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RAJAGIRI SCHOOL OF ENGINEERING & TECHNOLOGY
(AUTONOMOUS)

Project Phase II Report On

Fall Detection System for Senior Citizens

Submitted in partial fulfillment of the requirements for the award of the degree of

Bachelor of Technology

in

Computer Science and Engineering

By

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CERTIFICATE

This is to certify that the project report entitled ***"Fall detection system for senior citizens using Machine Learning"*** *is a bonafide record of the work done by* ***Govind Kiran (U2003088)****, submitted to the Rajagiri School of Engineering & Technology (RSET) (Autonomous) in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology (B. Tech.) in Computer Science and Engineering during the academic year 2023-2024.*

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Abstract

Falls represent a critical and unexpected issue, sometimes leading to severe consequences, including fatalities. Elderly individuals face a heightened risk, and their safety can be compromised. To address this, the development of an effective fall detection system is crucial, capable of promptly identifying fall events. Achieving accuracy in such a system requires meticulous preprocessing of images from the dataset.

In scenarios where a person is alone during a fall, the absence of immediate detection poses a significant challenge. If the fall is severe, the individual may not be able to seek help. In such situations, the proposed fall detection system becomes essential. The system employs different machine learning classifiers, particularly DNN, Decision Tree, and Random Forest Algorithm (RF). These classifiers assess the accuracy of the system based on key points obtained through the BRISK feature descriptor.

By leveraging the strengths of machine learning and feature descriptors, the system aims to provide reliable fall detection, particularly in instances where immediate human assistance may be lacking. The utilization of diverse classifiers allows for a comprehensive evaluation of the system's accuracy, contributing to the development of an efficient and robust fall detection solution.

Contents

List of Abbreviations

1. HOF - Histogram of Optical Flow
2. MBH - Motion Boundary Histogram
3. GMM - Gaussian Mixture Model
4. PDF- Probability Density Function
5. IMU - Inertial Measurement Unit
6. CNN - Convolutional Neural Network
7. DAG - Directed Acyclic Graph
8. FMV - Fall Motion Vector
9. LPN - Lightweight Pose Network
10. SVM - Support Vector Machine

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Chapter 1

Introduction

1.1 Background

In the present scenario, given the increasing elderly population on a global scale, the significance of innovative solutions like the described system cannot be overstated. Wearable sensor-based systems, although effective, often necessitate individuals to bear sensors, posing potential computational challenges and inconvenience for certain users. Therefore, the implementation of a fall detection system proves exceptionally advantageous.

The system holds various merits, including the prompt initiation of intervention through swift notifications to caretakers, leading to rapid responses and timely medical assistance, thereby potentially mitigating the severity of injuries. Moreover, it offers augmented support to caregivers by alleviating their responsibilities and supplying an additional layer of assistance, ensuring constant vigilance without being intrusive. Importantly, it promotes independent living for the elderly, enabling them to remain in their familiar environment while establishing a safety net for their well-being.

Harnessing the progress in computer vision and machine learning, a fall detection system effectively addresses the unique challenges confronted by elderly individuals. This initiative is part of a larger movement to utilize technology for enhancing healthcare outcomes and improving the overall quality of life for the elderly population. By seamlessly incorporating itself into the daily routines of seniors residing in elderly homes, the system strives to establish a safer and more secure environment, fostering a feeling of independence and well-being. This inventive strategy not only tackles present societal requirements but also plays a role in the continuous advancement of healthcare solutions in the contemporary era

1.2 Problem Definition

As the elderly population continues to expand rapidly, fall detection emerges as a critical concern within the medical and health sector. The precise identification of fall incidents in surveillance videos, coupled with prompt feedback, proves instrumental in mitigating injuries and potential fatalities resulting from such occurrences among the elderly. The challenge arises from the fact that a considerable number of elderly individuals reside alone, facing an elevated risk of accidents, particularly falls. Compounding the issue, these incidents are exacerbated by challenges in seeking assistance, stemming from limited access to technology and physical constraints. Consequently, there exists a pressing demand for a system capable of swiftly detecting falls and providing assistance, especially for elderly individuals living independently.

1.3 Scope and Motivation

The realm of fall detection for senior citizens extends widely, impacting not only the healthcare sector but also influencing technology, data analytics, and the assisted living industries. With the global aging of populations, there is an increasing need for dependable and non-intrusive fall detection systems. The impetus behind this initiative lies in the aspiration to improve the quality of life for seniors by guaranteeing their safety and offering peace of mind to their caregivers.

Motivations for developing fall detection systems encompass a range of objectives, such as diminishing healthcare costs linked to injuries resulting from falls, facilitating aging in place, and promoting independence for seniors as they will not have to be around their caretakers all the time. Moreover, progress in this field aligns with a larger societal objective of harnessing technology to confront challenges associated with an aging population.

1.4 Objectives

1. Develop a model that accurately and reliably detects falls based on pose estimation using OpenPose

2. Optimize the pose estimation model (OpenPose) to accurately capture and analyze

the body poses of elderly individuals.

3. Implement the fall detection system to operate in real-time, ensuring timely responses to fall events.

4. Integrate the fall detection model with existing surveillance camera systems in elderly care homes

5. Establish a robust alert mechanism to notify caretakers or relevant personnel when a fall is detected.

1.5 Challenges

- Data Collection and Annotation: Due to Limited Datasets obtaining diverse and representative datasets of falls can be challenging due to ethical concerns and the infrequency of fall events.

  Annotation Difficulty: Accurately annotating fall events in video data for training can be time-consuming and subjective.

- Model Training: Complexity of Poses: Elderly individuals may have diverse body shapes, movements, and postures, making it challenging to train a model that generalizes well across different scenarios.

  False Positives and Negatives: Balancing the detection of actual falls (true positives) while minimizing false positives and negatives is crucial for the system's reliability.

- Real-world Variability: Changes in lighting, shadows, and background clutter can impact the accuracy of pose estimation, leading to false detections. Camera Angles and Perspectives: The system may struggle with detecting falls accurately if the camera angles are not optimal or if there are occlusions.

- Privacy Concerns: Deploying surveillance systems raises privacy concerns. Ensuring that the system respects the privacy of the individuals being monitored is crucial.

1.6 Assumptions

- Clear video footage.

- Adequate Camera Coverage.
- User Acceptance of Video Surveillance.
- Continuous power supply.
- Internet Connectivity.

1.7 Societal / Industrial Relevance

This technology contributes to the enhancement of elderly care through the provision of timely alerts to caretakers, thereby minimizing response time in the event of falls and ultimately elevating the safety and well-being of elderly residents. Furthermore, it serves to alleviate the burden on caregivers, facilitating efficient and effective monitoring in the context of a rapidly aging population. The adoption of such technology aligns with the escalating demand for innovative solutions in healthcare and senior living, effectively addressing critical needs in an aging society.

1.8 Organization of the Report

The report begins with a brief introduction that outlines the context, problem and scope and motivation of the project. The report provides a detailed understanding on Fall Detection Model using OpenPose pose Estimation method. Comprehensive review and comparison of state of the art methods for skeleton-based fall detection in RGB videos currently in use are discussed with their advantages and disadvantages including traditional machine learning algorithms and deep learning networks. It discusses the potential software, hardware and functional requirements of the proposed method and its architecture consisting of breakdown of modules used along with diagrams for better understanding.

Chapter 2

Literature Survey

2.1 Deep Learning-Based Near-Fall Detection Algorithm for Fall Risk Monitoring System Using a Single Inertial Measurement Unit [1]

The critical issue of falls, particularly among the elderly, highlights the necessity for advanced detection systems. This study introduces an innovative fall detection algorithm grounded in deep learning, utilizing a Modified Directed Acyclic Graph Convolutional Neural Network (DAG-CNN). Departing from conventional approaches, the algorithm categorizes falls, near-falls, and activities of daily living (ADLs). The objective is not only to enhance safety measures but also to improve the quality of life for elderly populations at an elevated risk of falls.

The research methodology commences with the acquisition of 3-axis acceleration and angular velocity data through Inertial Measurement Unit (IMU) sensors. Rigorous preprocessing, including a sliding median filter and manual labeling, ensures the dataset's quality for accurate identification of ADLs, falls, and near-falls. Feature extraction plays a pivotal role, encompassing the computation of 40 features that include accelerometer and gyroscope features. The innovative Modified DAG-CNN architecture is introduced for efficient multilevel feature extraction, incorporating hierarchical structures, Leaky Rectified Linear Unit activation, and MaxPooling. Hyperparameter optimization through Bayesian optimization addresses concerns related to overfitting.

The methodology adopts leave-one-participant-out cross-validation, utilizing comprehensive metrics and analyzing results through accuracy curves, confusion matrices, ROC curves, and AUC values. Beyond technical aspects, the study explores broader implications for societal well-being and healthcare advancements, anticipating future work and applications. This research significantly contributes to reliable fall detection, a critical aspect for vulnerable populations.

