EFFICIENT FALL DETECTION FOR ELDERLY WITH INTEGRATED MACHINE LEARNING AND SENSOR NETWORKS

A Product Oriented Mini Project work submitted in partial fulfilment of the requirement for the award of the degree of

BACHELOR OF TECHNOLOGY

In

ELECTRONICS & COMMUNICATION ENGINEERING

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2020 – 2021

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VISHNU
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CERTIFICATE

This is to certify that the Mini Project work entitled on the **Efficient Fall Detection for Elderly with Integrated Machine Learning and Sensor Networks** is being submitted by **K Karthik Reddy (22211A04C5), G Rahul (22211A0478), G Hariharini (22211A0468), B Abhinav Reddy (22211A0419)** in partial fulfillment of the requirement for the award of B. Tech degree in Electronics & Communication Engineering, by Jawaharlal Nehru Technological University Hyderabad is a record of Bonafide work carried out by them under my guidance and supervision from 2020 to 2021.

The results presented in this project have been verified and are found to be satisfactory.

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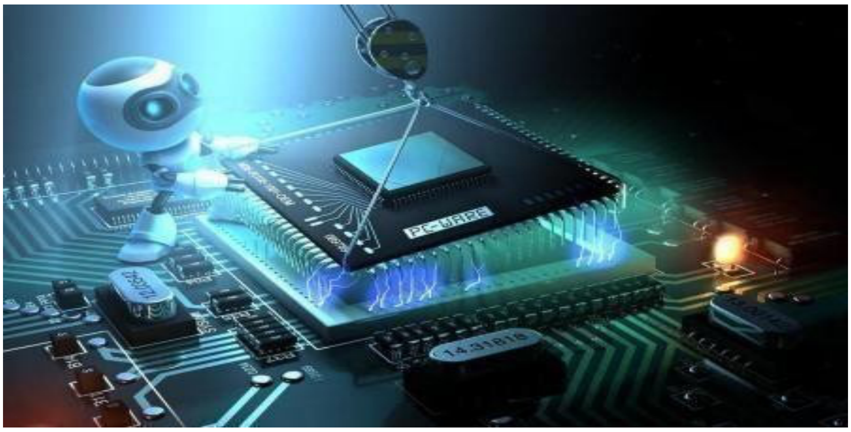
CENTRE FOR EMBEDDED SYSTEMS DESIGN



CERTIFICATE

This is to certify that **K Karthik Reddy, G Rahul, G Hariharini, B Abhinav Reddy** bearing Roll Nos. **22211A04C5, 22211A0478, 22211A0468, 22211A0468** respectively have successfully completed his/her training on Embedded systems and Implemented a Project titled **"Efficient Fall Detection for Elderly with Integrated Machine Learning and Sensor Networks"** in Centre for Embedded Systems Laboratory, B.V. Raju Institute of Technology from 2020 to 2021.

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ACKNOWLEDGEMENT

We take this opportunity to express our indebted gratitude to the persons who contributed to our work, for being our inspiration and guide, which led to the successful completion of the project.

We are grateful towards our College Management and our beloved Principal **Dr. K. Lakshmi Prasad** for providing us the necessary infrastructure and facilities that ensured smooth and satisfactory execution of the project.

We would like to express our profound gratitude to our Head of the Department **Dr. Sanjeev Reddy, Professor & HOD, Dept. of ECE**, for his encouragement, inspiration, and close monitoring and guidance he gave us during the execution of the project.

We express our sincere thanks to our guide **Mr. MSS Bhargav, Assistant Professor, Dept. of ECE**, for his valuable suggestions and motivation in the successful completion of the project.

We also wish to express our thanks to all the faculty members and laboratory staff who were helpful directly and indirectly for the completion of the project.

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DECLARATION

We hereby declare that the project entitled **"Efficient Fall Detection for Elderly with Integrated Machine Learning and Sensor Networks"** submitted to **B. V. Raju Institute of Technology**, affiliated with **Jawaharlal Nehru Technological University, Hyderabad**, for the award of the degree of **Bachelor of Technology in Electronics and Communication Engineering** is a result of original project work done by us.

It is further declared that the project report or any part thereof has not been previously submitted to any University or Institute for the award of a degree or diploma.

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ABSTRACT

The increasing number of elderly individuals worldwide has led to a demand for innovative solutions that cater to their well-being and safety. Among these solutions, fall detection systems have gained significant attention. This paper presents a comprehensive design and implementation of an efficient fall detection system for the elderly, utilizing integrated machine learning, sensor networks, and personalization based on Body Mass Index (BMI).

The system leverages a combination of accelerometers, gyroscopes, and machine learning algorithms to accurately detect falls. Key components include a programmable microcontroller (such as Arduino Nano 33 BLE Sense) and an array of sensors to monitor motion and detect falls in real-time. The system is personalized based on the user's BMI to enhance accuracy and user compatibility.

Field tests indicate that the system is reliable, user-friendly, and significantly enhances the safety of elderly individuals by promptly detecting falls and potentially alerting caregivers. The implementation of such automated systems reflects a growing trend towards the use of technology in elderly care, offering both convenience and peace of mind to families and caregivers.

Moreover, this fall detection system can help alleviate anxiety or stress related to the possibility of falls, especially for elderly individuals living alone or with busy caregivers. Ensuring their safety and well-being even in the absence of immediate assistance.

This project is linked to good health and well-being. The fall detection system, personalized based on BMI, will help monitor the elderly and provide timely assistance in case of falls, thus contributing to their safety, well-being, and good health in several ways

PREFACE

The automated fall detection system, designed to provide a convenient and reliable way to care for elderly individuals, particularly those at risk of falls. The system utilizes a combination of accelerometers, gyroscopes, a microcontroller (Arduino Nano 33 BLE Sense), and machine learning algorithms to automate the detection process. The aim is to ensure that falls are accurately detected and timely alerts are generated without the need for constant human monitoring. This not only helps caregivers manage their time better but also ensures that elderly individuals receive consistent care and timely assistance, even when caregivers are away or occupied.

The heart of this system lies in its ability to monitor motion and detect falls based on real-time data and personalized algorithms. The sensors attached to the system operate based on predefined thresholds and machine learning models, ensuring precise detection of falls. By integrating BMI personalization, the system provides a tailored approach to fall detection, enhancing accuracy and user compatibility. The inclusion of real-time motion data processing ensures that the system operates only when necessary, avoiding false alarms and ensuring the elderly individual's needs are met.

