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AI-Acoustic Guard: Real-Time Human Fall Detection using TinyML and Edge Computing

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Abstract- Falls are a leading cause of injury, particularly among elderly individuals and vulnerable populations, necessitating efficient and real-time monitoring solutions. This paper presents AI-Acoustic Guard, a novel human fall detection system leveraging TinyML and edge computing for low-latency, privacy-preserving operation. Unlike conventional vision-based approaches, the proposed system utilizes acoustic signals captured through low-power microphones to identify characteristic sound patterns associated with human falls. A lightweight deep learning model is trained and optimized using TinyML techniques, enabling deployment on resource-constrained edge devices such as microcontrollers. The system processes audio data locally, eliminating the need for continuous cloud connectivity and ensuring data security. Feature extraction methods, including Mel-frequency cepstral coefficients (MFCCs), are employed to enhance classification accuracy. Experimental results demonstrate high detection accuracy, low false alarm rates, and minimal power consumption. The proposed approach is cost-effective, scalable, and suitable for real-world applications such as smart homes, assisted living facilities, and healthcare monitoring systems, offering a reliable solution for timely fall detection and emergency response.

Keywords— TinyML, Edge Computing, Fall Detection, Acoustic Signal Processing, Human Activity Recognition, IoT, Real-Time Monitoring, MFCC, Embedded Systems, Smart Healthcare.

I. INTRODUCTION

Falls are a major global health issue, especially among older adults, individuals with physical impairments, and patients in recovery. They are a leading cause of injuries, often resulting in serious health complications, reduced quality of life, and increased healthcare costs. Immediate detection of falls is critical, as delays in providing assistance can worsen the condition and, in severe cases, lead to fatal consequences. This has driven significant research efforts toward developing efficient and reliable fall detection systems.

Conventional fall detection methods largely depend on wearable devices equipped with sensors like accelerometers and gyroscopes. Although these devices can capture precise motion data, their effectiveness is often limited by user compliance. Many individuals may forget to wear them or find them uncomfortable for continuous use. Alternatively, camera-based systems using computer vision techniques have been proposed, but they introduce privacy concerns and are sensitive to environmental factors such as lighting conditions and camera positioning. These drawbacks emphasize the need for a more user-friendly and non-intrusive solution.

Acoustic sensing has emerged as a viable alternative for fall detection. Falls typically generate unique sound signatures, including sudden impacts and unusual disturbances, which can be detected through microphones. Compared to visual systems, audio-based approaches are less intrusive and operate effectively regardless of lighting conditions. However, continuously analyzing audio signals in real time can be computationally demanding and may require efficient processing strategies to minimize latency and energy usage.

To overcome these limitations, this study proposes AI-Acoustic Guard, an innovative fall detection system that combines TinyML with edge computing. TinyML enables the deployment of compact machine learning models on low-power devices such as microcontrollers, making real-time inference feasible even with limited resources. Edge computing allows data processing to occur locally on the device, reducing dependency on cloud services, lowering latency, and enhancing data privacy.

The system utilizes advanced audio feature extraction methods, particularly Mel-frequency cepstral coefficients (MFCCs), to effectively represent fall-related sound patterns. A lightweight neural network is trained and optimized for embedded deployment, ensuring both high accuracy and efficiency. By integrating acoustic analysis with edge-based intelligence, the proposed solution offers a scalable, cost-effective, and privacy-conscious approach to fall detection, supporting applications in smart homes, healthcare monitoring, and assisted living environments.

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II. RELATED WORKS

TinyFallNet: A Lightweight Pre-Impact Fall Detection Model
Authors: Bummo Koo, Xiaoqun Yu, Seunghee Lee, Sumin Yang, Dongkwon Kim, Shuping Xiong, Youngho Kim proposes TinyFallNet, a lightweight deep learning model designed for pre-impact fall detection using wearable sensor data. The model combines convolutional and LSTM layers to capture both spatial and temporal features of human motion. It is specifically optimized for deployment on microcontroller units, making it suitable for TinyML applications. The study highlights the importance of reducing computational complexity while maintaining high accuracy. Experimental results show strong performance across datasets, emphasizing its potential for real-time fall detection in embedded systems and healthcare monitoring environments.

TinyML-Based Fall Detection for Connected Personal Mobility Vehicles Ramon Sanchez-Iborra, Luis Bernal-Escobedo, Jose Santa, Antonio Skarmet introduces a TinyML-based fall detection system integrated into personal mobility vehicles. The system uses onboard sensors and embedded machine learning models to detect accidents in real time. It addresses the constraints of low-power devices by optimizing model size, memory usage, and execution time. A dataset of real and simulated falls was used for training and validation. The results demonstrate efficient fall detection with minimal latency and energy consumption, making it suitable for IoT-enabled transportation and smart safety systems.

