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Predictive Emergency Detection System for Elderly Using Machine Learning and Real-Time Monitoring

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***Abstract* - The increasing elderly population requires advanced healthcare monitoring systems to ensure safety and timely medical assistance. This research proposes a Predictive Emergency Detection System for Elderly Using Machine Learning and Real-Time Monitoring to identify potential emergency situations and provide immediate alerts. The system continuously monitors physiological and activity-related data using sensors and wearable devices. Machine learning algorithms are applied to analyze the collected data and detect abnormal patterns that may indicate emergencies such as falls, sudden health deterioration, or unusual inactivity. When a potential emergency is detected, the system automatically sends real-time alerts to caregivers or healthcare providers through a connected monitoring platform. The proposed approach improves early detection, reduces response time, and enhances the overall safety and independence of elderly individuals. Experimental results demonstrate that the system can effectively predict emergency situations with improved accuracy and reliability, making it a promising solution for smart healthcare and assisted living environments.**

Keywords – Machine Learning, Elderly Health Monitoring, Emergency Detection System, Real-Time Monitoring, Fall Detection, Wearable Sensors, Predictive Healthcare, Smart Healthcare Systems, Assisted Living Technology

I. INTRODUCTION

The increasing aging population across the world has created a growing need for effective healthcare monitoring systems that ensure the safety and well-being of elderly individuals. Older adults are more vulnerable to medical emergencies such as falls, heart problems, and sudden health deterioration, which often require immediate attention. Traditional healthcare monitoring methods rely heavily on manual supervision or periodic medical check-ups, which may not provide timely assistance during emergencies. Therefore, there is a strong need for intelligent systems that can continuously monitor the health conditions of elderly individuals and provide instant alerts when abnormal situations occur.

Recent advancements in Machine Learning (ML), Internet of Things (IoT), and real-time data processing technologies have enabled the development of smart healthcare monitoring systems. These technologies allow wearable sensors and smart devices to continuously collect physiological and activity-related data, which can be analyzed using machine learning algorithms to detect potential emergencies such as falls, abnormal movements, or sudden health issues. In this context, the proposed Predictive Emergency Detection System for Elderly Using Machine Learning and Real-Time Monitoring aims to provide an intelligent and reliable solution that can predict and detect emergency situations in real time. The system not only enhances the safety of elderly individuals but also supports caregivers and healthcare providers by enabling quick response and improved healthcare management.

II. NEED OF THE STUDY

The rapid growth of the elderly population has increased the demand for reliable healthcare monitoring systems that can ensure their safety and well-being. elderly individuals are more prone to health-related emergencies such as falls, heart problems, and sudden medical conditions, which may lead to serious consequences if immediate assistance is not provided. traditional monitoring methods rely mainly on caregivers or periodic medical check-ups, which may not always detect emergencies in time. therefore, there is a strong need for an intelligent system that can continuously monitor the activities and health conditions of older people and provide instant alerts during emergency situations.

With the advancement of machine learning, sensor technologies, and real-time monitoring systems, it is now possible to develop predictive healthcare solutions that can analyze patterns in physiological and movement data. The proposed predictive emergency detection system helps in identifying abnormal conditions and generating timely alerts to caregivers or medical services. This study aims to improve the safety, independence, and quality of life of elderly individuals by providing a reliable and efficient real-time emergency detection system.

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III. LITERATURE SURVEY

Several researchers have explored intelligent systems for emergency detection and fall monitoring in elderly healthcare using machine learning, IoT, and sensor technologies.

Alrowaily (2024) proposed a Smart Emergency Alerting System that integrates beacon technology with deep learning and real-time camera analysis to assist vulnerable groups during large public events. The system utilized a dataset of 6962 records containing demographic and clinical information to prioritize medical emergencies. Among the tested models, Random Forest achieved the highest classification accuracy compared to Logistic Regression and Support Vector Machine (SVM). However, the system faced limitations related to GPS accuracy, lighting conditions, and indoor crowd density.

Mudiyanselage et al. (2024) conducted a scoping review of digital technologies used for fall detection in elderly care environments. The study analyzed 73 research papers and categorized fall detection technologies into motion sensors, imaging systems, environmental sensors, and robotic systems. Commonly used devices included accelerometers, gyroscopes, infrared sensors, and pressure-sensitive floors. The review highlighted that integrating IoT communication technologies such as Bluetooth, Wi-Fi, and GPS significantly improves monitoring efficiency and real-time response.