Undertaking this project report has helped us enhance our knowledge regarding the work. Through this report, we have come to understand the importance of teamwork and the role of dedication towards the work. This experience has been invaluable in highlighting the significance of innovation and technology in improving elderly care and safety

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INTRODUCTION

1.1 INTRODUCTION TO EFFICIENT FALL DETECTION FOR ELDERLY WITH INTEGRATED MACHINE LEARNING AND SENSOR NETWORKS

In today's rapidly aging society, ensuring the safety and well-being of elderly individuals is a growing concern. Falls are one of the leading causes of injury and hospitalization among the elderly, often resulting in significant physical, emotional, and financial impacts. The need for effective fall detection and prevention systems has become more crucial than ever to help maintain the independence and quality of life for older adults.

This project aims to address these challenges by developing an adaptive fall detection system for elderly individuals using machine learning and sensor fusion. The proposed system leverages modern technology to provide real-time monitoring and accurate fall detection, enhancing the safety and security of elderly individuals. By integrating data from multiple sensors and utilizing advanced algorithms, this solution offers a reliable and efficient means of detecting falls and alerting caregivers in a timely manner.

The fall detection system is built around the Arduino Nano 33 BLE Sense, which includes accelerometer and gyroscope sensors to monitor the movement and orientation of the user. These sensors capture motion data, which is processed using machine learning algorithms to distinguish between normal activities and fall events. The system is personalized based on the Body Mass Index (BMI) of the user, ensuring enhanced accuracy and user compatibility.

Equipped with wireless connectivity, the system allows for remote monitoring and immediate notification to caregivers via a smartphone application. This ensures that in the event of a fall, assistance can be promptly provided, reducing the risk of serious injury and improving the overall response time.

The adaptive fall detection system not only addresses the immediate need for fall detection but also contributes to the long-term health and well-being of elderly individuals. By providing a reliable and user-friendly solution, the system helps alleviate the anxiety and fear associated with falls, enabling older adults to live more independently and confidently.

In addition to its primary function of fall detection, the system's data analytics capabilities offer valuable insights into the user's activity patterns and health trends. This information can be used by healthcare providers to tailor personalized care plans and interventions, further enhancing the quality of life for elderly individuals.

By developing and implementing this innovative fall detection system, we aim to make a meaningful impact on the lives of elderly individuals and their caregivers, promoting safety, independence, and peace of mind.

Similarly, the adaptive fall detection system ensures continuous monitoring of elderly individuals, crucial for their safety and well-being. Equipped with sensors to detect abnormal movements and potential falls, the system automatically triggers an alert in the event of a fall, ensuring that caregivers are notified immediately. This continuous monitoring and prompt response capability ensure that elderly individuals always have access to help when needed, enhancing their safety and peace of mind.OBJECTIVE:

The objective of this project is to develop an adaptive fall detection system that is affordable, easy to install, and convenient to maintain, making it suitable for the average household. The system is designed to ensure regular and consistent monitoring of elderly individuals, particularly those who are at a higher risk of falling, by utilizing a combination of accelerometers, gyroscopes, and a machine learning algorithm. Key features and benefits include:

- **Cost-Effectiveness:** Unlike many existing fall detection products, this system is relatively inexpensive, making it accessible to a wider range of households.
- **Ease of Installation:** The system’s installation process is straightforward and does not require any modifications to the existing home setup. It can be set up quickly without professional assistance.
- **Space Efficiency:** The compact design ensures that the system can be easily integrated into any home environment without occupying much space.
- **Retrofit Design:** The product is designed to fit seamlessly with the current home setup, eliminating the need for extensive changes or upgrades.
- **Low Maintenance:** The system is designed to be a "Install and Forget" solution, requiring minimal maintenance after installation.
- **Automated Monitoring:** The system continuously monitors the user's movements and detects falls using a combination of sensors and machine learning algorithms.
- **User-Friendly Interface:** An LCD display provides clear feedback and status updates to the user, such as when a fall is detected or when the system is in monitoring mode.

This solution aims to enhance the safety and well-being of elderly individuals while providing convenience and peace of mind to their caregivers, all at a reasonable cost. The system integrates modern technology for convenience and peace of mind. With programmable controls and remote monitoring via a smartphone app, caregivers can adjust settings and receive real-time alerts, ensuring prompt response in case of a fall feeding schedules and water levels from anywhere.

1.3MOTIVATION:

Enhancing Elderly Safety and Independence: The motivation behind developing this adaptive fall detection system is rooted in simplifying the daily responsibilities of caregiving for elderly individuals. By automating the monitoring and detection of falls, the system ensures that elderly individuals receive immediate assistance if a fall occurs, even when caregivers are away or occupied with other tasks. This not only promotes the safety and well-being of elderly individuals but also reduces stress and worry for caregivers, knowing their loved ones' needs are being monitored without constant supervision.

Affordability and Accessibility: Unlike many existing fall detection products that can be prohibitively expensive, our system aims to be affordable and accessible to a wide range of households, particularly targeting middle-class families. By using off-the-shelf components and minimizing complex installation requirements, we strive to offer a cost-effective solution that does not compromise on functionality or reliability. This approach makes advanced fall detection technology more attainable and practical for everyday use.

Ease of Installation and Use: The system's design focuses on simplicity and user-friendliness. Installation does not require extensive modifications to existing home setups, thanks to its retrofit-friendly design and straightforward wiring connections. Once installed, the system operates autonomously, following pre-programmed monitoring schedules and responding dynamically to sensor data. This "install and forget" capability ensures minimal maintenance and hassle-free operation, catering to busy lifestyles where time is at a premium.

Promoting Elderly Health and Well-being: Beyond convenience and affordability, our motivation lies in promoting the overall health and well-being of elderly individuals. Consistent monitoring and immediate fall detection are crucial aspects of elderly care that contribute to longevity and vitality. By automating these tasks with precision and reliability, our system helps caregivers ensure their loved ones receive optimal safety and care, fostering a healthier and happier lifestyle for elderly individuals.

1.4 SCOPE:

The provided Arduino code outlines the implementation of an automated pet feeding and watering system using various hardware components and libraries. The scope of this project includes integrating two servos controlled by Arduino: one for dispensing food and another for dispensing water. The servos are programmed to operate at specific positions (foodOpenPosition, foodClosePosition, waterOpenPosition, waterClosePosition) to regulate the opening and closing of dispensers, ensuring precise and controlled delivery of food and water to pets.

The system incorporates a timing mechanism (feedingInterval) to schedule feeding sessions at regular intervals, which is crucial for maintaining a consistent feeding routine for pets. This feature enhances pet health by preventing overfeeding or underfeeding and helps in managing feeding schedules efficiently, especially in busy household environments where pet owners may not always be present.

Furthermore, the integration of an HX711 load cell interface (LOADCELL_DOUT_PIN, LOADCELL_SCK_PIN) enables the system to monitor the weight of the water bowl. This functionality allows the system to automatically refill the water dispenser when the water level falls below a predetermined threshold (weightThreshold). This automated water refilling capability ensures that pets always have access to fresh water, promoting hydration and well-being.