SAFE: Sound Analysis for Fall Event Detection Using Machine Learning Authors: Antony Garcia, Xinming Huang focuses on acoustic-based fall detection using machine learning and deep learning models. The SAFE dataset, containing 950 audio samples, is used to evaluate different algorithms. Spectrogram-based features and audio signal processing techniques are applied to classify fall events. Deep learning models achieved up to 99% accuracy, outperforming traditional machine learning approaches. The research demonstrates the effectiveness of sound as a non-intrusive sensing modality and highlights its potential for real-time fall detection in smart environments without relying on cameras or wearable devices.

TinyML-Driven Sensor Nodes for Energy-Efficient Acoustic Event Detection in Pervasive Acoustic WSNs
Authors: Bibek B. Roy, Sushovan Das, Uttam Kr. Mondal
presents an energy-efficient acoustic event detection framework using TinyML in wireless sensor networks. The system filters relevant acoustic signals locally, reducing unnecessary data transmission and conserving energy. It demonstrates how TinyML enables real-time processing of sound events on low-power devices. Although not limited to fall detection, the methodology is highly applicable to acoustic fall detection systems. The study emphasizes scalability, reduced communication overhead, and improved battery life, making it suitable for large-scale smart monitoring applications.

Fall Detection Systems Supported by TinyML and Accelerometer Sensors

Authors: Yeliz Durgun explores the integration of TinyML with accelerometer-based fall detection systems for elderly care. It focuses on improving quality of life through real-time monitoring using embedded devices. The study discusses system design, sensor data acquisition, and model deployment on constrained hardware. It highlights the benefits of TinyML in reducing latency and ensuring privacy by processing data locally. The proposed approach demonstrates reliable detection performance and emphasizes the feasibility of implementing cost-effective, wearable fall detection solutions.

A Review of Fall Detection Research Based on Deep Learning

Authors: Ruisheng Liprovides a comprehensive overview of fall detection techniques using deep learning. It categorizes methods into vision-based and non-vision-based approaches, including wearable sensors and acoustic systems. The paper discusses datasets, algorithms, and evaluation metrics used in recent studies. It highlights the advantages of deep learning in automatic feature extraction and improved detection accuracy. Additionally, it identifies challenges such as data scarcity, privacy concerns, and real-world deployment issues, offering insights into future research directions.

Fall: Fall Detection using 4D MmWave Radar and a Hybrid Variational RNN AutoEncoder

Authors: Feng Jin, Arindam Sengupta, Siyang Cao introduces a radar-based fall detection system using 4D mmWave sensors and a hybrid variational recurrent autoencoder. The model detects anomalies in human motion patterns and identifies falls without requiring labeled fall data. The approach enhances privacy compared to camera-based systems and provides high detection accuracy. The system achieved approximately 98% detection rate with minimal false alarms. This work highlights the potential of non-intrusive sensing technologies combined with deep learning for robust fall detection applications.

SiFall: Practical Online Fall Detection with RF Sensing

Authors: Sijie Ji, Yaxiong Xie, Mo Li proposes an RF-based fall detection system using WiFi channel state information (CSI). Instead of directly detecting falls, the system learns normal human activities and identifies deviations as anomalies. A self-supervised learning framework is used to improve adaptability and robustness. The approach offers privacy-preserving monitoring without requiring wearable devices. Experimental results demonstrate reliable real-time detection across multiple subjects, making it suitable for smart home and healthcare environments.

Based Human Fall Detection Systems Using Deep Learning: A Review

Authors: Ekram Alam, Abu Sufian, Paramartha Dutta, Marco Leo

reviews vision-based fall detection systems that use deep learning techniques. It discusses convolutional neural networks, pose estimation, and video-based activity recognition methods. The study evaluates performance metrics and available datasets while highlighting limitations such as privacy concerns and sensitivity to environmental conditions. It also explores future directions, including hybrid approaches that combine multiple sensing modalities. The paper serves as a benchmark for comparing vision-based systems with alternative methods like acoustic and TinyML-based solutions.

Review of Fall Detection Techniques: A Data Availability Perspective

Authors: Shehroz S. Khan, Jesse Hoeyexamines fall detection methods from the perspective of data availability. It categorizes approaches based on supervised, semi-supervised, and unsupervised learning techniques. The authors highlight the challenge of limited fall data and propose treating falls as anomalies rather than standard classification problems. The study emphasizes the importance of robust datasets and adaptive models for real-world applications. It provides valuable insights into designing efficient fall detection systems, particularly in scenarios where labeled data is scarce.