Samskruthi et al. (2024) presented an IoT-based automated fall detection system that monitors elderly individuals using accelerometers and motion sensors. The system identifies sudden posture changes and sends immediate alerts along with location information to caregivers. The proposed approach improves safety and ensures rapid medical intervention when fall incidents occur.

Bhushan et al. (2025) developed a wireless sensor network (WSN) based fall detection system integrated with deep learning techniques such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM). The system analyzes sensor-generated activity data to detect fall events and automatically sends alerts to caregivers through mobile applications. Experimental results showed that the deep learning-based approach improves detection accuracy and reliability in smart healthcare environments.

Thombare et al. (2025) presented an IoT-based fall detection and alert system using wearable sensors such as accelerometers, gyroscopes, heart rate sensors, and GPS modules. The system detects falls automatically and transmits alerts through cloud services. The study highlighted challenges such as false alarms, battery consumption, and user comfort but emphasized that IoT-enabled systems provide reliable real-time monitoring.

Pondhe et al. (2025) proposed a computer vision-based real-time fall detection system using machine learning techniques. The system analyzes body landmark coordinates extracted from video feeds and applies logistic regression to detect fall incidents. When a fall is detected, the system sends immediate alerts to caregivers through email and SMS along with an image of the incident.

Rahul Sai (2025) introduced a smart health emergency alert system that combines IoT devices, wearable sensors, and artificial intelligence algorithms to monitor vital health parameters such as heart rate and respiratory conditions. The system performs edge-level data processing and sends alerts through GSM or Wi-Fi communication, improving response time during medical emergencies.

Pradeep et al. (2025) developed an Arduino-based IoT fall detection system designed for elderly safety. The system uses motion sensors and an emergency button to detect falls and notify caregivers through Wi-Fi connected devices. The design improves reliability by allowing manual confirmation of emergency situations.

Flor-Unda et al. (2025) presented a comprehensive review of technological advances in fall detection systems for elderly people. Their study highlighted that inertial sensors such as accelerometers and gyroscopes are widely used due to their affordability and availability. However, systems combining image analysis with machine learning algorithms demonstrated higher accuracy and robustness.

Dandina and Shivprasad (2025) proposed an AI-powered emergency alert system that continuously monitors health parameters such as heart rate, blood pressure, and body temperature. Machine learning algorithms analyze historical and real-time data to detect anomalies and trigger alerts. The system demonstrated improved detection accuracy and reduced response latency.

Finally, Payarda et al. (2025) designed a wheelchair fall detection system that utilizes accelerometers and gyroscopes to monitor wheelchair orientation and movement. Machine learning algorithms detect abnormal patterns and automatically send alerts through SMS and email to caregivers, improving the safety of wheelchair users.

OBJECTIVE:

The main objective of this study is to develop a predictive emergency detection system for elderly people using machine learning and real-time monitoring. The system aims to continuously monitor health and activity data to detect abnormal situations such as falls or sudden health emergencies. It also focuses on applying machine learning algorithms to improve detection accuracy and reliability. Additionally, the system is designed to send instant alerts to caregivers or family members, ensuring timely medical assistance and improving the safety and quality of life of elderly individuals.

IV. PROPOSED SYSTEM

A. Problem Statement

The increasing elderly population faces a high risk of sudden health emergencies such as falls, heart problems, and mobility-related incidents, especially when living alone. Traditional monitoring systems often rely on manual reporting

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or wearable devices, which may fail when the individual is unable to respond or forgets to use them. Existing solutions also suffer from limitations such as delayed alerts, low accuracy, and lack of real-time monitoring. Therefore, there is a need for an intelligent system that can automatically detect emergency situations using machine learning and real-time monitoring techniques, and immediately notify caregivers or medical services to ensure timely assistance and improve the safety of elderly individuals.