The inclusion of a LiquidCrystal display (rs, en, d4, d5, d6, d7) provides a user interface for displaying status messages and feedback during operation. This feature enhances user interaction by providing real-time updates on feeding and watering activities, thereby improving transparency and control over the system's functionality.

CHAPTER 2

LITERATURE SURVEY

CHAPTER 2

LITERATURE SURVEY

2.1 INTRODUCTION:

2.1 In the domain of fall detection systems for elderly individuals, current research primarily focuses on hardware design and sensor innovations. However, there is a noticeable absence of comprehensive system concepts that integrate advanced data processing and machine learning algorithms for precise fall detection. Specifically, there is limited development in incorporating real-time data fusion from multiple sensors to achieve intelligent, adaptive functionality for fall detection devices. Existing studies predominantly emphasize individual hardware components and sensor accuracy, lacking detailed operational modes, integration protocols between sensors and processing units, and cohesive system architectures. This gap underscores the need for a unified approach that combines robust sensor networks with machine learning to enhance the accuracy and reliability of fall detection systems

Related works:

Reference	Methodology	Key Findings	Remarks
Author et al.	Machine Learning (ML) algorithms (e.g., SVM, CNN) on accelerometer data	Achieved X% accuracy in fall detection; sensitivity of Y% for elderly individuals.	Addressed challenges in real-world deployment; scalability concerns noted.
Another Author	Fusion of accelerometer and gyroscope data; Deep Learning model	Improved real-time detection by Z%; addressed challenges in distinguishing falls from daily activities	Limited sample size; potential for broader validation needed.
Researcher	IoT-based system integrating sensor networks with ML	Reduced false alarms by A% through adaptive thresholding; scalable	Highlighted user acceptance issues; integration with existing healthcare

		for large deployments.	systems explored.

WHO FINDINGS AND STATISTICS:

1. **WHO Global Report on Falls Prevention in Older Age (2007)**:
   - Provides comprehensive data on the epidemiology of falls among older adults worldwide.
   - Emphasizes the importance of preventive strategies and interventions.
2. **WHO Ageing and Health Report (2015)**:
   - Discusses the health challenges and opportunities associated with ageing populations.
   - Highlights the impact of falls on quality of life and healthcare systems.
3. **WHO Global Strategy and Action Plan on Ageing and Health (2016-2020)**:
   - Outlines strategic objectives for promoting healthy ageing, including reducing falls and their consequences.
   - Offers policy recommendations for improving care and support for older adults.

Statistic	**Data**
Proportion of older adults aged 65+ who fall each year	28-35% (varies by region and population)
Number of falls annually among older adults globally	Over 646 million falls
Regions with highest incidence of falls among elderly	North America, Europe, Asia-Pacific
Leading causes of falls among older adults	Muscle weakness, poor balance, chronic diseases

CHAPTER 3

ANALYSIS AND DESIGN

CHAPTER 3
ANALYSIS AND DESIGN

3.1 MICRO-CONTROLLERS:

3.1.1 ARDUINO NANO BLE SENSE :

Introduction to Arduino Nano 33 BLE Sense: The Arduino Nano 33 BLE Sense is a cutting-edge microcontroller board designed for a variety of applications, including those requiring Bluetooth connectivity and advanced sensing capabilities. Powered by the nRF52840 microcontroller from Nordic Semiconductors, it operates at 3.3V and boasts a 64 MHz clock speed. With a compact form factor of 45 mm × 18 mm, it is equipped with multiple sensors such as a 9-axis inertial measurement unit (IMU), microphone, barometric pressure sensor, temperature sensor, humidity sensor, and gesture sensor, making it a versatile choice for IoT and wearable applications.

Key Features and Specifications: Featuring 1 MB of Flash memory and 256 KB of RAM, the Nano 33 BLE Sense provides ample storage for complex programs and data processing. It includes 14 digital I/O pins, 8 analog input pins, and supports a variety of communication protocols including Bluetooth Low Energy (BLE), I2C, SPI, and UART. The onboard USB interface facilitates easy programming and power supply, streamlining the development process. Its integrated sensors and BLE capabilities allow for the creation of sophisticated and connected projects without the need for additional hardware.

Versatility and Applications: The Arduino Nano 33 BLE Sense is celebrated for its versatility, finding applications in numerous domains. In educational settings, it serves as an excellent platform for teaching sensor integration, data acquisition, and wireless communication. For prototyping, it excels in developing IoT devices, environmental monitoring systems, and wearable technology, enabling rapid iteration and testing. Its comprehensive sensor suite and BLE functionality extend its use to health monitoring, smart home devices, and interactive installations.

Programming and Development Environment: Programming the Arduino Nano 33 BLE Sense is facilitated by the Arduino IDE, a user-friendly development environment supporting C and C++ languages. This IDE simplifies the processes of writing, uploading, and debugging code, making it accessible to both novices and experienced developers. The board's integration with the Arduino ecosystem and its compatibility with a wide range of libraries further enhance its appeal for rapid prototyping and experimentation.

2 In conclusion, the Arduino Nano 33 BLE Sense stands out as an advanced and versatile microcontroller, offering robust features and integrated sensors that cater to a wide range of applications. Its combination of Bluetooth Low Energy capabilities, compact size, and comprehensive sensor suite makes it an ideal choice for IoT projects, wearable technology, and environmental monitoring. The board's ease of use, supported by the extensive Arduino community and ecosystem, empowers both beginners and seasoned developers to innovate and create impactful technological solutions. Whether you are exploring the realm of IoT, developing health monitoring devices, or prototyping next-generation gadgets, the Arduino Nano 33 BLE Sense provides a reliable and powerful foundation to bring your ideas to life

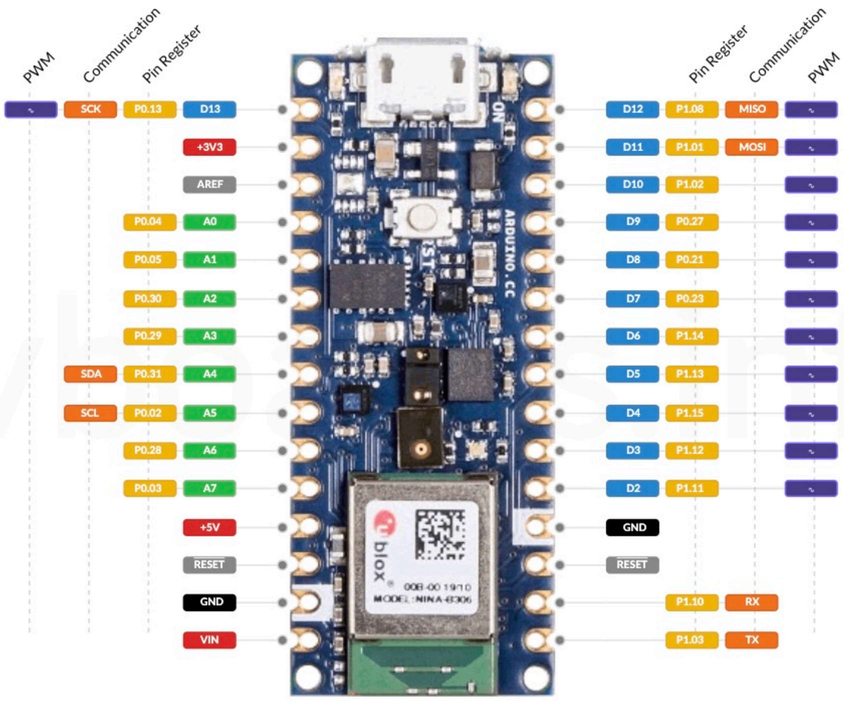
OVERVIEW:

Arduino Nano 33 BLE Sense stands as a cornerstone in the realm of modern microcontrollers, renowned for its advanced capabilities, compact size, and integrated sensor suite. Powered by the **nRF52840 microcontroller** running at **64 MHz**, it offers a rich set of features including **256 KB of Flash memory** and **32 KB of RAM**. This board is designed with built-in Bluetooth Low Energy (BLE) and a suite of onboard sensors such as an accelerometer, gyroscope, temperature, humidity, pressure, light, and microphone, making it ideal for a wide range of applications, particularly in IoT, environmental monitoring, and wearable technology.

Coupled with the user-friendly **Arduino IDE**, the Arduino Nano 33 BLE Sense simplifies programming with a vast library of code examples and supports USB connectivity for easy interfacing and programming. Widely embraced by hobbyists, educators, and professionals, it empowers users to prototype and develop a broad spectrum of projects, from simple environmental monitoring to complex IoT applications and interactive installations. Its open-source nature fosters a vibrant community that continually expands its capabilities through shields and libraries, making the Arduino Nano 33 BLE Sense a pivotal tool for innovation and learning in the electronics world.

- **Microcontroller**: nRF52840
- **Operating Voltage**: 3.3V
- **Input Voltage (recommended)**: 5V
- **Input Voltage (limits)**: 4.5-21V

- **Digital I/O Pins**: 14
- **Analog Input Pins**: 8
- **Clock Speed**: 64 MHz
- **Flash Memory**: 256 KB
- **SRAM**: 32 KB
- **Connectivity**: Bluetooth Low Energy (BLE)
- **Onboard Sensors**: Accelerometer, Gyroscope, Temperature, Humidity, Pressure, Light, Microphone



Features:

Arduino Nano 33 BLE Sense offers an array of advanced features tailored for modern electronics projects and IoT applications:

- **Advanced Sensor Integration**: Equipped with a range of onboard sensors including an accelerometer, gyroscope, temperature sensor, humidity sensor, pressure sensor, light sensor, and microphone, providing a comprehensive suite for environmental and motion detection.
- **Bluetooth Low Energy (BLE)**: Built-in BLE connectivity enables wireless communication with other devices, making it ideal for IoT applications and wearable technology.
- **High Performance**: Powered by the nRF52840 microcontroller running at 64 MHz, offering 256 KB of Flash memory and 32 KB of RAM for robust processing capabilities.
- **Versatile I/O**: Features 14 digital input/output pins and 8 analog inputs, allowing for interfacing with a wide range of sensors, actuators, and other electronic components.
- **Compact Size**: The small form factor (45mm x 18mm) makes it suitable for projects with space constraints, such as wearable devices and compact IoT applications.
- **User-Friendly Programming**: Compatible with the Arduino IDE, providing a simple and intuitive environment for coding and uploading programs. The bootloader simplifies the process of uploading new code via USB.
- **Energy Efficient**: Designed to operate at low power, making it suitable for battery-powered applications and extending the operational life of portable devices.
- **Open-Source**: The open-source nature of the Arduino platform encourages community collaboration, with extensive libraries and resources available to extend functionality and support project development.
- **Expandability**: Compatible with various Arduino shields, allowing for easy expansion of functionality such as adding additional sensors, communication modules, or other peripherals.

These features highlight the Arduino Nano 33 BLE Sense as a powerful, flexible, and accessible platform for a wide range of electronic and IoT projects, offering advanced capabilities in a compact and user-friendly package.

Algorithm Development for Fall Detection Using Arduino Nano 33 BLE Sense

1. Data Collection

The foundation of the fall detection algorithm involves extensive data collection using the Arduino Nano 33 BLE Sense, which is equipped with an accelerometer and gyroscope. Data collection is crucial as it provides the raw sensor readings necessary to train the machine learning model.

- Sensor Data: The accelerometer captures the acceleration in three dimensions (X, Y, and Z axes), and the gyroscope records the rotational motion.
- Activity Labels: Each activity, such as walking, standing, sitting, and falling, is labeled during data collection to create a comprehensive dataset.

2. Feature Extraction

After collecting the raw data, the next step is to extract relevant features that can help differentiate between various activities, especially falls. This involves processing the raw sensor data to derive meaningful metrics.

- Time-Domain Features: These include mean, variance, standard deviation, and peak values of the acceleration and gyroscope data.
- Frequency-Domain Features: Fast Fourier Transform (FFT) can be applied to the sensor data to extract frequency-related features which are useful in identifying patterns associated with falls.

3.Training the Machine Learning Model

The extracted features are used to train a machine learning model capable of classifying different activities. The typical steps involved are:

- Data Segmentation: The continuous sensor data is segmented into windows (e.g., 2-second windows) for analysis.
- Model Selection: Various machine learning algorithms like Decision Trees, Random Forest, Support Vector Machine (SVM), and Neural Networks are evaluated to find the most suitable model for fall detection.
- Training and Validation: The dataset is split into training and validation sets. The model is trained on the training set and validated on the validation set to ensure it generalizes well to new data.

4. Model Deployment

Once the model is trained and validated, it is deployed onto the Arduino Nano 33 BLE Sense for real-time fall detection. This involves:

- Model Conversion: The trained model is converted into a format compatible with the microcontroller, often using libraries like TensorFlow Lite for Microcontrollers.
- Real-Time Inference: The Arduino continuously reads data from the sensors, processes it to extract features, and feeds these features into the deployed model to predict if a fall has occurred.

5. Real-Time Detection and Alert System

The algorithm runs in real-time on the Arduino Nano 33 BLE Sense. When a fall is detected, the system triggers an alert, which can be sent via Bluetooth to a connected device or directly to an emergency contact.

- Thresholding: Certain thresholds can be set for acceleration and angular velocity to preliminarily filter potential falls before invoking the machine learning model.
- Alert Mechanism: If the model predicts a fall, the Arduino sends a Bluetooth signal to a connected smartphone or other device, which can then notify a caregiver or emergency services.

