies identified areas for deployment in future prototype fall detection model. The accuracy of 91.8% obtained here shows high accuracy which indicate that the model is performing well. The result gave Sensitivity (%) = 92.3%. The significance of sensitivity in a fall detection system lies in its capacity to explicitly indicate the system's proficiency in accurately detecting falls. A high level of sensitivity in a fall detection system enables accurate identification of falls, therefore minimizing the likelihood of overlooked falls that can have serious health implications for elderly individuals.

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