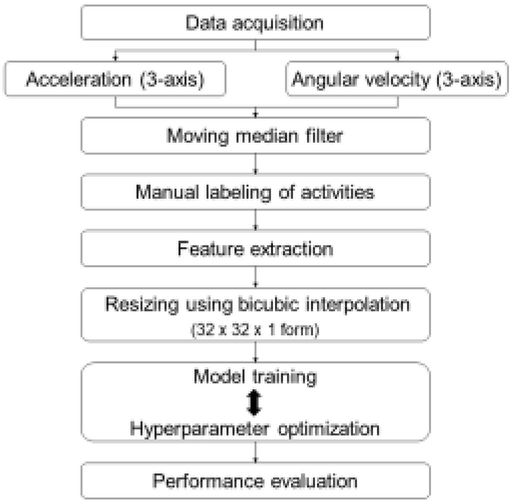
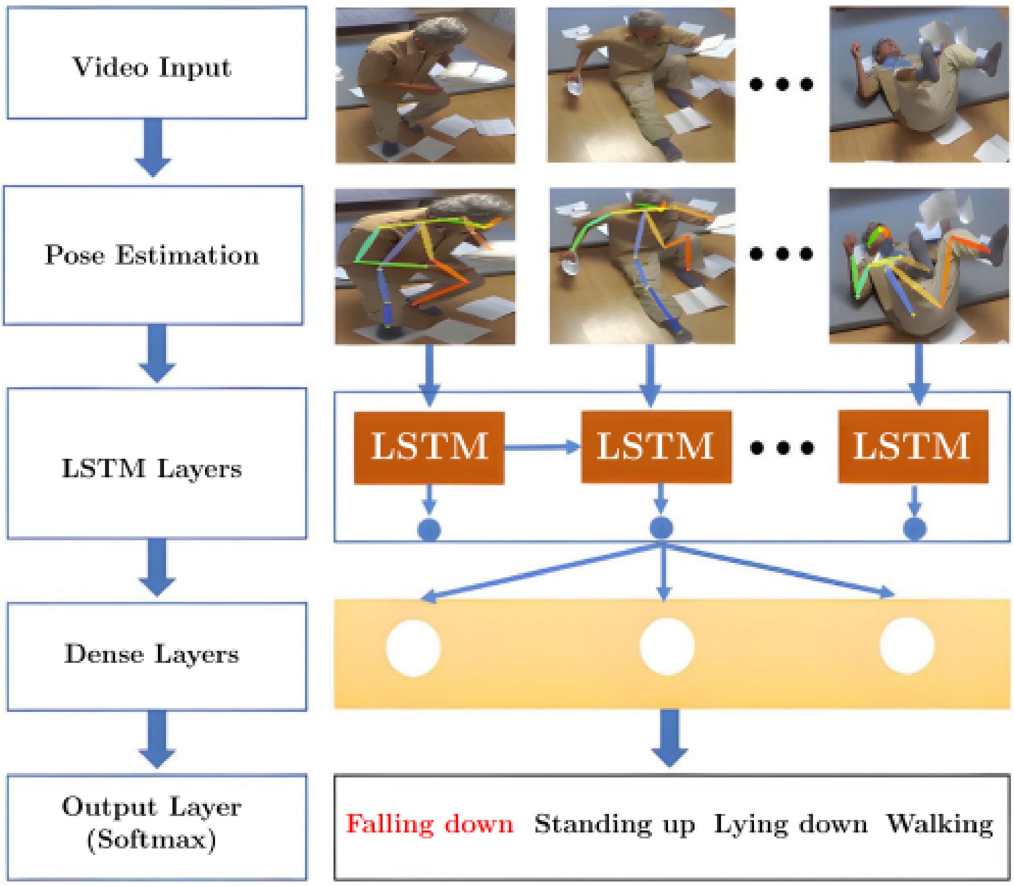


Figure 2.1: Flowchart of the proposed procedure to discriminate between falls, near-falls, and ADLs.

2.2 Advances in Skeleton-Based Fall Detection in RGB Videos: From Handcrafted to Deep Learning Approaches [2]

The increasing global elderly population underscores the imperative to develop intelligent healthcare systems, specifically for effective fall detection, a significant contributor to injuries in this demographic. While various sensors, including wearables and ambient devices, have been explored , RGB cameras stand out for their non-intrusive nature and cost-effectiveness. However, depending solely on RGB video data may result in inaccuracies, prompting researchers to advocate for the extraction of skeleton data. This paper aims to comprehensively review both handcrafted and deep learning approaches for skeleton-based fall detection in RGB videos, providing performance comparisons and outlining future directions in this evolving field.

The methodology in skeleton-based fall detection involves extracting intricate skeletal information from RGB videos for in-depth analysis. Researchers often employ pretrained models like OpenPose, recognized for generating 2D keypoints for individuals in images. To enhance efficiency, exploration extends to lightweight versions of OpenPose, such as MobileNetV2, which are extensively trained with augmented datasets to address challenges in real-world scenarios. Alternative frameworks like MediaPipe Pose, which includes the conversion of 2D keypoints to 3D using techniques like the Lightweight Pose



(a) LSTM

Figure 2.2: Fall detection using LSTM

Network (LPN), contribute to the diverse approaches in this field. AlphaPose emerges as a leading pose estimation framework, demonstrating high accuracy in skeleton-based fall detection, particularly in surveillance settings. This rigorous methodology underscores the ongoing advancements in intelligent healthcare systems, striving for precision and reliability in fall detection mechanisms.

The evaluation of skeleton-based fall detection methods reveals distinct effectiveness in both handcrafted and deep learning approaches. Handcrafted methods, relying on manually designed features, demonstrate limitations in adaptability, while deep learning methods, especially those employing neural networks like stacked LSTM, exhibit superior accuracy and flexibility. The choice of the pose estimation framework is pivotal, with AlphaPose consistently emerging as a leader in accuracy.

2.3 Human Fall Detection in Surveillance Videos Using Fall Motion Vector Modeling [3]

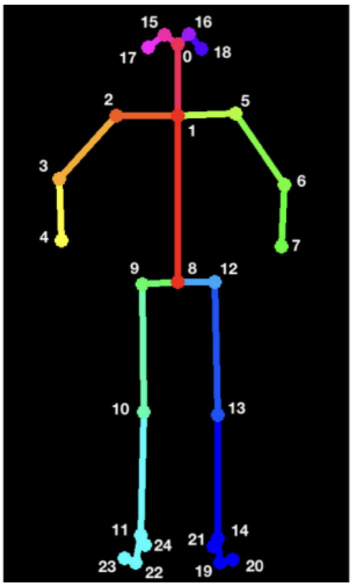
Surveillance systems play a crucial role in ensuring the safety and security of various environments, including public spaces, healthcare facilities, and residential areas. One essential application of surveillance technology is fall detection, especially in situations where continuous monitoring is needed for the well-being of individuals, such as in elderly care or crowded public spaces. Advanced computer vision techniques, specifically histograms of optical flow (OF) and motion boundary histograms (MBH), have proven effective for fall detection by analyzing motion patterns in surveillance videos.

Optical flow, a computer vision technique, measures the motion of objects between consecutive frames in a video sequence, offering valuable insights into dynamic changes in a scene. Motion Boundary Histograms, an extension of optical flow, concentrate on the boundaries of moving objects, providing a detailed representation of motion patterns. These techniques use histograms to visually depict the distribution of motion magnitudes and directions. Optical flow histograms summarize the overall motion characteristics of a scene, while MBH provides a more detailed analysis by focusing on motion along specific boundaries, aiding in distinguishing between intentional movements and falls.

In the context of fall detection, histograms are employed to capture the unique spatial and temporal characteristics of fall events. Fall motion vectors, representing the direction, magnitude, and duration of motion during a fall, undergo factor analysis for dimensionality reduction. Gaussian mixture models (GMM) are then utilized to construct a fall motion mixture model (FMMM), offering a probabilistic framework to categorize fall and non-fall events. Finally, a polynomial support vector machine is applied to fall motion vectors, providing a robust classification method for identifying fall and non-fall videos within surveillance footage. This intricate process exemplifies the integration of advanced computer vision and machine learning techniques to enhance surveillance capabilities for fall detection.

2.4 Automatic Fall Risk Detection Based on Imbalanced Data[4]

Examining the complexities of fall risk detection within imbalanced datasets, this study addresses challenges posed by traditional approaches using balanced data. Through the



Number	Body Part
0	Nose
1	Neck
2	R Shoulder
3	R Elbow
4	R Wrist
5	L Shoulder
6	L Elbow
7	L Wrist
8	Mid Hip
9	R Hip
10	R Knee
11	R Ankle
12	L Hip
13	L Knee
14	L Ankle
15	R Eye
16	L Eye
17	R Ear
18	L Ear
19	L BigToe
20	L SmallToe
21	L Heel
22	R BigToe
23	R SmallToe
24	R Heel

Figure 2.3: OpenPose Keypoint Diagram and Keypoint Table

deployment of diverse machine learning algorithms and a comprehensive comparative analysis, the research seeks to enhance the effectiveness of fall risk detection systems, offering tailored solutions for scenarios characterized by imbalanced data. In the realm of supervised machine learning, the first algorithm under scrutiny is the K-nearest Neighbours (KNN). Renowned for its maturity and simplicity, KNN functions as a versatile pattern classification method, adeptly handling both classification and regression challenges. During classification, the algorithm utilizes local distance features to calculate distances between predicted data points, identifies the "k" closest data points, and assigns a class based on the prevailing category within this set. In regression scenarios, the predicted value is determined from the average of the "k" closest data points, showcasing the algorithm's adaptability to various problem domains.