III. PROPOSED METHOD

The proposed framework, AI-Acoustic Guard, is a real-time fall detection system that utilizes TinyML and edge computing to deliver an efficient, non-intrusive, and privacy-focused solution. Instead of relying on cameras or wearable sensors, the system is designed to detect human falls through acoustic signals. It consists of four key components: sound acquisition, signal preprocessing and feature extraction, TinyML-based classification, and alert notification.

The system begins with the audio acquisition module, where low-power microphones embedded in an edge device continuously capture ambient sounds. These microphones are capable of detecting distinctive audio cues associated with falls, such as sudden impacts or unusual disturbances. This approach eliminates the need for users to wear devices and avoids the privacy issues linked with vision-based monitoring systems.

In the next stage, the captured audio signals undergo preprocessing to improve data quality. Background noise and irrelevant sounds are filtered out, while normalization and segmentation techniques are applied to prepare the signals for further analysis. The system then extracts meaningful features from the processed audio, primarily using Mel-frequency cepstral coefficients (MFCCs). These features effectively capture the essential characteristics of sound patterns, enabling accurate classification of fall events.

At the core of the system is a compact deep learning model developed using TinyML techniques. This lightweight model is specifically optimized to run on resource-constrained devices such as microcontrollers. A convolutional neural network (CNN) architecture is typically employed to analyze the extracted features and recognize patterns indicative of falls. To ensure efficiency, optimization methods like quantization and pruning are applied, significantly reducing memory usage and computational load while maintaining reliable performance.

Once the model analyzes the input data, it classifies the event as either a fall or a normal activity. If a fall is detected, the system activates the alert mechanism, which can instantly notify caregivers, family members, or emergency responders through connected IoT platforms, including mobile applications or cloud-based systems. This rapid response capability is essential for minimizing the risks associated with delayed assistance.

Edge computing enhances the overall system by enabling on-device data processing, thereby reducing latency, ensuring data privacy, and minimizing dependence on internet connectivity. The proposed solution is highly scalable, cost-effective, and well-suited for deployment in environments such as smart homes, healthcare facilities, and assisted living centers, providing continuous monitoring and timely intervention.

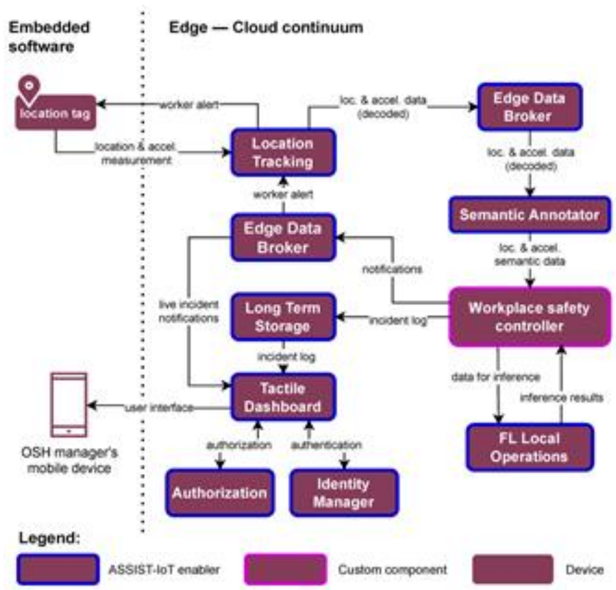

Fig.1.System Architecture

The AI-Acoustic Guard system is organized into four functional modules, each responsible for a specific stage in the fall detection process. These modules work together to ensure accurate, real-time detection while maintaining efficiency and low power consumption.

The first module is the Audio Acquisition Module, which continuously captures environmental sounds using low-power microphones integrated into the edge device. This module operates in real time and is designed to detect acoustic events such as sudden impacts, crashes, or unusual disturbances that may indicate a fall. It ensures continuous monitoring without requiring any user interaction.

The second module is the Preprocessing and Feature Extraction Module. In this stage, the raw audio signals are cleaned and prepared for analysis. Noise reduction techniques are applied to eliminate background interference, and the signals are normalized and segmented into smaller frames. The system then extracts key acoustic features, particularly Mel-frequency cepstral coefficients (MFCCs), which effectively represent the sound patterns associated with fall events. These features provide a compact and meaningful representation of the audio data.