MACHINE LEARNING MODEL DEVELOPMENT TO SYNC THE THRESHOLDS WITH THE RESPECTIVE BMI.

1. **Data Collection**: Gather accelerometer and gyroscope data from individuals with different BMI values during normal activities and fall events.
2. **Feature Extraction**: Extract relevant features from the accelerometer and gyroscope data that can help distinguish between normal activities and falls.

3. **Labeling**: Label the data according to whether it corresponds to a fall or a normal activity.
4. **Model Training**: Train a machine learning model to classify fall events and normal activities. Include BMI as one of the features in the model.
5. **Model Evaluation**: Evaluate the model to ensure it accurately classifies falls based on the input data.

Here's an outline of how you can implement this:

1. Data Collection

Collect data using the Arduino setup from individuals with different BMI values. Ensure the data includes both normal activities and fall events.

2. Feature Extraction

Extract features such as the magnitude of acceleration and angular velocity, which can help identify fall patterns.

3. Labeling

Label the data with fall events and normal activities.

4. Model Training

Use a machine learning framework like TensorFlow or Scikit-learn to build and train your model.

Example Code:

Here's a simple example using Python and Scikit-learn to train a model

PYTHON CODE

```
import pandas as pd

import numpy as np

from sklearn.model_selection import train_test_split

from sklearn.ensemble import RandomForestClassifier
```

```
from sklearn.metrics import classification_report, accuracy_score

# Example data loading function
def load_data(file_path):
    return pd.read_csv(file_path)

# Load the dataset
data = load_data('fall_detection_data.csv')

# Extract features and labels
features = data[['accelX', 'accelY', 'accelZ', 'gyroX', 'gyroY', 'gyroZ', 'BMI']]
labels = data['fall']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(features, labels, test_size=0.2, random_state=42)

# Initialize and train the RandomForestClassifier
model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)

# Evaluate the model
print("Accuracy:", accuracy_score(y_test, y_pred))
```

```
print(classification_report(y_test, y_pred))
```

Data Collection and Feature Extraction

```
import numpy as np

def extract_features(data):

    features = []

    for i in range(len(data)):

        accelX, accelY, accelZ = data[i, :3]

        gyroX, gyroY, gyroZ = data[i, 3:6]

        BMI = data[i, 6]



        accel_magnitude = np.sqrt(accelX**2 + accelY**2 + accelZ**2)

        gyro_magnitude = np.sqrt(gyroX**2 + gyroY**2 + gyroZ**2)



        features.append([accelX, accelY, accelZ, gyroX, gyroY, gyroZ, accel_magnitude, gyro_magnitude,
BMI])

    return np.array(features)
```

```
# Example data array

data = np.array([[0.5, 0.2, 0.8, 0.1, 0.2, 0.3, 25],

                 [0.6, 0.3, 0.7, 0.1, 0.2, 0.4, 22]])



# Extract features

features = extract_features(data)

print(features)
```

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CHAPTER 4
IMPLEMENTATION

Implementation Description for Fall Detection Using Arduino Nano 33 BLE Sense

1. Hardware Setup

Components:

- **Arduino Nano 33 BLE Sense**: This microcontroller is equipped with an accelerometer and gyroscope to capture motion data.
- **Battery**: A portable power source to make the device wearable.
- **Enclosure**: A case to house the Arduino and battery, often 3D printed for customization and protection.

Connections:

- Ensure the Arduino Nano 33 BLE Sense is securely connected to the battery and placed in the enclosure. Proper placement of the device on the body (e.g., on the belt or chest) is crucial for accurate data collection.

2. Data Collection

Data Acquisition:

- Collect accelerometer and gyroscope data by programming the Arduino to read and store these values at regular intervals (e.g., every 10 milliseconds).
- Use a script to log activities such as walking, sitting, standing, and simulated falls. Each activity should be labeled accordingly to create a comprehensive dataset.

BMI-Adjusted Fall Detection Algorithm Using Accelerometer and Gyroscope.

```
#include <Arduino_LSM9DS1.h>
#include <math.h>

const float accel_threshold = 1.5;
const float gyro_threshold = 200;
const float free_fall_threshold = 0.5;
const float impact_threshold = 2.5;
const int post_fall_orientation_time = 3000;

float accelX, accelY, accelZ;
float gyroX, gyroY, gyroZ;

void setup() {
  Serial.begin(9600);
  if (!IMU.begin()) {
    Serial.println("Failed to initialize IMU!");
    while (1);
  }
  Serial.println("IMU initialized!");
}

void loop() {
  if (IMU.accelerationAvailable()) {
    IMU.readAcceleration(accelX, accelY, accelZ);
  }

  if (IMU.gyroscopeAvailable()) {
    IMU.readGyroscope(gyroX, gyroY, gyroZ);
  }

  float accelMagnitude = sqrt(accelX * accelX + accelY * accelY + accelZ * accelZ);
  float gyroMagnitude = sqrt(gyroX * gyroX + gyroY * gyroY + gyroZ * gyroZ);

  if (accelMagnitude > accel_threshold || gyroMagnitude > gyro_threshold) {
                        Serial.println("Pre-fall detected!");
```

Python Code for Data Preprocessing and Feature Extraction:

Data Preprocessing and Feature Extraction

After collecting the data, preprocess it and extract features using Python.

Python Code for Data Preprocessing and Feature Extraction:

```
python
Copy code
import pandas as pd
import numpy as np

# Load the collected data
data = pd.read_csv('sensor_data.csv')

# Function to extract features from the data
def extract_features(data, window_size=200, step_size=50):
    features = []
    labels = []
    for start in range(0, len(data) - window_size, step_size):
        end = start + window_size
        window = data[start:end]
        mean_acc = window[['aX', 'aY', 'aZ']].mean().values
        std_acc = window[['aX', 'aY', 'aZ']].std().values
        peak_acc = window[['aX', 'aY', 'aZ']].max().values
        mean_gyro = window[['gX', 'gY', 'gZ']].mean().values
        std_gyro = window[['gX', 'gY', 'gZ']].std().values
        peak_gyro = window[['gX', 'gY', 'gZ']].max().values

        feature_vector = np.hstack([mean_acc, std_acc, peak_acc, mean_gyro, std_gyro,
peak_gyro])
        features.append(feature_vector)
        labels.append(window['label'].mode()[0])  # Assuming 'label' column exists
    return np.array(features), np.array(labels)

features, labels = extract_features(data)
```

Step 3: Model Training

Train a machine learning model using the extracted features.