Shifting focus to another prominent algorithm, Support Vector Machines (SVM) emerge as widely embraced tools in supervised machine learning, particularly in industrial applications. SVMs distinguish themselves by seeking an optimal hyperplane within the training data, strategically establishing boundaries that maximize the separation between different classes. Their effectiveness extends to cases where data is linearly inseparable, employing kernel functions to transform features from a lower to a higher dimension, simplifying the process of establishing a separation hyperplane. Crucially, SVMs demonstrate robustness when handling sparse data, characterized by datasets with a significant portion of zero values in the feature space. This resilience solidifies SVMs as reliable solutions in real-world scenarios marked by data sparsity.

2.5 An Elderly Fall Detection Method Based on Federated Learning and Extreme Learning Machine (Fed-ELM)[5]

The Fed-ELM Fall Detection Method is designed to address significant concerns related to falls among the elderly, known for causing injuries and fatalities. Existing fall detection methods are categorized as nonwearable or wearable-based. Nonwearable methods, like visual and environmental fall detection, have limitations in space and monitoring capabilities. Wearable methods, although offering unlimited space, often rely on youth-centric data, impacting their effectiveness for the elderly[8]. The Fed-ELM method combines Federated Learning and Extreme Learning Machine, training the ELM with young data and updating parameters using sparse individual consumer data. Federated Learning facilitates information sharing while ensuring privacy. This innovative approach aims to enhance the performance and generalizability of fall detection algorithms for both young and elderly individuals, addressing current limitations in the field.

The Fed-ELM Fall Detection approach integrates Federated Learning and Extreme Learning Machine (ELM) to enhance the efficacy of fall detection for individuals of varying age groups, encompassing both the young and elderly. The online ELM component is utilized to continuously update parameters based on minimal misclassified user data, thereby improving individual user performance. Federated Learning is employed to facilitate the exchange of data information among diverse users, ensuring privacy while enhancing the overall adaptability and performance of the fall detection algorithm. Experimental evaluations are carried out to assess the algorithm's effectiveness across different age demographics, including both young and elderly individuals. Performance metrics, encompassing accuracy, sensitivity, and specificity, are meticulously measured for each group, demonstrating consistently high accuracy levels. Comparative analyses are conducted, pitting the algorithm against other methods such as SVM, KNN, and RF, particularly in distinguishing falls from Activities of Daily Life (ADLs) among elderly individuals.

The Fed-ELM Fall Detection Method offers several advantages in enhancing fall detection capabilities. By seamlessly integrating Federated Learning and Extreme Learning Machine (ELM), the method achieves notable improvements in fall detection accuracy, sensitivity, and specificity for individuals across diverse age groups, encompassing both the young and elderly. The online ELM component plays a crucial role in elevating individual user performance by continuously updating parameters based on a minimal amount of misclassified user data. Moreover, the application of Federated Learning facilitates the secure sharing of data information among various users, ensuring privacy while significantly enhancing the overall generalizability of the fall detection algorithm. The method's efficacy is further demonstrated through its age-specific performance, with high accuracy achieved in the analysis of different age groups, including both young individuals and the elderly. In comparative evaluations with alternative fall detection methods such as SVM, KNN, and RF, the Fed-ELM method consistently outperforms, particularly excelling in distinguishing falls from Activities of Daily Life (ADLs) for elderly individuals.

One of the prominent issues faced by the fall detection community is the scarcity of elderly fall data, posing a significant challenge in adequately training and testing fall detection algorithms for this demographic. The differences in movement patterns between young and elderly individuals, attributed to bone aging, introduce complexities that can result in a decline in algorithm performance specifically within the elderly population. Additionally, the method grapples with the limitation of individual user data, as the data from a single user may be insufficient, potentially impacting the accuracy of the fall detection algorithm. While the Fed-ELM approach demonstrates improved performance, it is crucial to consider and evaluate the effectiveness of other existing fall detection methods, such as SVM, KNN, and RF, to gain a comprehensive understanding of its overall efficacy and limitations in comparison to alternative approaches.

In conclusion, the Fed-ELM Fall Detection Method, a fusion of Federated Learning and Extreme Learning Machine, exhibits promising outcomes by significantly enhancing the accuracy, sensitivity, and specificity of fall detection for both young and elderly individuals.

2.6 Summary and Gaps Identified

This section gives a brief understanding of some of the various Fall Detection Systems in use along with their advantage and disadvantage for easier comparisons between them.

Paper Name	Advantages	Disadvantages
[1]	The utilization of a single IMU simplifies the hardware requirements, making the fall detection system more practical and cost-effective. It enhances the system's feasibility for widespread adoption in various environments.	Depending on the study's specific conditions or dataset, the algorithm may have limitations in generalizing to diverse scenarios. The effectiveness of the algorithm might be influenced by variations in the user population or environmental factors, impacting its applicability across different fall risk scenarios.
[9]	Radar signals from humans display nonstationary behaviour, and techniques like short-time Fourier transform (STFT) and wavelet transform (WT) can effectively analyze and extract fall features.	False alarms may result from confusion between falls and similar motions. Feature choice impacts classification more than the specific classifier used.

Table 2.1: Advantages and Disadvantages of existing models

Paper Name	Advantages	Disadvantages
[3]	The use of fall motion vector modeling provides a unique and potentially effective approach to human fall detection. This method can capture specific characteristics of fall motions, enhancing the accuracy of detection by focusing on distinctive features associated with falls.	Limitation in terms of the diversity and complexity of the evaluated scenarios. If the evaluation is conducted in a controlled environment or specific surveillance setting, the generalizability of the proposed fall detection method to different real-world conditions may be uncertain.
[4]	Focuses on automatic fall risk detection based on imbalanced data. This is crucial as imbalanced datasets are common in real-world scenarios. The methodology proposed in the paper likely includes techniques or algorithms specifically designed to handle imbalanced data, enhancing the robustness and practicality of the fall risk detection system.	The approach may be highly tailored to the characteristics of the dataset used in the study. If the imbalanced data distribution in the paper's dataset significantly differs from other real-world datasets, the proposed method might have limitations in generalizing to diverse scenarios or populations.

Table 2.2: Comparative Analysis of existing methods

2.6.1 Gaps identified

- Lack of fall data for the elderly: The fall detection community grapples with the significant challenge of insufficient fall data specifically tailored to the elderly population. This scarcity adversely impacts the efficacy of fall detection algorithms, limiting their ability to accurately identify falls in older individuals.

- Differences in movement patterns: Movement patterns exhibit disparities between young and elderly individuals due to the aging of bones, introducing complexities that result in a decline in algorithm performance within the elderly population. Recognizing and adapting to these distinct movement patterns is crucial for the effectiveness of fall detection algorithms.

- Limited space coverage: Nonwearable-based fall detection methods, such as environmental fall detection, face the constraint of operating within a confined space. This limitation may pose challenges in detecting falls when the elderly move beyond the designated detection area, highlighting a need for more versatile and expansive coverage in fall detection solutions.

- Performance comparison with other algorithms: While the Fed-ELM algorithm demonstrates high accuracy, sensitivity, and specificity in fall detection, it is essential to consider its performance in comparison to other machine learning-based algorithms. Alternatives such as Gradient Boosting (GB), K-Nearest Neighbor (KNN), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) also exhibit proficiency in distinguishing falls from Activities of Daily Life (ADLs). A comprehensive performance evaluation ensures a well-informed choice among available algorithms for fall detection applications.

Chapter 3

Requirements

3.1 Hardware and Software Requirements

3.2 Hardware Requirements

1. Motion Capture Systems:

   Utilizing high-quality cameras or motion sensors, such as Kinect, OptiTrack, or specialized cameras designed for motion capture, to capture precise gait data. These systems enable accurate tracking of body movements for comprehensive analysis.

2. Computer System:

   Deploying a robust computer or server equipped to handle substantial datasets and execute complex algorithms for data processing and analysis. The computational power of the system is crucial for efficient and timely analysis of the captured gait data.

3. Hardware Requirements:

   -Intel Core processors: Opting for processors from the Intel Core series, such as i3, i5, or i7, to ensure sufficient processing power for data analysis.
   -Storage: Allocating a minimum of 100GB on the hard disk to accommodate the storage requirements of large datasets generated during gait analysis.
   -Memory (RAM): Ensuring a minimum of 8GB RAM or higher to facilitate smooth data processing and algorithm execution on the computer system. A higher RAM capacity enhances the system's capability to handle more extensive datasets and computational tasks.

These specifications ensure a decent computing capability for various tasks related to data processing, analysis, and software execution.

3.3 Software Requirements

- Motion Capture Software: Employing dedicated software for capturing and processing motion data obtained from cameras or sensors. Examples include OptiTrack Motive or OpenPose, which facilitate the extraction of precise motion information for subsequent analysis.

- Data Processing Tools: Utilizing versatile tools for data processing, including MATLAB, Python (with libraries like NumPy and SciPy), or R. These tools enable preprocessing, cleaning, and transformation of raw gait data into formats suitable for further analysis and interpretation.