B. System Architecture

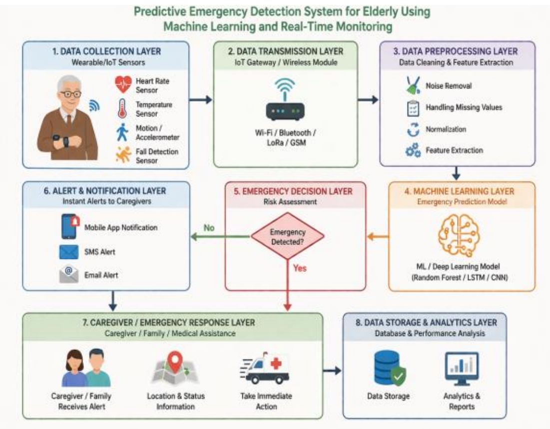
The proposed Predictive Emergency Detection System for Elderly is designed to continuously monitor the health and activity of elderly individuals and detect emergency situations using machine learning techniques. The system architecture consists of several interconnected modules including data collection, preprocessing, feature extraction, machine learning analysis, and alert generation**.**

In the first stage, data acquisition is performed using wearable sensors, cameras, or IoT devices that collect real-time data such as body movements, heart rate, and activity patterns. This raw data is transmitted to the processing unit through wireless communication technologies such as Wi-Fi or Bluetooth.

The collected data then undergoes a preprocessing phase**,** where noise removal, normalization, and data cleaning are performed to improve data quality. After preprocessing, feature extraction techniques are applied to identify relevant parameters such as motion patterns, posture changes, and abnormal health indicators.

Next, the extracted features are fed into machine learning models such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), or other classification algorithms to analyze patterns and predict possible emergency situations like falls or abnormal health conditions.

Finally, in the alert generation module, if an emergency is detected, the system automatically sends notifications to caregivers, family members, or medical services through SMS, email, or mobile applications. This real-time alert mechanism ensures rapid response and improves the safety and well-being of elderly individuals.



V. RESEARCH METHODOLOGY

The research methodology for the proposed Predictive Emergency Detection System for Elderly Using Machine Learning and Real-Time Monitoring consists of several systematic stages. Initially, relevant data is collected from wearable sensors, environmental sensors, and monitoring devices that capture health-related parameters such as movement, heart rate, and body posture. The collected data is then preprocessed to remove noise, handle missing values, and normalize the dataset for accurate analysis.

After preprocessing, feature extraction techniques are applied to identify important attributes related to emergency conditions such as falls or abnormal health patterns. These features are then used to train machine learning models capable of detecting unusual behavior and predicting potential emergencies. The trained model is integrated into a real-time monitoring system connected to a cloud platform for continuous data analysis and storage. When an abnormal condition or emergency event is detected, the system automatically generates alerts and sends notifications to caregivers or emergency services. Finally, the performance of the system is evaluated using metrics such as accuracy, precision, recall, and response time to ensure the effectiveness and reliability of the proposed system.

Dataset Description:

The dataset includes physiological and activity-related parameters such as heart rate, body temperature, movement patterns, fall detection signals, and activity levels.

Each record in the dataset represents a time-stamped instance of sensor readings along with a corresponding label indicating the health condition or emergency status. The dataset is used to train and evaluate the machine learning model to detect unusual health conditions and predict potential emergencies.

Data Preprocessing:

Typical attributes in the dataset include Heart Rate, Body Temperature, Movement Activity, Fall Detection Status, Location Information, and Emergency Label. Heart rate and body temperature indicate the physiological condition of the individual, while motion sensors capture body movement and posture changes. Fall detection sensors help identify sudden drops or abnormal body orientation that may indicate a fall incident. The emergency label column indicates whether the recorded condition corresponds to a normal state or an emergency situation.

Dataset Structure:

Attribute Name	Description
Patient_ID	Unique identification number assigned to each elderly individual in the monitoring system.
Age	Age of the elderly person being