The third module is the TinyML-Based Classification Module, which serves as the core of the system. A lightweight deep learning model, typically based on a convolutional neural network (CNN), is deployed on the edge device. The model is optimized using TinyML techniques such as quantization and pruning to reduce memory usage and computational complexity. It processes the extracted features and classifies the event as either a fall or a non-fall activity with high accuracy.

The final module is the Alert and Notification Module. When a fall is detected, this module immediately generates alerts and sends notifications to caregivers or emergency contacts via IoT-enabled platforms. This ensures rapid response and enhances user safety by enabling timely assistance in critical situations.

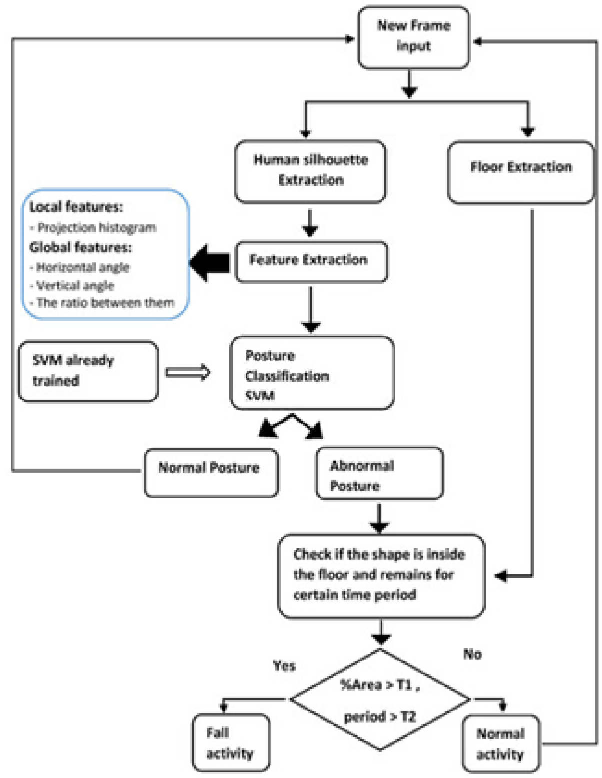

Fig.2.Methodology workflow of the Real-Time Human Fall Detection

Overall Working Flow of the Proposed System:
The overall operation of AI-Acoustic Guard is structured to provide continuous monitoring and accurate real-time detection of human falls using acoustic signals. The system follows a streamlined process that integrates sound capture, signal processing, intelligent classification, and alert generation within an edge computing environment.
The workflow begins with the audio sensing stage, where embedded microphones continuously record ambient sounds from the surrounding environment. These microphones capture a wide range of audio inputs, including routine daily noises as well as sudden impact sounds that may indicate a fall. The system operates autonomously, requiring no active involvement from the user.

Following data collection, the audio signals enter the preprocessing phase, where they are refined to enhance clarity and consistency. Unwanted background noise is filtered out, and normalization is applied to standardize the signal amplitude. The audio stream is then divided into smaller segments to enable efficient analysis. Once preprocessed, the system performs feature extraction, primarily using Mel-frequency cepstral coefficients (MFCCs). These features capture essential frequency characteristics of the sound, allowing the system to distinguish between normal activities and fall-related events.

The processed features are then passed to the classification stage, which forms the core of the system. A lightweight deep learning model, typically a compact convolutional neural network (CNN), analyzes the extracted features to identify patterns associated with falls. The model is specifically optimized using TinyML techniques such as quantization and pruning, enabling it to run efficiently on resource-constrained edge devices. Since all computations are performed locally, the system achieves low latency and preserves user privacy by avoiding cloud-based data transmission.
After classification, the system moves to the decision-making and alert stage. If a fall is detected, an immediate alert is generated and transmitted to designated contacts, including caregivers or emergency responders, through IoT-based communication platforms such as mobile applications. Additional responses, such as triggering alarms, can also be implemented to ensure prompt attention.

In summary, the workflow of AI-Acoustic Guard ensures a smooth and efficient sequence of operations, combining real-time sensing, intelligent processing, and rapid response. By utilizing edge computing, the system minimizes delay, reduces dependence on network connectivity, and enhances data security, making it highly suitable for smart healthcare and assisted living applications.