- Machine Learning or Statistical Software: Leveraging powerful software tools like TensorFlow, PyTorch, scikit-learn, or MATLAB's Machine Learning Toolbox for building and training classification models. These models are instrumental in identifying specific gait patterns associated with conditions such as Parkinson's disease or arthritis.

- Statistical Analysis Tools: Employing software designed for statistical analysis to extract meaningful insights from collected data. Popular tools for this purpose include SPSS, RStudio, or Jupyter Notebooks, providing a robust platform for conducting statistical assessments and drawing conclusions.

- Visualization Tools: Utilizing visualization tools to present gait patterns, classification results, and statistical findings in a comprehensible manner. Examples include Matplotlib and Seaborn in Python, as well as visualization capabilities within MATLAB, offering effective ways to communicate complex data visually.

3.4 Functional Requirements (Numbered List/ Description in Use Case Model)

1. Real-time Detection: The system should provide real-time fall detection capabilities to promptly identify and respond to fall events.

2. Accurate Detection: The model should achieve a high level of accuracy in distinguishing between fall and non-fall events, minimizing false positives and false negatives.

3. Adaptability to Environmental Variations: The model should be designed to perform effectively in various environments, accommodating factors such as lighting conditions, flooring types, and room layouts.

4. Low Resource Consumption: - Efficient resource utilization to ensure that the fall detection model can run on devices with limited computational resources, such as edge devices or wearables.

5. User Identity Verification: - Capability to verify the identity of the person involved in the fall, ensuring that alerts are relevant to the specific user being monitored.

6. Post-Fall Verification: Incorporation of a mechanism to verify if the person has successfully recovered from the fall, reducing false alarms and improving system reliability.

7. Alert Notification System: - Integration with an alert system to notify caregivers, emergency services, or designated contacts in case of a confirmed fall event.

8. Data Logging and Reporting: - Logging and reporting features to store information about fall events, including timestamps, user activities, and system responses for analysis and monitoring.

9. Machine Learning Model Explainability: Integration of mechanisms to elucidate the decision-making process of the machine learning model, guaranteeing clarity and interpretability.

Chapter 4

System Architecture

4.1 System Overview

- Live Video Input: The system begins by capturing live video footage using a camera or webcam placed in the monitored area.
- Preprocessing: The incoming video frames undergo preprocessing to enhance the quality and optimize them for analysis.
- Object Detection with OpenPose KeyPoint Detection: OpenPose identifies key points on the human body in each video frame, including joints and body parts crucial for fall detection. Analyzing body poses, OpenPose detects abnormalities or specific pose patterns indicative of a fall event, enabling real-time fall detection.
- Fall Classification: Detected objects, especially humans, are then classified to determine if a fall event has occurred.
- Decision Logic If a fall is detected, the system proceeds to verify the person's status by monitoring their subsequent actions.
- Post-Fall Verification The system tracks the person's movements after a fall is detected. If the person stands up within a specified timeframe, the event is classified as a non-fall, and no further action is taken.
- Alert Generation (Twilio API Integration) If the person does not stand up within the specified timeframe, an alert message is generated. The system uses the Twilio API to send an alert message to the designated caretaker, notifying them of the potential fall event.

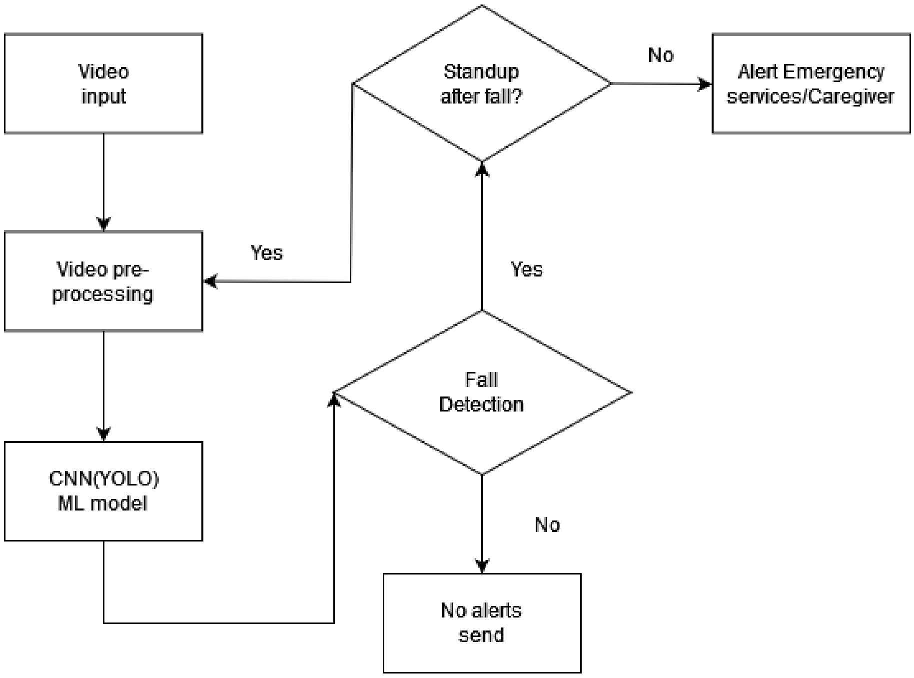


Figure 4.1: Architecture Diagram.

4.2 Architectural Design

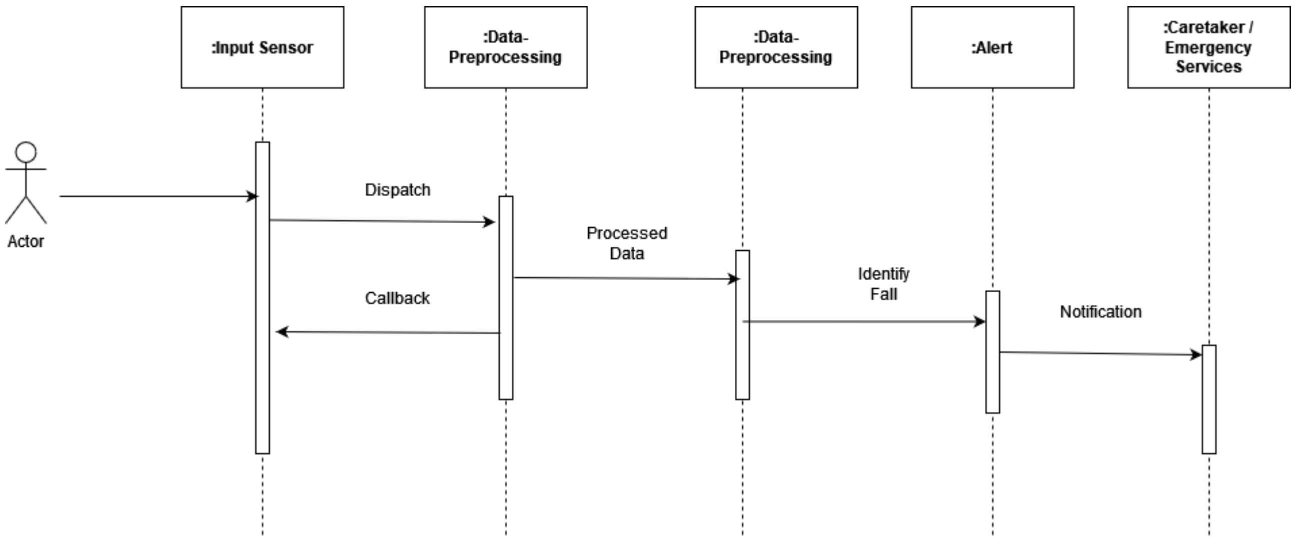


Figure 4.2: Sequence Diagram.

4.3 Module Division

4.3.1 Data Collection

The process of gathering data for fall detection involves the acquisition of RGB videos capturing both fall and non-fall events through conventional cameras. Various widely used fall datasets contribute to this effort, each offering diverse scenarios and environmental conditions for comprehensive analysis. Notable datasets include the Multiple Cameras Fall Dataset (MultiCam), Le2i Fall Detection Dataset (Le2i), UR Fall Detection Dataset (URFD), and UP-Fall Detection Dataset (UP-Fall). The Le2i Dataset, consisting of 130 scenes recorded at 25 frames per second, provides a range of scenarios for fall detection research. URFD, with 100 RGB videos recorded using two Kinect cameras, includes both fall events and daily living activities. These datasets encompass different camera setups and environmental conditions, presenting researchers with a rich array of real-world scenarios for the development and evaluation of effective fall detection algorithms. Such datasets are integral in training and testing machine learning models, ensuring their adaptability and reliability in diverse situations.

4.3.2 Keypoint Extraction

Keypoint extraction is a crucial process involving the identification and localization of specific points of interest within an image or video, often corresponding to anatomical landmarks or objects of significance. In the context of fall detection in RGB videos, this entails the recognition and continuous tracking of key body joints or keypoints, including but not limited to the neck, hip, shoulders, and knees, in each frame of the video. Several frameworks and algorithms serve this purpose, among which are OpenPose, Alpha-Pose, and MediaPipe Pose. OpenPose, a widely adopted framework, stands out for its real-time performance and capability to extract 2D keypoints from RGB videos. It provides multiple pretrained models, each capable of generating different quantities of 2D keypoints for every individual in the image. The selection of a keypoint extraction framework depends on factors such as pose quality, inference speed, availability of source code, ease of use, and hardware specifications.

