IoT-Based Fall Detection System using LSTM Networks: An Edge-Deployable Approach with SisFall Evaluation

Aman Tiwari[1], Rahul Dilla[2], Siddharth Singh[3], and Abhinav Singh[4]

Department of Computer Science, Lovely Professional University, Phagwara, India
{amankt3002, rahuldilla.2003, siddhartsingh10454}@gmail.com,
abhinav.32351@lpu.co.in

Abstract. Falls among elderly individuals remain a significant global health concern, often resulting in severe injuries and loss of independence. Traditional fall detection systems, primarily based on threshold or rule-based algorithms, suffer from limited adaptability and high false alarm rates. To overcome these challenges, this paper presents an IoT-based Fall Detection System powered by Deep Learning using Long Short-Term Memory (LSTM) networks. The system utilizes triaxial accelerometer and gyroscope data obtained from the SisFall dataset, one of the most comprehensive public datasets for human fall detection. The collected signals are preprocessed and segmented into fixed-length temporal windows, which are then fed into an LSTM model capable of learning sequential motion dynamics. Experimental results demonstrate that the proposed model achieves an accuracy of 87.07%, precision of 72.76%, recall of 78.84%, and F1-score of 75.68% under subject-wise validation. Furthermore, the system is designed for IoT-edge deployment, enabling real-time fall detection and alert notification through cloud or local communication networks. The proposed approach effectively bridges the gap between rule-based IoT devices and data-driven intelligent systems, providing a robust, adaptive, and scalable solution for real-world fall detection applications.

Keywords: IoT-based Fall Detection · Deep Learning · LSTM · Accelerometer and Gyroscope Sensors · SisFall Dataset · Edge Computing · Real-time Monitoring · Human Activity Recognition (HAR)

1 Introduction

Falls are one of the most critical health risks among elderly individuals and patients with physical disabilities, often leading to fractures, head injuries, or even fatalities. According to the World Health Organization (WHO), falls account for nearly 37 million severe injuries every year, resulting in significant social and economic burdens on families and healthcare systems. Early and accurate detection of such events is essential to ensure rapid medical response and minimize post-fall complications. With the rapid growth of Internet of Things (IoT) technologies, there has been a paradigm shift toward intelligent, sensor-based monitoring systems capable of continuous health observation in real-world environments.

Traditional fall detection systems primarily rely on threshold-based algorithms that compare accelerometer or gyroscope readings against predefined limits. Although these systems are simple and easy to implement, they often suffer from false alarms, limited adaptability, and poor generalization across users and activities. Human motion is highly dynamic and varies according to age, physical condition, and environment; therefore, static thresholds cannot effectively distinguish between normal daily activities (such as sitting, bending, or running) and actual fall incidents. Moreover, threshold-based methods lack the ability to learn complex temporal dependencies present in motion data.

Recent advancements in Artificial Intelligence (AI) and Deep Learning (DL) have significantly improved the performance of human activity recognition and fall detection systems. Among various DL architectures, Long Short-Term Memory (LSTM) networks have demonstrated strong capabilities in modeling sequential time-series data, making them highly suitable for understanding motion dynamics from wearable sensor signals. By leveraging LSTM's ability to retain long-term temporal context, fall detection systems can be trained to automatically learn discriminative patterns between fall and non-fall activities without manual threshold tuning.

In this research, we propose an IoT-based Fall Detection System using Deep Learning that integrates LSTM-based temporal modeling with real-time IoT communication. The system utilizes triaxial accelerometer and gyroscope signals from the SisFall dataset, which includes a wide variety of fall and Activities of Daily Living (ADL) recordings across multiple subjects. The preprocessed data is segmented into fixed-length windows and fed into an optimized LSTM model that learns temporal motion variations corresponding to different activity types. Once trained, the model can be deployed on an IoT-edge device, enabling real-time fall detection and alert generation via cloud or local network channels.