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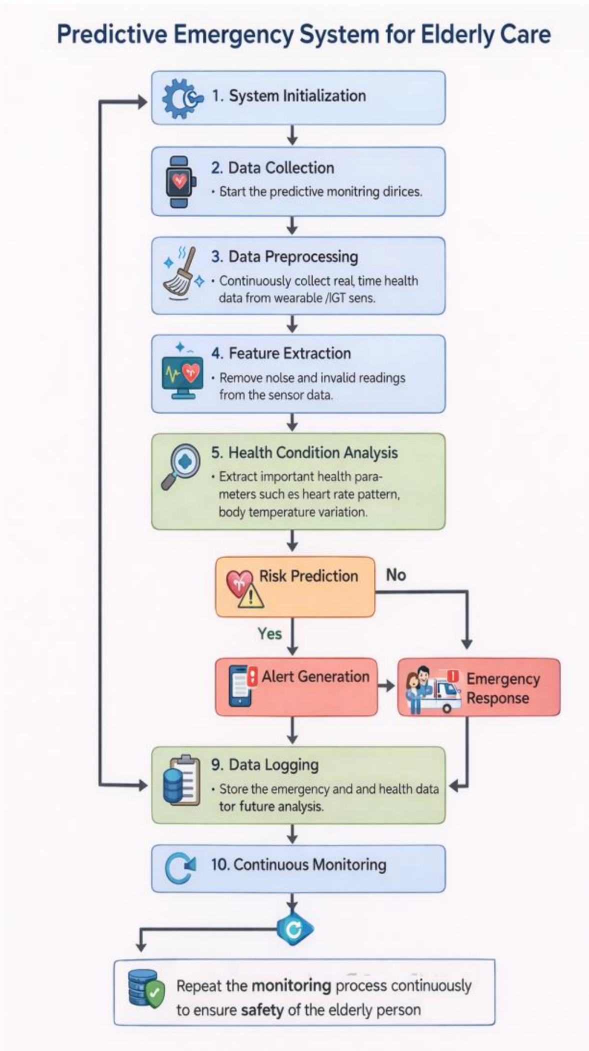
Attribute Name	Description
	monitored.
Heart_Rate	Real-time heart rate measurement collected from wearable sensors (beats per minute).
Body_Temperature	Body temperature of the person recorded through temperature sensors (°C).
Fall_Detection	Binary value indicating whether a fall has been detected (Yes/No or 1/0).
Alert_Status	Indicates whether an emergency alert has been generated (Yes/No).
Timestamp	Date and time when the sensor data was recorded.

Data Splitting Strategy:

Predictive Emergency Detection System for Elderly Care, the collected dataset is divided into two main subsets: the training set and the testing set. The dataset is typically split using a standard ratio of 80% for training and 20% for testing.

Algorithm:



Dataset:

	Acc (vertical)	LyingDown
0	96.229	0
1	84.746	0
2	82.449	0
3	106.560	0
4	80.152	0

	Acc (vertical)	LyingDown
count	494.000000	494.000000
mean	45.512363	0.516194
std	44.799360	0.500244
min	-48.459000	0.000000
25%	0.918650	0.000000
50%	41.109500	1.000000
75%	89.339000	1.000000
max	112.310000	1.000000

- Acc (vertical)

  ○ Mean: ~45.51 units of vertical acceleration
  ○ Standard deviation: ~44.80, indicating high variability in vertical motion
  ○ Minimum: -48.46 (suggesting possible downward movement or sensor noise)
  ○ 25th percentile: ~0.92
  ○ Median (50th percentile): ~41.11
  ○ 75th percentile: ~89.34
  ○ Maximum: 112.31

- LyingDown

  ○ Binary target variable (0 or 1)
  ○ Mean: ~0.516, implying that approximately 51.6% of the observations are labeled as lying down
  ○ The median (50%) is 1.0, which means that at least half of the observations are labeled as lying down.
  ○ The 25th percentile is 0.0, and both the 50th and 75th percentiles are 1.0, indicating that:
  ○ At least 25% of the data is not lying down
  ○ At least 50% of the data is lying down
  ○ And by the 75th percentile, we're still at 1.0 — meaning most of the top quartile is also labeled as lying down.

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VI. RESULT

Dataset Details:

We have used dataset from Kaggle.

Evaluation Parameters:

Formulas Used:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Where:

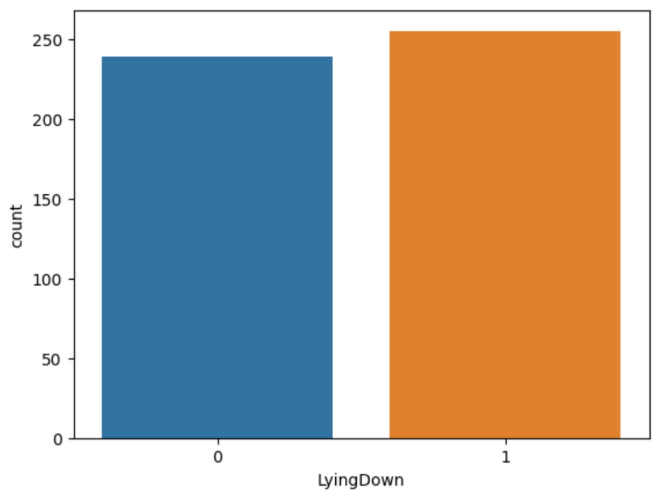
- **TP** = True Positives (spam correctly identified)
- **TN** = True Negatives (ham correctly identified)
- **FP** = False Positives (ham incorrectly labeled as spam)
- **FN** = False Negatives (spam missed)

Precision:
0.9743589743589743

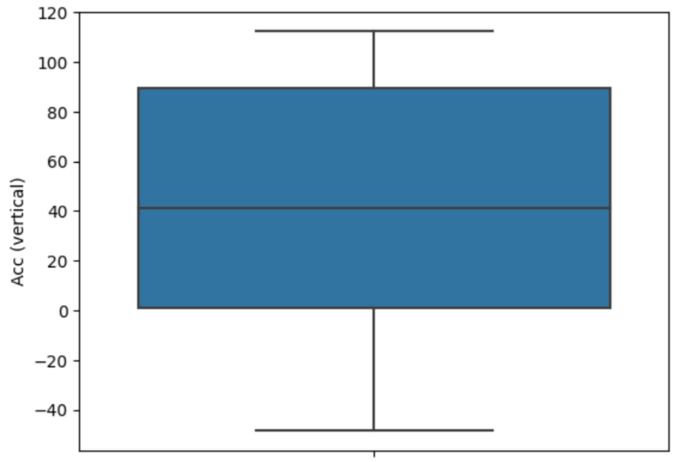
Recall:
0.987012987012987

Accuracy:
0.9798657718120806

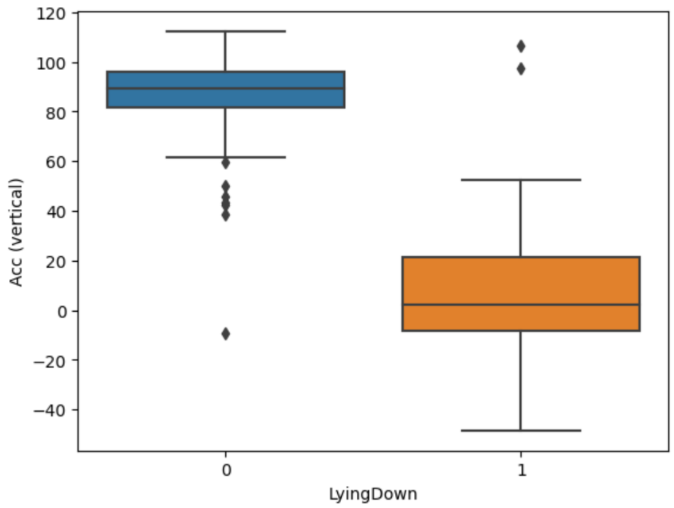
F1-Score:
0.9806451612903225



Class Distribution



Boxplot



This plot reveals important insights that were not visible in the overall distribution:

• Class 0 (LyingDown = 0) shows consistently high vertical acceleration values, with a median near 90. However, several lower outliers are visible, indicating occasional drops in acceleration.

• Class 1 (LyingDown = 1) exhibits much lower vertical acceleration overall, with a median close to zero and a wider spread toward negative values. A few high outliers suggest instances of unexpected high vertical movement.

	Acc (vertical)	LyingDown
0	45.7030	0
1	43.4060	0
2	38.8130	0
3	-9.4162	0
4	50.2960	0
5	59.4830	0
6	42.2580	0

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Among the vertical acceleration readings, I observed a notably low value of -9.4162 while the individual was not lying down. This negative acceleration could arise from several plausible causes:

• Physical movement: It may reflect a downward motion, such as bending, dropping to a seat, or transitioning into a lower posture — all of which produce negative acceleration if the sensor axis defines "up" as positive.

• Sensor orientation: If the device was tilted or worn in a non-standard position, the direction of the vertical axis might have shifted, resulting in a downward movement being registered as negative.