4.3.3 Data Preprocessing

In the data cleaning phase, the focus is on eliminating invalid or extraneous data from the extracted skeleton data. Invalid data encompasses keypoints associated with a person not implicated in the fall event or the absence of specific keypoints like the neck or hip keypoints. Additionally, incorrect keypoint data, such as the misidentification of other objects as a human body, is filtered out.

Addressing missing data is another crucial aspect of the data cleaning process. Typically, when dealing with gaps in the skeleton data, linear interpolation is employed. This method serves to fill in the spaces between available keypoints, ensuring a more complete and continuous representation of the motion or posture captured by the skeleton data.

4.3.4 Skeletal Feature Extraction

Handcrafted features: Handcrafted features refer to manually designed characteristics of the skeleton data, capturing specific attributes. Examples of such features include joint angles, joint velocities, or spatial relationships between joints. Techniques such as angle calculation, distance measurement, or statistical analysis are employed to extract these features, providing a tailored understanding of the skeleton data.

Deep learning features: In contrast, deep learning techniques automatically learn features from the skeleton data. This involves training deep neural networks, such as stacked LSTM networks, to extract high-level representations of the skeleton data. These learned features possess the ability to capture intricate patterns and relationships within the data, offering a more abstract and nuanced representation.

Normalization: Incorporating mechanisms to clarify the decision-making process of the machine learning model, ensuring transparency and interpretability. Various techniques can be employed for normalization, including centering, scaling, and rotation operations, or adjusting the keypoints to fit within a specific range.

Data cleaning: The data cleaning process involves removing invalid or unnecessary data from the skeleton data. This includes the exclusion of keypoints associated with unrelated persons or those lacking specific keypoints. Missing data can be addressed using techniques like linear interpolation.

Sample selection: Following preprocessing, samples are chosen for feature extraction. These samples can be frame-based, consisting of keypoints from a single frame, or sequence-based, encompassing keypoints from all frames in a video. The selection of samples is a crucial step in determining the input data for subsequent feature extraction processes.

4.3.5 Recognition

The intricate process of fall recognition relies heavily on the insightful extraction of features. These extracted features serve as the bedrock for the recognition mechanism, which can be executed through the application of either rule-based approaches or more sophisticated machine learning (ML) methodologies. Furthermore, a state-of-the-art alternative entails employing deep neural networks equipped with a softmax activation function at the output layer. This advanced approach enhances the discriminative capabilities of the system, ensuring a higher degree of accuracy and reliability in identifying instances of falls.

4.3.6 Alert Mechanism

For alerting corresponding officials, the Twilio API serves as a valuable tool. Twilio is a cloud communications platform offering a range of APIs and services tailored for diverse communication needs, including sending messages, making phone calls, and managing various communication channels. The Twilio API facilitates the transmission of text, images, videos, documents, and other media types as part of a WhatsApp message.

Developers can utilize the Twilio Python library or other Twilio SDKs available in multiple programming languages to interact with the Twilio API and initiate the alerting process. By integrating Twilio's capabilities into their applications, developers can seamlessly send alerts to designated officials, enhancing communication efficiency and enabling rapid response to critical situations. The versatility of Twilio's API ensures that alerts can include various forms of media, providing a comprehensive means of conveying information to the intended recipients.

4.4 Work Breakdown

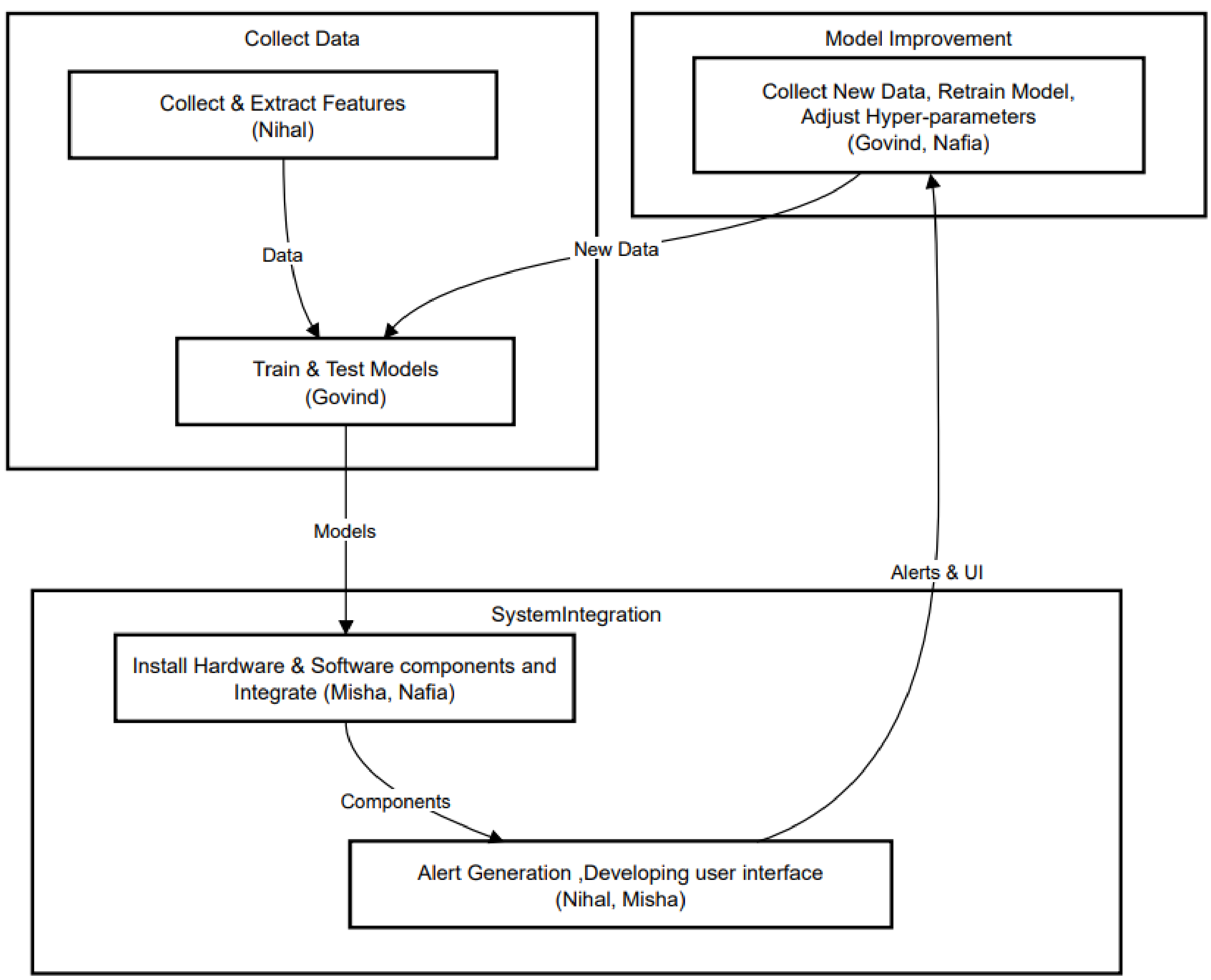


Figure 4.3: Module Division

4.5 Work Schedule - Gantt Chart

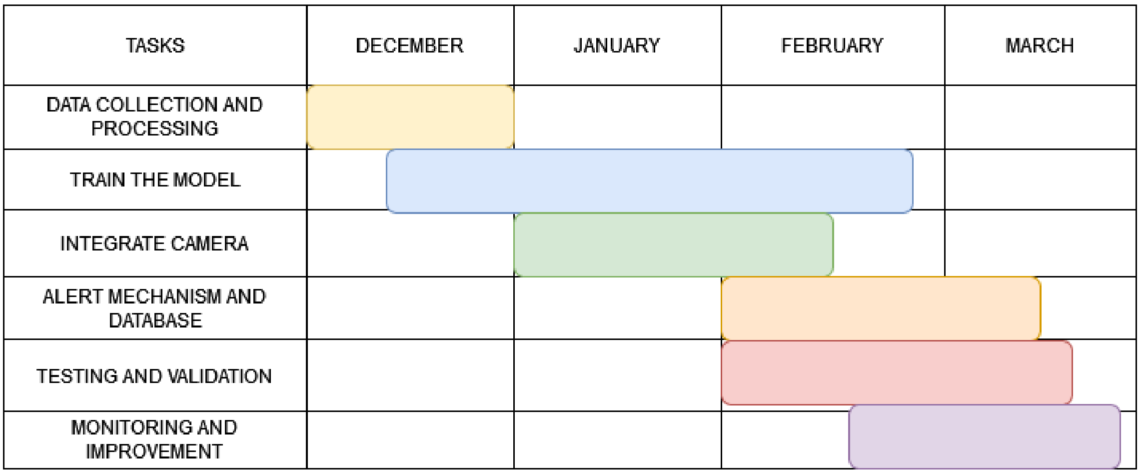


Figure 4.4: Gantt Chart.