Key Contributions:

1. Development of a deep learning–based fall detection framework capable of learning temporal motion features directly from sensor signals.
2. Implementation of a lightweight LSTM architecture optimized for real-time inference on edge IoT devices.
3. Comprehensive evaluation using the SisFall dataset, reporting performance through accuracy, precision, recall, and F1-score metrics.
4. Design of a scalable IoT-based deployment architecture that supports real-time monitoring and alert notifications.

2 Related Work

The development of fall detection systems has evolved significantly over the past decade, transitioning from traditional threshold-based techniques to intelligent, data-driven solutions. Early IoT-based fall detection systems primarily relied on accelerometer and gyroscope sensors to measure body orientation and sudden motion variations. These systems used predefined thresholds to classify activities as normal or fall events [1]. Although computationally inexpensive, threshold-based methods are highly sensitive to sensor placement, user-specific behavior, and environmental conditions, often resulting in a high number of false positives or missed detections.

To enhance reliability, several researchers integrated IoT communication modules such as Wi-Fi, GSM, or Bluetooth for real-time alert generation [5]. While these systems could transmit fall alerts to caregivers or medical personnel, they still lacked adaptive intelligence, as decisions were based solely on raw sensor readings rather than learned motion patterns. With the rise of Machine Learning (ML) and Deep Learning (DL), researchers began incorporating algorithms capable of automatically learning fall patterns from labeled data [6]. CNN-based approaches were effective in feature learning but limited in temporal modeling, motivating the adoption of RNN and LSTM networks [2,7].

Recent studies have extended this work by integrating attention mechanisms and transformer-based architectures to enhance interpretability and context awareness [4]. However, such models are computationally expensive and less feasible for edge deployment. Kumar et al. [3] introduced a smartwatch-based fall detection model focusing on on-device inference. Comprehensive reviews like Zhao et al. [8] highlight the lack of systems integrating deep learning with IoT communication pipelines. The proposed study addresses this gap.

3 Methodology and Proposed System Architecture

The proposed system integrates Deep Learning–based fall detection with IoT-enabled communication, enabling real-time monitoring and automated alert generation. It consists of three primary stages: Data Acquisition and Preprocessing, LSTM-based Fall Detection Model, and IoT Integration and Alert Mechanism.

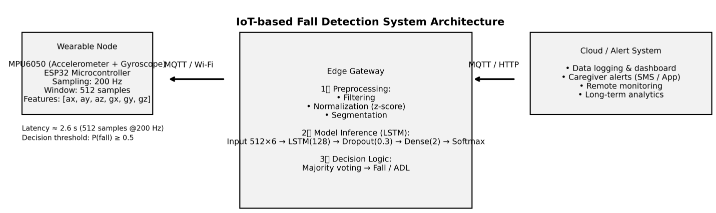

Fig. 1: Proposed system architecture: wearable sensor node → edge gateway → LSTM inference → alerting and cloud logging.

3.1 Data Acquisition

The system uses triaxial accelerometer and gyroscope signals from the SisFall dataset (38 subjects, 200 Hz). Each record includes six raw channels: $[a_x, a_y, a_z, g_x, g_y, g_z]$.

3.2 Preprocessing

Preprocessing includes:

1. Low-pass filtering to remove noise.
2. Window segmentation (512 samples, 50% overlap).
3. Z-score normalization.
4. Label encoding (Fall / ADL).
5. Subject-wise split: Train 70%, Validation 15%, Test 15%.

3.3 LSTM Model

LSTM architecture: Input (512×6), one LSTM layer (128 units), Dropout 0.3, Dense layer (2 outputs), Softmax. Training used Adam optimizer (lr = 1e-3), cross-entropy loss, batch size = 64, 50 epochs, early stopping.