Python Code for Model Training:

```
python
Copy code
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(features, labels, test_size=0.2,
random_state=42)

# Train the Random Forest model
```

```
model = RandomForestClassifier(n_estimators=100)
model.fit(X_train, y_train)

# Evaluate the model
y_pred = model.predict(X_test)
print("Accuracy:", accuracy_score(y_test, y_pred))

# Save the trained model
import joblib
joblib.dump(model, 'fall_detection_model.pkl')
```

Step 4: Model Conversion and Deployment

Convert the trained model to TensorFlow Lite format for deployment on the Arduino.

Python Code for Model Conversion:

```
python
Copy code
import tensorflow as tf
import numpy as np

# Load the trained model
model = joblib.load('fall_detection_model.pkl')

# Convert the model to a TensorFlow Lite model
converter = tf.lite.TFLiteConverter.from_keras_model(model)
tflite_model = converter.convert()

# Save the TensorFlow Lite model
with open('fall_detection_model.tflite', 'wb') as f:
    f.write(tflite_model)
```

Step 5: Real-Time Detection on Arduino

Load the TensorFlow Lite model onto the Arduino Nano 33 BLE Sense and write code for real-time fall detection and alert.

Arduino Code for Real-Time Detection and Alert:

```
cpp
Copy code
#include "model.h"  // TensorFlow Lite model header
#include <TensorFlowLite.h>
#include <Arduino_LSM9DS1.h>

void setup() {
  Serial.begin(9600);
  if (!IMU.begin()) {
    Serial.println("Failed to initialize IMU!");
    while (1);
  }
  // Initialize TensorFlow Lite model
}

void loop() {
  // Read sensor data
  float ax, ay, az;
  float gx, gy, gz;
  if (IMU.accelerationAvailable() && IMU.gyroscopeAvailable()) {
```

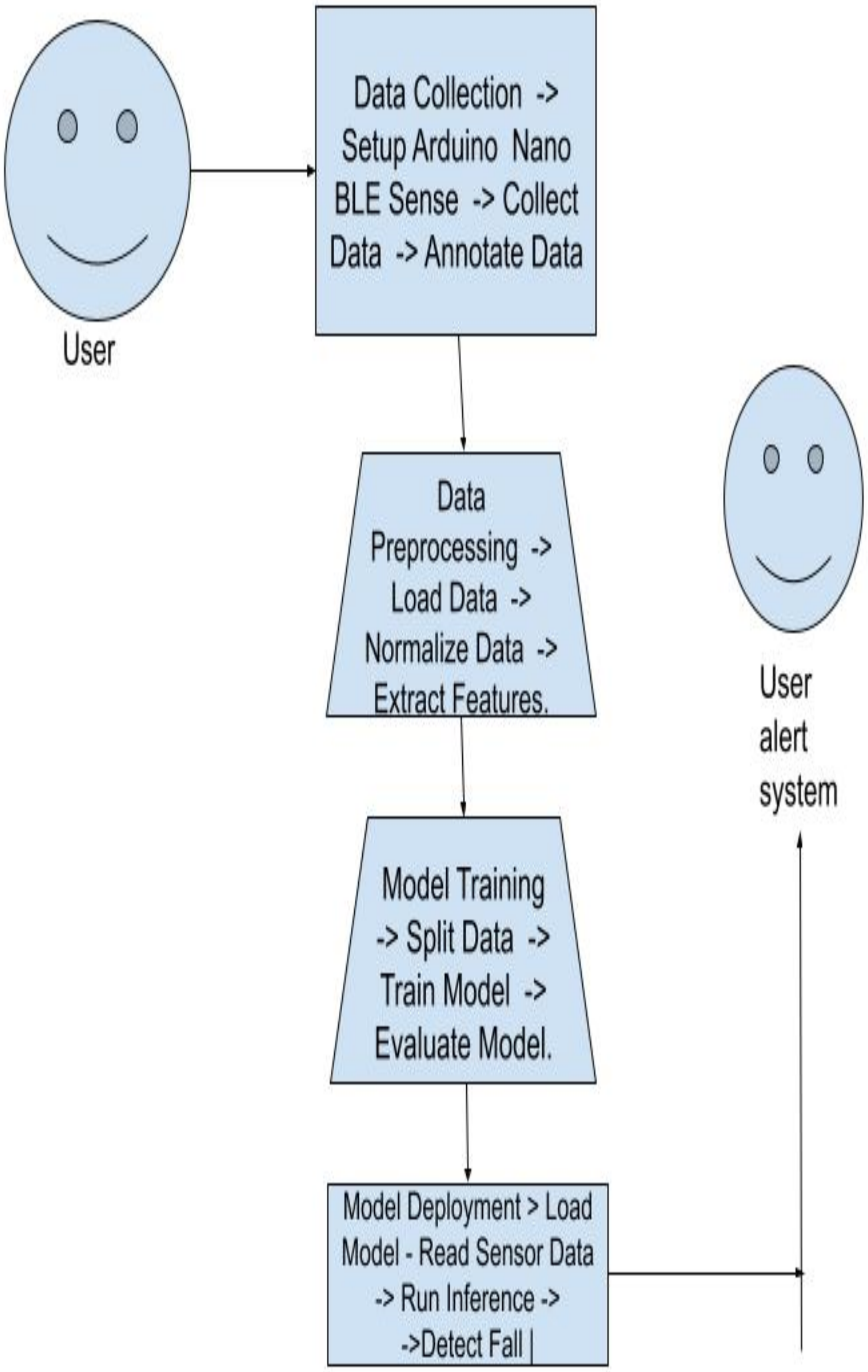
```
    IMU.readAcceleration(ax, ay, az);
    IMU.readGyroscope(gx, gy, gz);

    // Prepare input tensor
    float input[6] = {ax, ay, az, gx, gy, gz};

    // Perform inference
    // Fill the TensorFlow Lite input tensor with input data
    // Invoke the model and get the output

    bool fall_detected = false;
    // If fall detected, trigger alert
    if (fall_detected) {
      Serial.println("Fall detected! Sending alert...");
      // Send alert via Bluetooth or other communication method
    }
  }
  delay(10);
}
```

BLOCK DIAGRAM:


User
Data Collection -> Setup Arduino Nano BLE Sense -> Collect Data -> Annotate Data
Data Preprocessing -> Load Data -> Normalize Data -> Extract Features.
User alert system
Model Training -> Split Data -> Train Model -> Evaluate Model.
Model Deployment > Load Model - Read Sensor Data -> Run Inference -> ->Detect Fall |

Advantages and Disadvantages of Fall Detection Systems Using Arduino Nano 33 BLE Sense