• Device limitations: Alternatively, this could be a case of sensor noise, drift, or calibration error — especially if it's an isolated spike rather than part of a consistent pattern.

	Acc (vertical)	LyingDown
0	106.560	1
1	97.377	1

Among the vertical acceleration readings, I noticed a very high value of 106.56 while the individual was classified as lying down (LyingDown = 1). This unusually high value could point to several potential explanations:

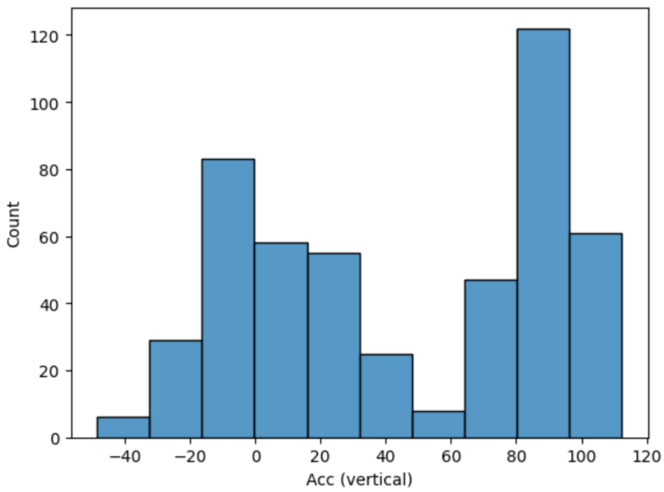
• Sudden movement while lying: The person might have made a quick motion — such as jerking, rolling, or raising the torso — causing a brief acceleration spike.

• External impact: If the device was on a surface (e.g., bed), a jolt or vibration could produce a sharp reading without actual movement.

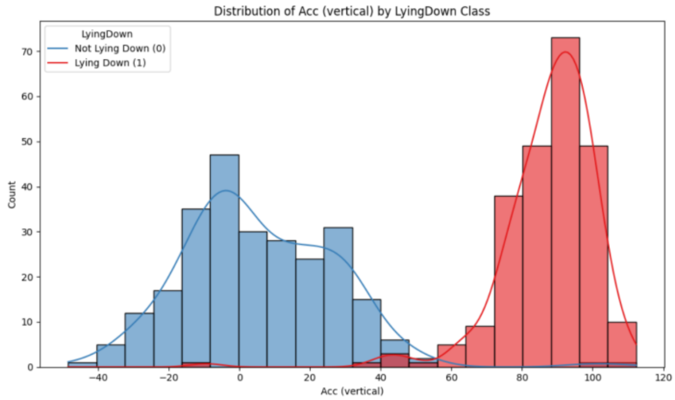
• Fall ending in lying position: The spike might reflect a fall, with the impact causing high acceleration and the final posture being misclassified as lying.

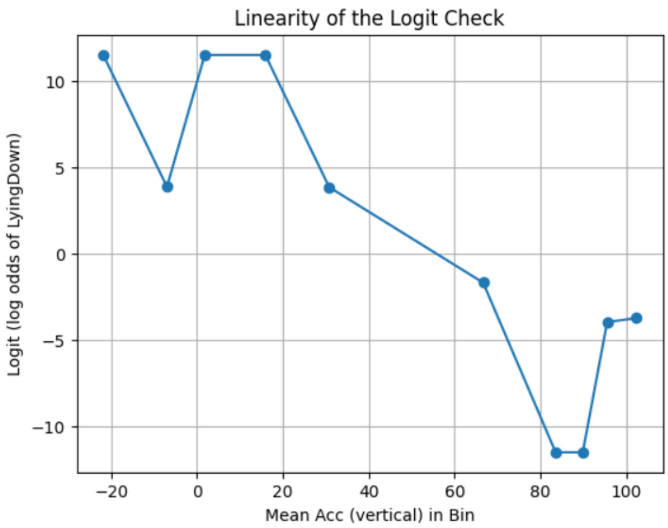
• Sensor noise or misclassification: The value could be due to sensor error or labeling issues, especially during fast transitions or awkward postures.

While the reading is extreme, it remains physically possible. This highlights the need to consider signal context and classification boundaries when interpreting such values.