3.4 IoT Integration and Deployment

The trained model is integrated into an IoT pipeline:

– **Sensor Node:** MPU6050 + ESP32 streaming via Wi-Fi/MQTT.
– **Edge Gateway:** Raspberry Pi running LSTM inference (TensorFlow Lite/ONNX).
– **Alert Mechanism:** Cloud/local alerts (Twilio/Firebase).
– **Decision Smoothing:** Majority voting over consecutive windows.

4 Results and Discussion

4.1 Performance Metrics

Table 1: Performance of the proposed LSTM model on SisFall (subject-wise test set).

Metric	**Value (%)**
Accuracy	87.07
Precision	72.76
Recall (Sensitivity)	78.84
F1-score	75.68

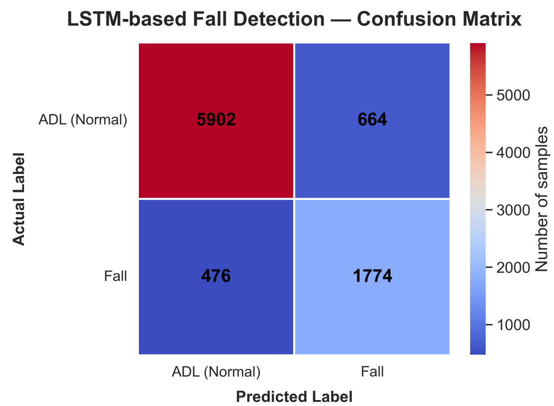

Fig. 2: Confusion matrix showing classification of fall and ADL events.

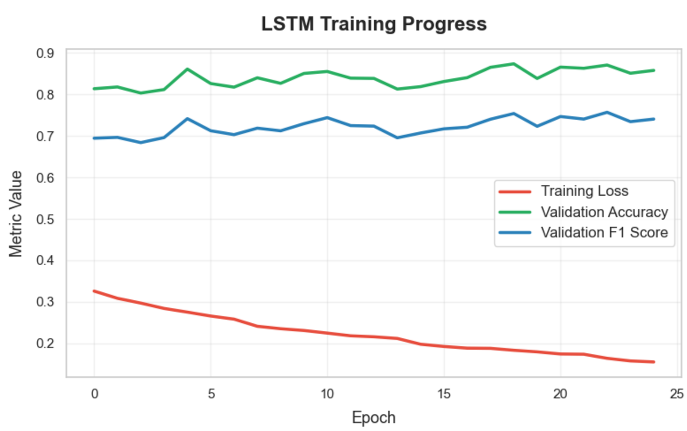

Fig. 3: Training loss and validation metrics across epochs.

4.2 Confusion Matrix Analysis

4.3 Training Behaviour

4.4 Comparative Evaluation

Table 2: Comparative analysis with selected studies.

Study	Approach	Dataset	Accuracy (%)	IoT Integration	Remarks
Devansh & Rao (2020)[1]	Threshold-based	Custom	79	Yes	Rule-based prototype
Zhang et al. (2023)[7]	CNN-LSTM	Private	92	No	High complexity
Haque et al. (2024)[2]	LSTM	Public	88	No	LSTM baseline
Kumar et al. (2023)[3]	Smartwatch CNN	Private	84	Yes	Wearable-focused
Proposed (2025)	LSTM (Edge)	SisFall	87.07	Yes	Balanced and deployable

4.5 Discussion

The LSTM model offers a balance between accuracy and edge efficiency. It generalizes across subjects while keeping computational demands low. More complex architectures (e.g., transformers) may yield higher accuracy but are less suitable for real-time IoT inference.

5 Conclusion and Future Scope

This paper presented an IoT-based Fall Detection System powered by LSTM networks and evaluated on the SisFall dataset. The lightweight LSTM architecture achieved an accuracy of 87.07% and F1-score of 75.68% under subject-wise validation. The system is designed for edge deployment, enabling low-latency real-time fall detection and caregiver notification. Future work includes exploring CNN-LSTM hybrids, model quantization for microcontrollers, and federated learning for personalization.

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