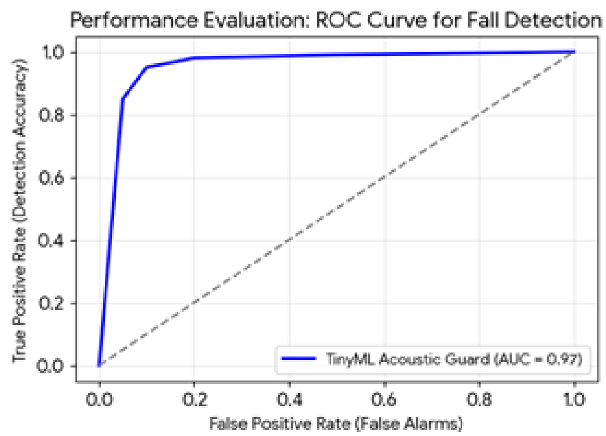

Fig.3.Performance Evaluation of Real-Time Human Fall Detection Framework

$$MFCC(n) = \sum_{k=1}^{K} \log(S(k)) \cos\left[n\left(k - \frac{1}{2}\right)\frac{\pi}{K}\right]$$

Mel-Frequency Cepstral Coefficients (MFCCs) are widely used in audio signal processing to extract meaningful features from sound signals. This equation represents the transformation of the logarithmic power spectrum into the cepstral domain using the discrete cosine transform (DCT). Here, S(k)denotes the Mel-scaled filter bank energies, and Kis the number of filters. MFCCs effectively capture perceptually relevant frequency characteristics of audio signals. In the proposed system, MFCCs help distinguish fall-related sounds (like impacts) from normal environmental noises, improving classification accuracy while maintaining a compact feature representation.

$$(f * g)(t) = \sum_{\tau} f(\tau) g(t - \tau)$$

The convolution operation is fundamental to convolutional neural networks (CNNs) used in the classification module. This equation describes how an input signal fis combined with a filter gto produce a feature map. The operation slides the filter across the input to detect local patterns such as edges or sound features. In the context of acoustic fall detection, convolution helps identify temporal and spectral patterns in MFCC features that correspond to fall events. This enables the model to learn discriminative features automatically, reducing the need for manual feature engineering.

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$$

The cross-entropy loss function measures the difference between the predicted probabilities and the actual class labels. Here, y_iis the true label, and y^_iis the predicted probability for class i. This loss function is commonly used in classification problems to optimize neural networks. During training, the model adjusts its parameters to minimize this loss, thereby improving prediction accuracy. In the fall detection system, cross-entropy loss helps the model learn to correctly distinguish between fall and non-fall audio events.

V. CONCLUSION

The proposed system, AI-Acoustic Guard, demonstrates an effective and innovative approach to real-time human fall detection by integrating TinyML and edge computing with acoustic signal analysis. Unlike traditional methods that rely on wearable devices or camera-based monitoring, this system offers a non-intrusive and privacy-preserving alternative by utilizing sound patterns to identify fall events. This makes it particularly suitable for deployment in environments where user comfort and data security are critical.

By leveraging lightweight machine learning models optimized for resource-constrained devices, the system achieves a balance between high detection accuracy and low computational overhead. The use of TinyML enables on-device processing, reducing latency and eliminating the need for continuous cloud connectivity. This ensures faster response times and reliable operation even in areas with limited or unstable internet access. Additionally, the integration of edge computing enhances data privacy, as sensitive audio data is processed locally rather than transmitted to external servers.

The incorporation of efficient feature extraction techniques, such as Mel-frequency cepstral coefficients (MFCCs), further strengthens the system's ability to accurately distinguish between fall and non-fall events. The modular design, consisting of audio acquisition, preprocessing, classification, and alert generation, allows for scalability and adaptability across various applications, including smart homes, healthcare facilities, and assisted living environments.

VI. FUTURE WORK

While AI-Acoustic Guard demonstrates promising performance in real-time fall detection, several enhancements can be explored to further improve its effectiveness and adaptability. One important direction is the integration of multi-modal sensing, combining acoustic data with additional inputs such as vibration sensors, accelerometers, or radar-based signals. This fusion of data can significantly enhance detection accuracy and reduce false positives in complex environments.

Another area for future development is the improvement of the TinyML model's robustness by training on larger and more diverse datasets that include various environmental conditions, background noises, and different types of fall scenarios. This will help the system generalize better in real-world deployments. Additionally, advanced model optimization techniques can be explored to further reduce power consumption and memory usage, enabling deployment on even smaller and more energy-efficient devices.

Future work may also focus on adaptive learning mechanisms, allowing the system to personalize detection based on user behavior and environment. Enhancing the alert system with features such as real-time location tracking and integration with emergency response services can further improve usability. Overall, these advancements will make the system more intelligent, reliable, and suitable for widespread smart healthcare applications.

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