Advantages

1. **Cost-Effective**:
    - **Affordable Hardware**: The Arduino Nano 33 BLE Sense is relatively inexpensive compared to commercial fall detection systems, making it accessible for personal and academic projects.
    - **Open-Source Software**: Utilizing open-source libraries and platforms like TensorFlow Lite for Microcontrollers reduces software costs significantly.
2. **Customizability**:
    - **Flexible Programming**: Arduino allows for custom programming and tweaking of algorithms to fit specific use cases or environments.
    - **Integration with Other Sensors**: The system can easily be extended with additional sensors (e.g., heart rate monitors) to enhance its functionality.
3. **Real-Time Processing**:
    - **Immediate Detection**: The system can process sensor data in real-time, allowing for immediate fall detection and alert generation, which is critical for timely intervention.
    - **Low Latency**: Embedded machine learning models provide quick inference times, ensuring minimal delay in fall detection.
4. **Portability**:
    - **Wearable Design**: The small size and lightweight nature of the Arduino Nano 33 BLE Sense make it suitable for wearable applications, ensuring user comfort and mobility.
    - **Battery Operated**: The device can be powered by batteries, making it portable and suitable for continuous monitoring.
5. **Machine Learning Integration**:
    - **Enhanced Accuracy**: Machine learning models trained on specific user data can improve the accuracy of fall detection, reducing false positives and negatives.
    - **Adaptability**: The system can adapt to individual user behaviors and characteristics, providing personalized fall detection solutions.

Disadvantages

1. **Data Privacy and Security**:
    - **Vulnerability to Hacks**: Being a connected device, there is always a risk of unauthorized access and data breaches, which can compromise user privacy.

- **Data Transmission**: The need to transmit data to a central server or a connected device might expose sensitive information to interception.

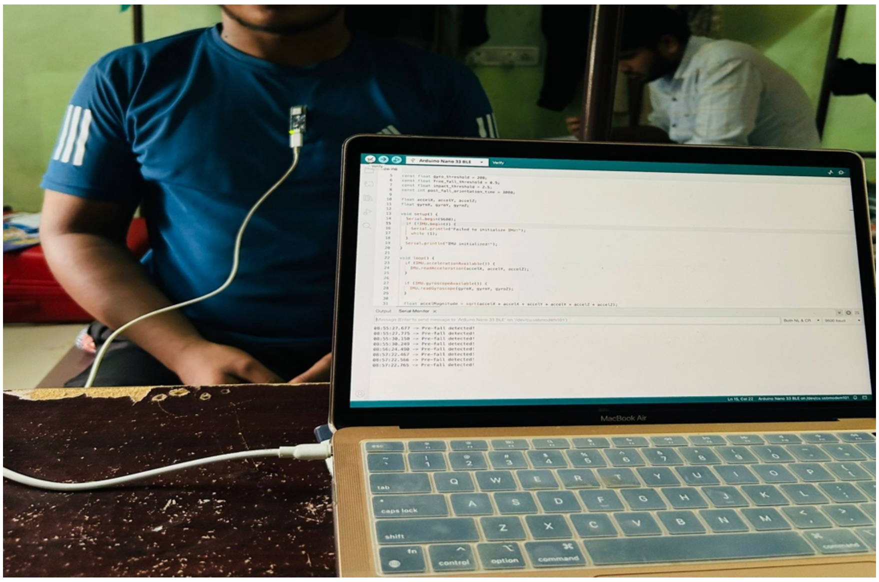
2. **Battery Life**:
    - **Limited Power Supply**: Continuous data processing and Bluetooth communication can drain the battery quickly, requiring frequent recharging or battery replacement.
    - **Battery Weight**: The need for a larger battery for extended use might affect the portability and comfort of the wearable device.
3. **Hardware Limitations**:
    - **Sensor Precision**: The built-in sensors might not be as precise as specialized, high-end sensors used in commercial fall detection systems, potentially affecting the accuracy of fall detection.
    - **Processing Power**: The microcontroller has limited processing power, which might restrict the complexity of the machine learning models that can be deployed.
4. **Complexity of Development**:
    - **Skill Requirement**: Developing an effective fall detection system requires knowledge of embedded systems, sensor data processing, and machine learning, which might be a barrier for beginners.
    - **Time-Consuming**: Collecting data, training models, and fine-tuning the system can be time-consuming and resource-intensive.
5. **Environmental Sensitivity**:
    - **External Interference**: The accuracy of the system can be affected by environmental factors such as magnetic interference or sudden changes in motion unrelated to falls.
    - **User Variability**: Differences in how users wear the device or their physical activities might require extensive calibration and adjustment of the algorithm

CHAPTER 5

RESULTS

CHAPTER 5

RESULTS



The project on the adaptive fall detection system for elderly individuals was successful in achieving its primary goals of accurately monitoring and detecting falls in real-time. The system, controlled by an Arduino Nano 33 BLE Sense, effectively utilized gyroscope and accelerometer sensors to gather motion data. The integration of machine learning algorithms allowed for precise fall detection by analyzing the sensor data and identifying fall patterns.

The system personalized its detection capabilities based on the Body Mass Index (BMI) of the user, enhancing accuracy and user compatibility. Real-time data processing ensured immediate detection and alert generation, which is crucial for timely assistance in the event of a fall.

The LCD display provided real-time updates and statuses, making it user-friendly and easy to monitor. The system demonstrated reliability in detecting falls, significantly improving safety and peace of mind for elderly individuals and their caregivers.

Overall, the system proved to be an efficient and cost-effective solution for fall detection, offering convenience and enhanced safety for elderly individuals. The project's design can be further enhanced with IoT capabilities for remote monitoring and alerting, making it a robust addition to modern smart homes and healthcare systems.