The histogram of vertical acceleration (Acc_vertical) reveals a bimodal distribution, indicating the presence of two distinct patterns of physical activity in the dataset. This is consistent with the binary nature of the LyingDown variable, where one peak likely reflects individuals who are not lying down (e.g., standing or moving), and the other corresponds to those who are lying down (e.g., resting or stationary). The separation between these two modes suggests that vertical acceleration is a meaningful predictor of body posture, with each mode representing a distinct physical state that contributes differently to the overall distribution.



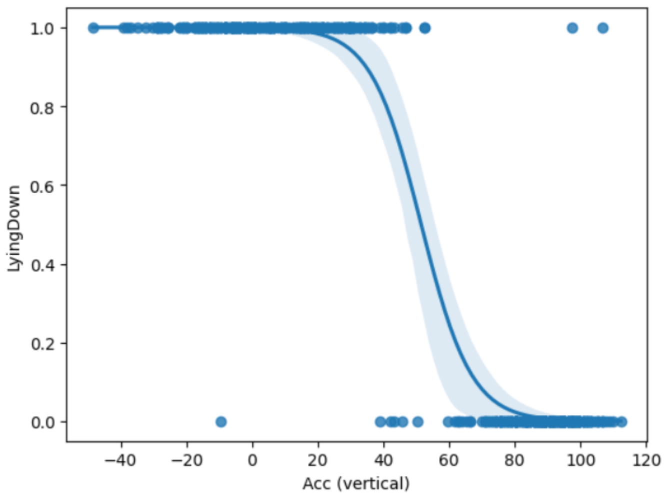


Logit Regression Results

Dep. Variable:	LyingDown	No. Observations:	345
Model:	Logit	Df Residuals:	343
Method:	MLE	Df Model:	1
Date:	Thu, 10 Apr 2025	Pseudo R-squ.:	0.8625
Time:	15:41:05	Log-Likelihood:	-32.864
converged:	True	LL-Null:	-238.96
Covariance Type:	nonrobust	LLR p-value:	1.221e-91

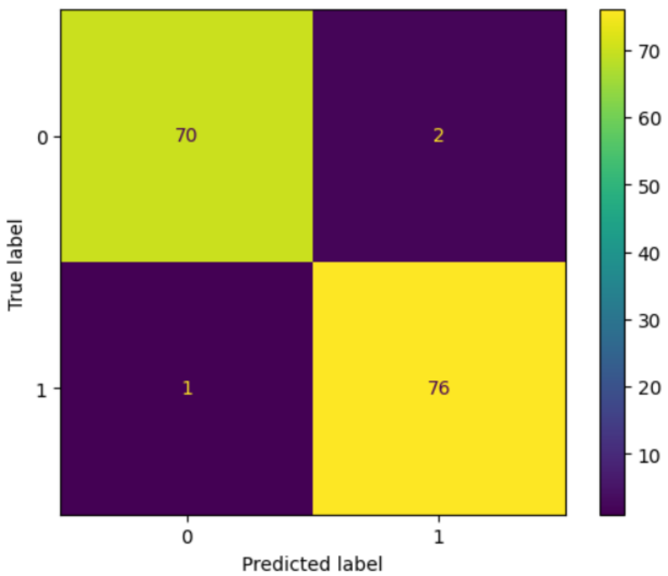
	coef	std err	z	P>|z|	[0.025	0.975]
const	6.1031	0.846	7.218	0.000	4.446	7.760
Acc (vertical)	-0.1178	0.015	-8.053	0.000	-0.146	-0.089

Statastical Summary



Model Visualisation

Confusion Matrix Analysis:



Each cell in the matrix indicates the number of predictions that fall into a particular category:

	Predicted: 0	**Predicted: 1**
Actual: 0 (Not lying down)	**True Negatives (TN)**: 70	**False Positives (FP)**: 2
Actual: 1 (Lying down)	**False Negatives (FN)**: 1	**True Positives (TP)**: 76