In this chapter, overview of the entire system is explained along with diagrams explaining the overall architecture of the project. Module division gave a clear and concise idea of tasks performed in each step of the system, other information such as work breakdown and schedule has also been discussed.

Chapter 5

Results and Discussions

The fall detection system utilizing pose estimation and OpenCV represents a significant advancement in eldercare technology. By leveraging computer vision techniques, it offers a proactive approach to fall prevention and intervention, ultimately contributing to the well-being and safety of elderly individuals in care facilities. Welcome to the future of old age homes.

5.1 Overview

The system can detect human beings and identify when a fall has occurred. When a person does fall, it is recognized and a red box along with a message is shown. This triggers our tool and gives a phone call on the user's phone. Which can then be used to help the person who fell down in any scenario.

5.2 Testing

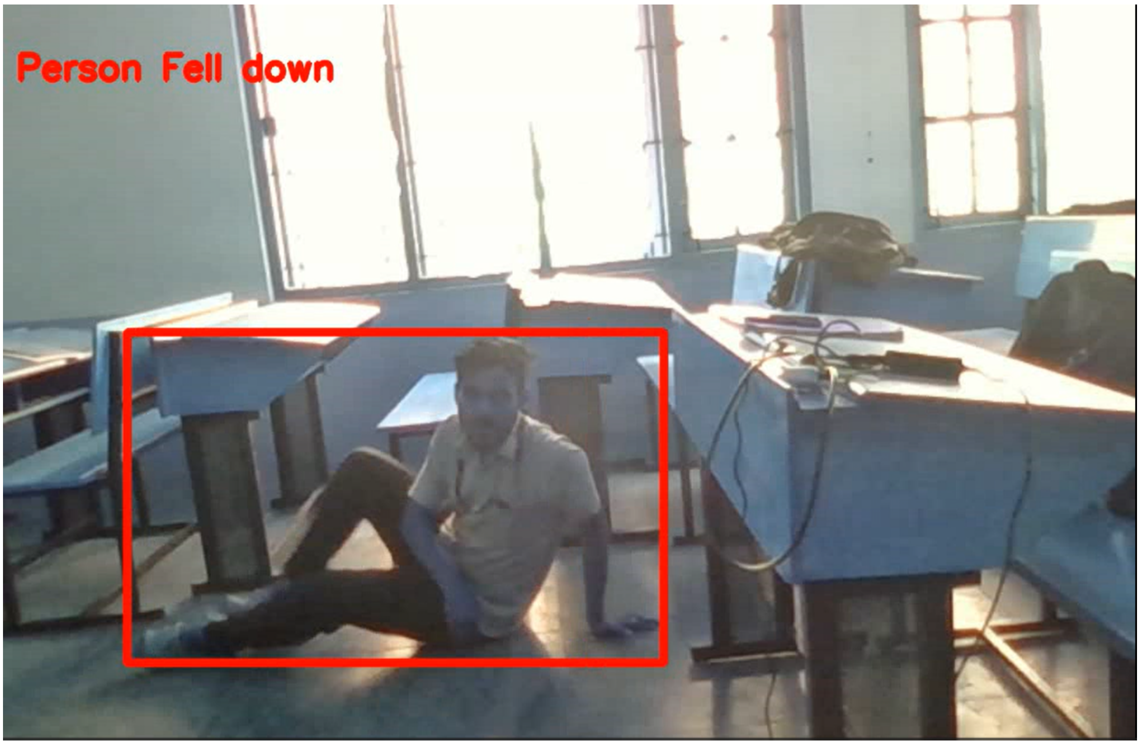


Figure 5.1: Identification of fall

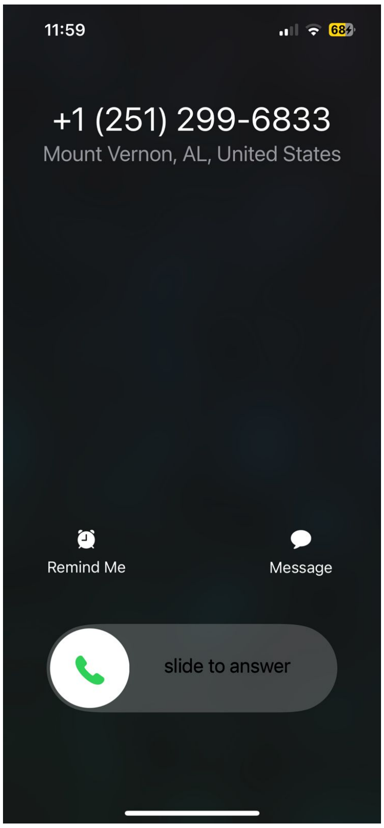


Figure 5.2: Phone call to user

5.3 Discussion

When a person falls it is identified and the user is notified with a phone call. The model has proved to be successful in various testing scenarios and also posesses a few limitations. The integration of OpenCV into a fall detection system represents a crucial step forward in this regard. By harnessing the power of computer vision, A robust mechanism for detecting falls in real-time has been developed, coupled with an automatic alert system that notifies caregivers promptly.

5.4 Conclusion

In the realm of elderly care, the implementation of innovative technological solutions can significantly enhance the safety and well-being of senior citizens. The utilization of OpenCV's capabilities has allowed us to create a solution that not only accurately identifies fall events but also ensures minimal latency in alerting caregivers. This real-time response is paramount in emergency situations, where timely intervention can mitigate the severity of injuries or even save lives. Furthermore, the scalability and adaptability of our system make it suitable for deployment in various settings, including elderly care homes, hospitals, and assisted living facilities.

By incorporating automatic call functionality to notify caregivers, our system adds an extra layer of security and reassurance for both seniors and their families. Caregivers can rest assured knowing that they will be promptly alerted in the event of a fall, enabling them to provide immediate assistance and support to the individual in need.

Chapter 6

Conclusions

The overarching concern for the well-being of the elderly is evident throughout these studies. Identified limitations in traditional fall detection systems, including issues related to data transfer, costs, and privacy concerns, drive the pursuit of alternative solutions. Proposals such as the integration of neuromorphic computing, edge computing, and artificial intelligence showcase a commitment to overcoming these challenges, It was discovered that the modified DAG-CNN structure produced predictions that were roughly 7% more accurate than those of the conventional CNN structure. By incorporating gyroscope and accelerometer data, the modified DAG-CNN showed outstanding prediction ability with accuracy of over 98 percent for the case of near-falls. Furthermore, the trained model outperformed each acceleration and angular velocity model separately by merging the two. It is thought that by tracking near-falls, data will be available to prevent falls and assess the rehabilitation state of older adults with poor balance objectively. By merging Federated Learning and Extreme Learning Machine, the Fed-ELM method presents a revolutionary strategy that improves the fall detection algorithms' generalizability for both young and old people.

Advanced computer vision techniques, such as optical flow and motion boundaryhistograms, prove effective in detecting falls through motion pattern analysis in surveillance videos. Collectively, these findings contribute to a nuanced understanding of falldetection, addressing privacy concerns, adaptability, and generalizability across diverse settings and user demographics. Fall detection using keypoint extraction from OpenPose to classify fall and non fall action, which can use twilio api for alert generation gives hope on a great way of making life easier for the elders and their caretakers with minimal disadvantages.

References

[1] A. Choi, T. Kim, O. Yuhai, S. Jeong, K. Kim, H. Kim, and J. Mun, "Deep learning-based near-fall detection algorithm for fall risk monitoring system using a single inertial measurement unit," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 30, pp. 2385–2394, 2022, epub 2022 Sep 1.

[2] V.-H. Hoang, J. W. Lee, M. J. Piran, and C.-S. Park, "Advances in skeleton-based fall detection in rgb videos: From handcrafted to deep learning approaches," *IEEE Access*, vol. 11, pp. 92 322–92 352, 2023.

[3] C. Vishnu, R. Datla, D. Roy, S. Babu, and C. K. Mohan, "Human fall detection in surveillance videos using fall motion vector modeling," *IEEE Sensors Journal*, vol. 21, no. 15, pp. 17 162–17 170, 2021.

[4] Y.-H. Liu, P. C. K. Hung, F. Iqbal, and B. C. M. Fung, "Automatic fall risk detection based on imbalanced data," *IEEE Access*, vol. 9, pp. 163 594–163 611, 2021.

[5] Z. Yu, J. Liu, M. Yang, Y. Cheng, J. Hu, and X. Li, "An elderly fall detection method based on federated learning and extreme learning machine (fed-elm)," *IEEE Access*, vol. 10, pp. 130 816–130 824, 2022.

[6] B.-S. Lin, T. Yu, C.-W. Peng, C.-H. Lin, H.-K. Hsu, I.-J. Lee, and Z. Zhang, "Fall detection system with artificial intelligence-based edge computing," *IEEE Access*, vol. 10, pp. 4328–4339, 2022.

[7] F. Shu and J. Shu, "An eight-camera fall detection system using human fall pattern recognition via machine learning by a low-cost android box," *Sci Rep*, vol. 11, no. 1, p. 2471, 2021.

[8] E. Torti, A. Fontanella, M. Musci, N. Blago, D. Pau, F. Leporati, and M. Piastra, "Embedded real-time fall detection with deep learning on wearable devices," in *2018 21st Euromicro Conference on Digital System Design (DSD)*, 2018, pp. 405–412.