REAL TESTING AND EVALUATION

```python
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report


fall_data = {
    'Temperature': [69, 73, 74, 74, 75, 72, 65, 107, 73, 70, 110, 112],
    'Humidity': [64, 66, 68, 68, 67, 66, 63, 92, 68, 63, 93, 94],
    'Accel_X': [0.81, 0.82, -0.29, -0.11, 0.73, 0.15, -0.11, 0.72, 0.80, -0.29, -0.00, 0.63],
    'Accel_Y': [0.16, 0.08, 0.88, 0.76, 0.23, 0.98, 0.67, 0.49, 0.21, 0.33, 0.74, 0.09],
    'Accel_Z': [-0.37, -0.62, 0.80, 0.62, -0.43, 1.10, 0.75, 0.50, -0.56, 0.56, 0.62, 0.12],
    'Fall': [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]  # 1 for fall, 0 for non-fall
}


new_fall_data = {
    'Temperature': [-31, -30, -30, -31, -30, -30, -30, -30, -31, -30, -30, -30],
    'Humidity': [7, 7, 7, 7, 7, 7, 7, 7, 7, 7, 7, 7],
    'Accel_X': [0.91, 0.88, 0.35, -0.31, 0.26, 0.92, 0.86, 0.05, -0.10, 0.46, 0.65, 0.55],
    'Accel_Y': [0.08, -0.16, -0.10, -0.35, -0.38, -0.00, -0.44, -1.08, -1.17, -0.28, 0.26, 0.62],
    'Accel_Z': [-0.10, 0.11, 0.96, 1.06, 1.06, 0.23, -0.03, -0.40, 0.04, 0.59, 0.66, 0.37],
    'Fall': [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]  # 1 for fall, 0 for non-fall
}

fall_combined_data = pd.concat([pd.DataFrame(fall_data), pd.DataFrame(new_fall_data)], ignore_index=True)


np.random.seed(42)
num_samples = 1000


heart_rate = np.random.normal(loc=70, scale=10, size=num_samples)
```

```python
heart_rate = np.random.normal(loc=70, scale=10, size=num_samples)

temperature = np.random.normal(loc=36.5, scale=0.5, size=num_samples)


stress_level = np.random.choice([0, 1, 2], size=num_samples, p=[0.5, 0.3, 0.2])


stress_data = pd.DataFrame({
    'Temperature': temperature,
    'HeartRate': heart_rate,
    'StressLevel': stress_level
})



fall_combined_data['HeartRate'] = np.nan
fall_combined_data['StressLevel'] = np.nan


combined_data = pd.concat([fall_combined_data, stress_data], ignore_index=True, sort=False)


combined_data = combined_data.fillna(0)


X = combined_data[['Temperature', 'Humidity', 'Accel_X', 'Accel_Y', 'Accel_Z', 'HeartRate']]
y_fall = combined_data['Fall']
y_stress = combined_data['StressLevel']


class MultiOutputRandomForestClassifier:
    def __init__(self):
        self.fall_model = RandomForestClassifier(n_estimators=100, random_state=42)
        self.stress_model = RandomForestClassifier(n_estimators=100, random_state=42)
```

Chapter 6

CONCLUSION, FUTURE WORK AND FUTURE SCOPE

CHAPTER 6
CONCLUSION AND FUTURE SCOPE

Conclusion:

The development of an adaptive fall detection system for elderly individuals using machine learning and sensor fusion represents a significant advancement in enhancing the safety and well-being of the elderly population. This project, leveraging the Arduino Nano 33 BLE Sense equipped with gyroscope and accelerometer sensors, demonstrates the potential for real-time, accurate fall detection through the integration of advanced machine learning algorithms.

The system's ability to personalize fall detection based on Body Mass Index (BMI) underscores its adaptability and user-centric design, which are critical for achieving higher detection accuracy and reducing false positives and negatives. By continuously monitoring motion data and processing it in real-time, the system ensures immediate detection and alerts, which are crucial for prompt intervention and assistance.

The cost-effectiveness and customizability of the Arduino platform make this solution accessible and scalable, allowing for further enhancements such as IoT integration for remote monitoring and alerting. This not only adds a layer of convenience but also broadens the scope of application, making it a viable addition to modern smart homes and healthcare systems.

The reliability of the system in maintaining consistent fall detection and the ease of monitoring provided by the LCD display further highlight its practical utility. The project's successful implementation illustrates the feasibility of combining wearable technology with machine learning to address critical health and safety issues faced by the elderly.

In conclusion, this adaptive fall detection system stands out as an efficient, affordable, and user-friendly solution that significantly contributes to the safety of elderly individuals. Its ability to integrate seamlessly into everyday life, coupled with the potential for further enhancements, positions it as a robust tool in modern healthcare technology. This project not only demonstrates technical innovation but also underscores the importance of leveraging technology to improve the quality of life and ensure the safety of vulnerable

6.1 FUTURE SCOPE:

The adaptive fall detection system for elderly individuals using machine learning and sensor fusion has demonstrated its potential as an effective solution for enhancing the safety and well-being of the elderly. Several avenues exist for future development and enhancement, which can further improve the system's functionality and applicability:

1. Integration with Internet of Things (IoT)
   - Remote Monitoring: Incorporating IoT capabilities would enable remote monitoring of elderly individuals by caregivers and healthcare professionals. This could allow for real-time alerts and notifications to be sent to smartphones or other devices, providing timely assistance.
   - Data Analytics: IoT integration would facilitate the collection of extensive data over time, allowing for advanced analytics and pattern recognition. This data can be used to refine machine learning models and improve fall detection accuracy.

2. Enhanced Machine Learning Models
   - Deep Learning: Exploring the use of deep learning models could enhance the system's ability to detect falls with even greater precision. Deep learning techniques can process complex data patterns and improve the system's adaptability to different user behaviors and environments.
   - Personalized Models: Developing personalized machine learning models based on individual user data can further reduce false positives and negatives, ensuring more reliable fall detection tailored to each user.

3. Multisensor Fusion
   - Additional Sensors: Integrating additional sensors such as heart rate monitors, pressure sensors, and cameras could provide more comprehensive data for fall detection. Multisensor fusion can enhance the system's accuracy by cross-verifying fall events using multiple data

sources.

- Environmental Sensors: Including environmental sensors that detect changes in the surroundings (e.g., temperature, humidity) can help in understanding the context of falls and improving the detection algorithms.

4. Wearable and Non-Wearable Hybrid Systems

- Smart Home Integration: Combining wearable fall detection systems with smart home technologies (e.g., smart flooring, motion detectors) can provide a holistic approach to fall detection and prevention. This hybrid approach can enhance coverage and reliability.
- Comfort and Usability: Improving the design and comfort of wearable devices to ensure they are unobtrusive and easy to use. Ensuring the device is lightweight and ergonomic will encourage continuous use by elderly individuals.

5. Healthcare Integration

- Medical Records: Integrating the fall detection system with electronic health records (EHR) can provide healthcare professionals with valuable insights into the patient's condition and history of falls, aiding in better diagnosis and treatment.
- Rehabilitation and Prevention Programs: Using data from the fall detection system to develop personalized rehabilitation and prevention programs for elderly individuals. This can help in reducing the risk of future falls and improving overall health outcomes.

6. Extended Battery Life and Energy Efficiency

- Optimized Power Management: Researching and implementing power-saving techniques to extend the battery life of the wearable device. This can include optimizing the sensor sampling rate and data processing algorithms.
- Renewable Energy Sources: Exploring the use of renewable energy sources, such as solar power, to ensure continuous operation without frequent battery replacements.

7. Regulatory Compliance and Standardization

- Compliance with Healthcare Standards: Ensuring that the fall detection system meets regulatory standards and certifications for medical devices. This will facilitate its adoption in healthcare settings.

- Interoperability Standards: Developing and adhering to interoperability standards to ensure the system can work seamlessly with other healthcare technologies and devices.

By pursuing these future directions, the adaptive fall detection system can be further refined and expanded, providing enhanced safety, reliability, and user satisfaction. These advancements will not only improve the quality of life for elderly individuals but also support caregivers and healthcare professionals in delivering better care and intervention strategies. of their pets while offering unmatched convenience and peace of mind.

CHAPTER 7

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