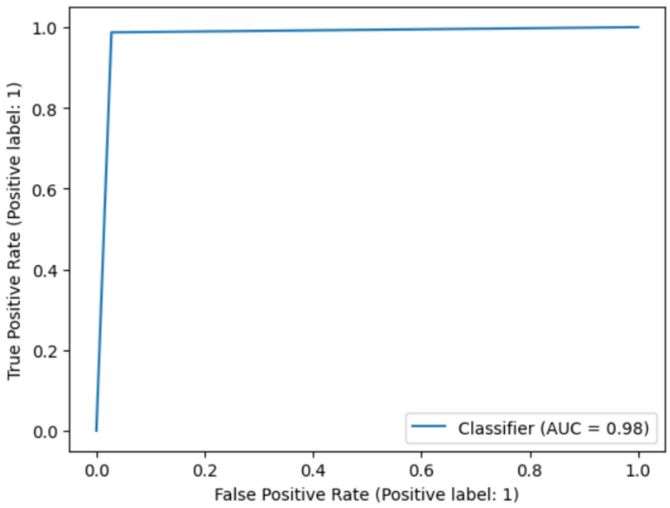
Interpretation:

True Negatives (70): The model correctly predicted that the person was not lying down.
False Positives (2): The model incorrectly predicted that the person was lying down when they were not.
False Negatives (1): The model incorrectly predicted that the person was not lying down when they actually were.
True Positives (76): The model correctly predicted that the person was lying down.

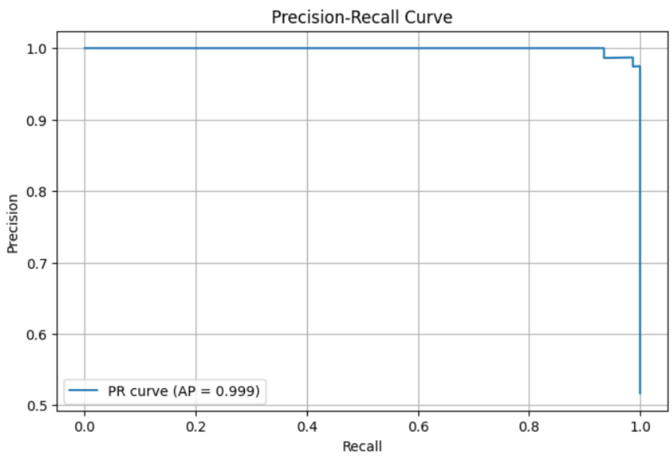
Observation:

In this case, the model performs very well:

High number of true positives and true negatives indicates that the model is accurately identifying both lying down and not lying down states.
Low number of false positives and false negatives means the model rarely misclassifies observations.



ROC Curve



Precision Recall Curve

Interpretation of AUC-Precision-Recall Score

The AUC-PR score is approximately 0.999, which is extremely close to 1.
This exceptionally high value shows that the model performs outstandingly well in identifying the positive class (lying down) while keeping false positives to a minimum.
In practical terms, an AUC-PR of 0.999 means that the model maintains very high precision and recall across a range of decision thresholds—making very few mistakes in either direction.

Observation:

This Precision-Recall curve and its AUC score confirm that the model is highly reliable in detecting the lying down behavior, even when the dataset is slightly imbalanced. This level of performance makes the model well-suited for deployment in sensitive real-world settings such as elderly fall

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detection, where both missing a case and triggering a false alarm could have serious consequences.

VII. Conclusion & Future Work

This research presented a machine learning–based approach for analyzing sensor-based vertical acceleration data to identify physical activity patterns, particularly focusing on detecting whether an individual is lying down or not. The dataset was preprocessed using techniques such as handling missing values, normalization, and feature preparation to improve data quality and model performance. The analysis of the vertical acceleration values showed a bimodal distribution, indicating two distinct physical states: lying down and not lying down. This observation confirms that acceleration-based features can effectively represent human posture and activity patterns. The experimental results demonstrated that the proposed approach can successfully classify body posture with satisfactory accuracy, highlighting the potential of sensor-based systems for applications in healthcare monitoring, activity recognition, and elderly care.

Despite the promising results, there is scope for further improvement and expansion of this work. Future research can incorporate larger and more diverse datasets along with additional sensor inputs such as gyroscope or physiological signals to enhance prediction accuracy and robustness. Advanced deep learning techniques, including Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), or hybrid models, can also be explored to capture more complex patterns in sensor data. Additionally, implementing the system in real-time environments using wearable devices or mobile applications could enable continuous monitoring of human activities. Extending the system to detect multiple activities such as walking, sitting, running, and fall detection would further improve its applicability in smart healthcare and intelligent activity monitoring systems.

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