[9] M. G. Amin, Y. D. Zhang, F. Ahmad, and K. D. Ho, "Radar signal processing for elderly fall detection: The future for in-home monitoring," *IEEE Signal Processing Magazine*, vol. 33, no. 2, pp. 71–80, 2016.

[10] H. Miawarni, T. A. Sardjono, E. Setijadi, Wijayanti, D. Arraziqi, A. B. Gumelar, and M. H. Purnomo, "Fall detection system for elderly based on 2d lidar: A preliminary study of fall incident and activities of daily living (adl) detection," in *2020 International Conference on Computer Engineering, Network, and Intelligent Multimedia (CENIM)*, 2020, pp. 1–5.

Appendix A: Presentation

Fall detection system for senior citizens using Machine Learning

Guide: Ms.Mehbooba P Shareef

.

Team Members:
Govind Kiran (U2003088)
Nafia Basheer(U2003139)
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Misha Mathew(U2003135)

Rajagiri School of Engineering and Technology,Kakkanad
Department of CSE

April 30, 2024

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Problem Definition

- As the aging population grows, fall detection has become a critical concern in healthcare.
- Accurately spotting fall behavior in surveillance footage and providing early feedback can lower the risk of injury and mortality among the elderly due to falls.
- The challenge is that many elderly individuals live alone, facing an increased risk of accidents such as falls.
- These incidents are worsen by difficulties in seeking help due to limited access to technology and physical limitations.
- As a result, there is an urgent need for a system that can detect falls and provide aid quickly, particularly for elderly people living independently.

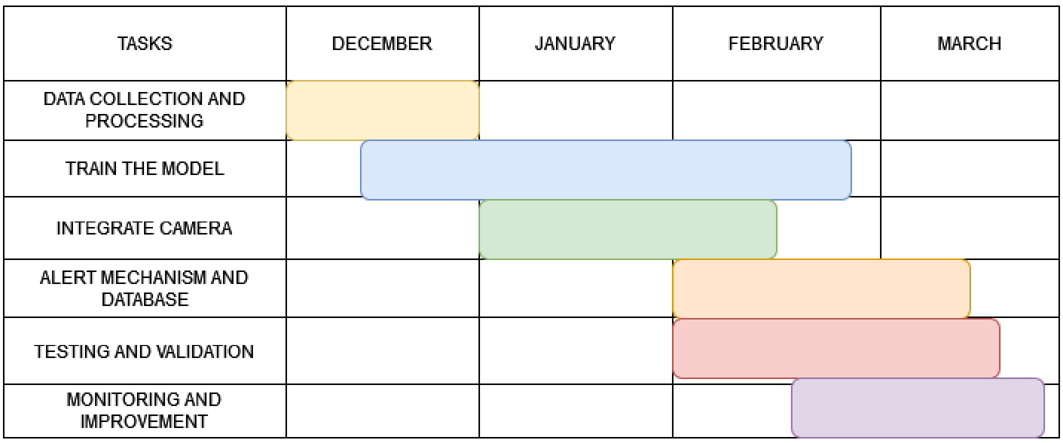
Objective

- To develop a fall detection system for elderly people using machine learning

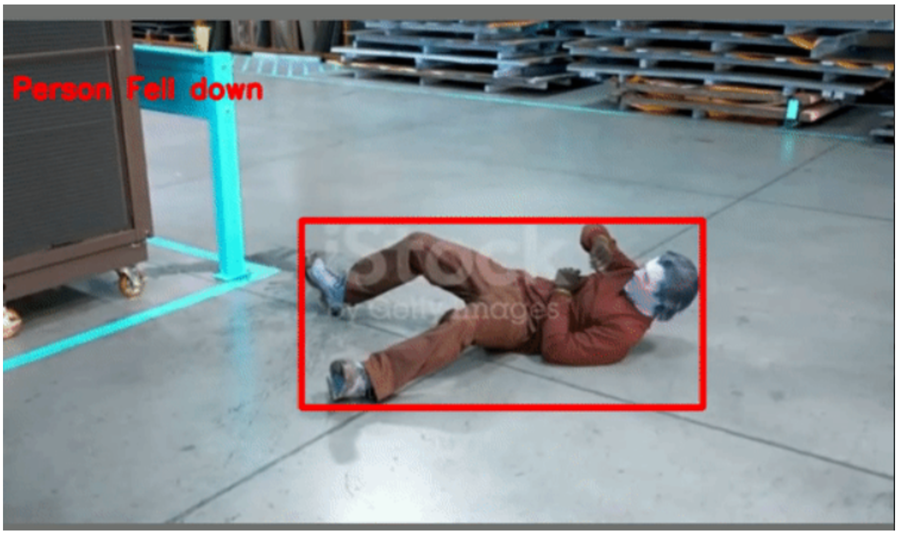
Novelty of Idea and Scope of Implementation

- Global Need: The demand for reliable fall detection systems is driven by the increasing aging population worldwide, necessitating solutions that ensure the safety and well-being of seniors.
- Enhanced Quality of Life: The primary goal of fall detection initiatives is to improve the quality of life for seniors by providing effective safety measures, offering peace of mind to both seniors and their caregivers.
- Interdisciplinary Collaboration: Collaboration between healthcare professionals, technologists, and caregivers is essential to address the multifaceted challenges associated with fall detection

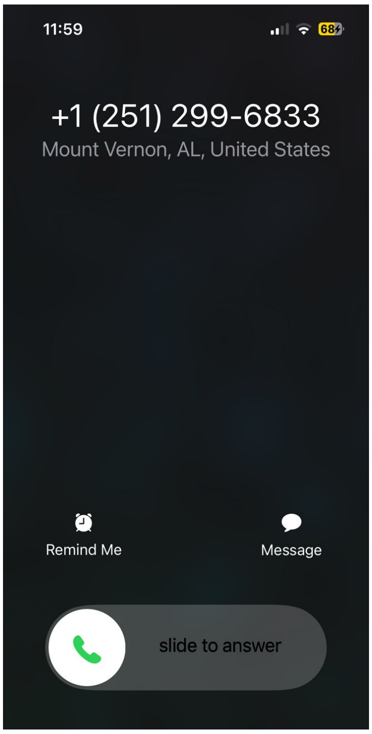
Gantt Chart



Output



Output



100% Evaluation

- Falls are accurately detected and a bounding box is drawn around them.
- After fall is detected an automated phone call is received on to the caretakers device.
- The video frames of the detected fall is saved for future analysis.

Task Distribution

- Collect and extract relevant features from the dataset.(Nihal)
- Train and test the detection models.(Govind)
- Implementation of Pose Estimation.(Nafia,Misha)
- Alert generation and send notifications to users.Develop a User Interface.(Nafia,Misha)
- Collect new data,retrain the model and adjusting the model's hyper-parameters to improve the model performance.(Govind,Nihal)

Conclusion

- A method to detect falls of elderly people have been proposed
- This approach detects falls using machine learning algorithms based on daily activities.
- Different fall videos were collected and they were trained. Keypoint extraction is done on this data

References

- S. Pires, S. Rodrigues and S. Chopra, "FallStop — A deep learning approach to real-time fall detection and monitoring of vital parameters," 2021 IEEE India Council International Subsections Conference (INDISCON), NAGPUR, India, 2021, pp. 1-6, doi: 10.1109/INDISCON53343.2021.9582207.
- I. Varalakshmi, A. Mahalakshmi and P. Sriharini, "Performance Analysis of Various Machine Learning Algorithm for Fall Detection-A Survey," 2020 International Conference on System, Computation, Automation and Networking (ICSCAN), Pondicherry, India, 2020, pp. 1-5, doi: 10.1109/ICSCAN49426.2020.9262318.

References

- Y. Chen, R. Du, K. Luo and Y. Xiao, "Fall detection system based on real-time pose estimation and SVM," 2021 IEEE 2nd International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering (ICBAIE), Nanchang, China, 2021, pp. 990-993, doi: 10.1109/ICBAIE52039.2021.9390068.
- T. Tongskulroongruang et al., "Comparative Study on Fall Detection using Machine Learning Approaches," 2022 19th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), Prachuap Khiri Khan, Thailand, 2022, pp. 1-4, doi: 10.1109/ECTI-CON54298.2022.9795445.

THANK YOU

Appendix B: Vision, Mission, Programme Outcomes and Course Outcomes

Vision, Mission, Programme Outcomes and Course Outcomes

Institute Vision

To evolve into a premier technological institution, moulding eminent professionals with creative minds, innovative ideas and sound practical skill, and to shape a future where technology works for the enrichment of mankind.

Institute Mission

To impart state-of-the-art knowledge to individuals in various technological disciplines and to inculcate in them a high degree of social consciousness and human values, thereby enabling them to face the challenges of life with courage and conviction.

Department Vision

To become a centre of excellence in Computer Science and Engineering, moulding professionals catering to the research and professional needs of national and international organizations.

Department Mission

To inspire and nurture students, with up-to-date knowledge in Computer Science and Engineering, ethics, team spirit, leadership abilities, innovation and creativity to come out with solutions meeting societal needs.

Programme Outcomes (PO)

Engineering Graduates will be able to:

1. Engineering Knowledge: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

2. Problem analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

3. Design/development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

4. Conduct investigations of complex problems: Use research-based knowledge including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

5. Modern Tool Usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

6. The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal, and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

7. Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

8. Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

9. Individual and Team work: Function effectively as an individual, and as a member or leader in teams, and in multidisciplinary settings.

10. Communication: Communicate effectively with the engineering community and with society at large. Be able to comprehend and write effective reports documentation. Make effective presentations, and give and receive clear instructions.

11. Project management and finance: Demonstrate knowledge and understanding of engineering and management principles and apply these to one's own work, as a member and leader in a team. Manage projects in multidisciplinary environments.

12. Life-long learning: Recognize the need for, and have the preparation and ability to engage in independent and lifelong learning in the broadest context of technological change.

Programme Specific Outcomes (PSO)

A graduate of the Computer Science and Engineering Program will demonstrate:

PSO1: Computer Science Specific Skills
The ability to identify, analyze and design solutions for complex engineering problems in multidisciplinary areas by understanding the core principles and concepts of computer science and thereby engage in national grand challenges.

PSO2: Programming and Software Development Skills
The ability to acquire programming efficiency by designing algorithms and applying standard practices in software project development to deliver quality software products meeting the demands of the industry.

PSO3: Professional Skills
The ability to apply the fundamentals of computer science in competitive research and to develop innovative products to meet the societal needs thereby evolving as an eminent researcher and entrepreneur.

Course Outcomes (CO)

Course Outcome 1: Model and solve real world problems by applying knowledge across domains (Cognitive knowledge level: Apply).

Course Outcome 2: Develop products, processes or technologies for sustainable and socially relevant applications (Cognitive knowledge level: Apply).

Course Outcome 3: Function effectively as an individual and as a leader in diverse teams and to comprehend and execute designated tasks (Cognitive knowledge level: Apply).

Course Outcome 4: Plan and execute tasks utilizing available resources within timelines, following ethical and professional norms (Cognitive knowledge level: Apply).

Course Outcome 5: Identify technology/research gaps and propose innovative/creative solutions (Cognitive knowledge level: Analyze).

Course Outcome 6: Organize and communicate technical and scientific findings effectively in written and oral forms (Cognitive knowledge level: Apply).

Appendix C: CO-PO-PSO Mapping

CO-PO AND CO-PSO MAPPING

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3
CO1	2	2	2	1	2	2	2	1	1	1	1	2	3		
CO2	2	2	2		1	3	3	1	1		1	1		2	
CO3									3	2	2	1			3
CO4					2			3	2	2	3	2			3
CO5	2	3	3	1	2							1	3		
CO6					2			2	2	3	1	1			3

3/2/1: high/medium/low

JUSTIFICATIONS FOR CO-PO MAPPING & CO-PSO MAPPING

MAPPING	LOW/MEDIUM/ HIGH	JUSTIFICATION
100003/ CS722U.1-PO1	M	Knowledge in the area of technology for project development using various tools results in better modeling.
100003/ CS722U.1-PO2	M	Knowledge acquired in the selected area of project development can be used to identify, formulate, review

		research literature, and analyze complex engineering problems reaching substantiated conclusions.
100003/ CS722U.1-PO3	M	Can use the acquired knowledge in designing solutions to complex problems.
100003/ CS722U.1-PO4	M	Can use the acquired knowledge in designing solutions to complex problems.
100003/ CS722U.1-PO5	H	Students are able to interpret, improve and redefine technical aspects for design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
100003/ CS722U.1-PO6	M	Students are able to interpret, improve and redefine technical aspects by applying contextual knowledge to assess societal, health and consequential responsibilities relevant to professional engineering practices.
100003/ CS722U.1-PO7	M	Project development based on societal and environmental context solution identification is the need for sustainable development.
100003/ CS722U.1-PO8	L	Project development should be based on professional ethics and responsibilities.
100003/ CS722U.1-PO9	L	Project development using a systematic approach based on well defined principles will result in teamwork.

100003/ CS722U.1-PO10	M	Project brings technological changes in society.
100003/ CS722U.1-PO11	H	Acquiring knowledge for project development gathers skills in design, analysis, development and implementation of algorithms.
100003/ CS722U.1-PO12	H	Knowledge for project development contributes engineering skills in computing & information gatherings.
100003/ CS722U.2-PO1	H	Knowledge acquired for project development will also include systematic planning, developing, testing and implementation in computer science solutions in various domains.
100003/ CS722U.2-PO2	H	Project design and development using a systematic approach brings knowledge in mathematics and engineering fundamentals.
100003/ CS722U.2-PO3	H	Identifying, formulating and analyzing the project results in a systematic approach.
100003/ CS722U.2-PO5	H	Systematic approach is the tip for solving complex problems in various domains.
100003/ CS722U.2-PO6	H	Systematic approach in the technical and design aspects provide valid conclusions.

100003/ CS722U.2-PO7	H	Systematic approach in the technical and design aspects demonstrate the knowledge of sustainable development.
100003/ CS722U.2-PO8	M	Identification and justification of technical aspects of project development demonstrates the need for sustainable development.
100003/ CS722U.2-PO9	H	Apply professional ethics and responsibilities in engineering practice of development.
100003/ CS722U.2-PO11	H	Systematic approach also includes effective reporting and documentation which gives clear instructions.
100003/ CS722U.2-PO12	M	Project development using a systematic approach based on well defined principles will result in better teamwork.
100003/ CS722U.3-PO9	H	Project development as a team brings the ability to engage in independent and lifelong learning.
100003/ CS722U.3-PO10	H	Identification, formulation and justification in technical aspects will be based on acquiring skills in design and development of algorithms.
100003/ CS722U.3-PO11	H	Identification, formulation and justification in technical aspects provides the betterment of life in various domains.
100003/ CS722U.3-PO12	H	Students are able to interpret, improve and redefine technical aspects with mathematics, science and

		engineering fundamentals for the solutions of complex problems.
100003/ CS722U.4-PO5	H	Students are able to interpret, improve and redefine technical aspects with identification formulation and analysis of complex problems.
100003/ CS722U.4-PO8	H	Students are able to interpret, improve and redefine technical aspects to meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.
100003/ CS722U.4-PO9	H	Students are able to interpret, improve and redefine technical aspects for design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
100003/ CS722U.4-PO10	H	Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools for better products.
100003/ CS722U.4-PO11	M	Students are able to interpret, improve and redefine technical aspects by applying contextual knowledge to assess societal, health and consequential responsibilities relevant to professional engineering practices.
100003/ CS722U.4-PO12	H	Students are able to interpret, improve and redefine technical aspects for demonstrating the knowledge of, and need for sustainable development.

100003/ CS722U.5-PO1	H	Students are able to interpret, improve and redefine technical aspects, apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.
100003/ CS722U.5-PO2	M	Students are able to interpret, improve and redefine technical aspects, communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.
100003/ CS722U.5-PO3	H	Students are able to interpret, improve and redefine technical aspects to demonstrate knowledge and understanding of the engineering and management principle in multidisciplinary environments.
100003/ CS722U.5-PO4	H	Students are able to interpret, improve and redefine technical aspects, recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.
100003/ CS722U.5-PO5	M	Students are able to interpret, improve and redefine technical aspects in acquiring skills to design, analyze and develop algorithms and implement those using high-level programming languages.
100003/ CS722U.5-PO12	M	Students are able to interpret, improve and redefine technical aspects and contribute their engineering skills in

		computing and information engineering domains like network design and administration, database design and knowledge engineering.
100003/ CS722U.6-PO5	M	Students are able to interpret, improve and redefine technical aspects and develop strong skills in systematic planning, developing, testing, implementing and providing IT solutions for different domains which helps in the betterment of life.
100003/ CS722U.6-PO8	H	Students will be able to associate with a team as an effective team player for the development of technical projects by applying the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.
100003/ CS722U.6-PO9	H	Students will be able to associate with a team as an effective team player to Identify, formulate, review research literature, and analyze complex engineering problems
100003/ CS722U.6-PO10	M	Students will be able to associate with a team as an effective team player for designing solutions to complex engineering problems and design system components.
100003/ CS722U.6-PO11	M	Students will be able to associate with a team as an effective team player, use research-based knowledge and research methods including design of experiments, analysis and interpretation of data.

100003/ CS722U.6-PO12	H	Students will be able to associate with a team as an effective team player, applying ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.
100003/ CS722U.1-PSO1	H	Students are able to develop Computer Science Specific Skills by modeling and solving problems.
100003/ CS722U.2-PSO2	M	Developing products, processes or technologies for sustainable and socially relevant applications can promote Programming and Software Development Skills.
100003/ CS722U.3-PSO3	H	Working in a team can result in the effective development of Professional Skills.
100003/ CS722U.4-PSO3	H	Planning and scheduling can result in the effective development of Professional Skills.
100003/ CS722U.5-PSO1	H	Students are able to develop Computer Science Specific Skills by creating innovative solutions to problems.
100003/ CS722U.6-PSO3	H	Organizing and communicating technical and scientific findings can help in the effective development of Professional Skills.