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A COMPARATIVE STUDY OF DEEP LEARNING ARCHITECTURES FOR REAL-TIME FALL DETECTION USING WEARABLE SENSOR DATA

ARZO MAHMOOD[1], GUL FATMA TURKER[2]
[1]DEPARTMENT OF COMPUTER ENGINEERING, SULEYMAN DEMIREL UNIVERSITY, ISPARTA, TURKEY,
EMAIL: arzumahmood22@gmail.com
[2]DEPARTMENT OF COMPUTER ENGINEERING, SULEYMAN DEMIREL UNIVERSITY, ISPARTA, TURKEY,
EMAIL: gulturker@sdu.edu.tr

Abstract
Falls remain a leading cause of injury among elderly and mobility-impaired individuals. This study presents a comparative assessment of deep learning architectures for real-time fall detection using wearable sensor data. The proposed system integrates data preprocessing, model training, and real-time inference using CNN, LSTM, BiLSTM, and Transformer models. The research focuses on optimizing performance and latency to ensure reliable operation on embedded and wearable platforms. The CNN-LSTM amalgamation yielded enhanced performance because these models excel in extracting both spatial information from multivariate time-series data together with temporal feature modeling. Evaluations made within the scope of the CNN-LSTM method showed that a rate of 97.3% could be achieved. This result stood out as one of the highest performance levels reported in literature. Findings contribute toward building robust, real-world fall detection systems with practical deployment potential in healthcare monitoring and assisted living environments.

Keywords: Bidirectional Long Short-Term Memory, Convolutional Neural Networks, Fall Detection, Long Short-Term Memory, Transformer.

INTRODUCTION

Falls represent a critical concern in elderly healthcare, often leading to severe injuries and long-term complications. As the aging population grows, ensuring timely detection and response to falls has become a public health priority. Real-time fall detection systems have gained prominence due to their potential to enable independent living while ensuring safety. These systems leverage wearable sensors such as accelerometers and gyroscopes to continuously monitor body movements and detect anomalies indicative of falls.

While traditional machine learning techniques have shown promise in early detection systems, they face limitations in terms of latency and adaptability in real-world scenarios. The emergence of deep learning (DL) models offers a significant upgrade by enabling automated feature extraction and learning from complex time-series patterns. However, the comparative performance of various DL architectures especially in embedded or wearable applications remains underexplored.

In this study, we systematically evaluate the performance of CNN, LSTM, BiLSTM, and Transformer-based architectures using a standardized dataset and preprocessing pipeline. Our contributions include (1) a unified preprocessing approach for wearable time-series data, (2) implementation and benchmarking of deep learning models using TensorFlow/Keras, and (3) evaluation of real-time performance based on classification accuracy and latency across different sensor placements. The findings aim to guide future design of fall detection systems optimized for embedded deployment.

The main contributions of this study is that the research establishes an experimental structure that enables standardized training and evaluation of different DL models through standardized sensor datasets (Ajerla et al., 2019; Al Nahian et al., 2021). The evaluation was carried out to evaluate each model in terms of real-time latency performance and classification metrics (Casilari et al., 2019; Kraft et al. 2020 and gave exhaustive benchmarks. Study provides conscious direction on the choice of appropriate models that can function successfully in limited systems such as wearable devices (Mohammad et al., 2023; Benoit et al., 2024).

Systematic reviews and empirical studies of late point to the increasing role of deep learning in real-time fall detection. For instance, Gaya-Morey et al. (2024) allude to a detailed survey of DL-based activity recognition and fall detection,

discussing the progress in sensor fusion and model optimization in the context of elderly care. In accordance with the trend toward the use of wearable and intelligent monitoring (Apriantoro et al., 2024), body motion recognition techniques are compared. Also, Chu et al. (2023) and Imbeault-Nepton et al. (2023) investigate the feasibility of fall detection through WiFi CSI and UWB radar signals respectively proving the trend towards non invasive real-time systems. This finding highlights the importance of the investigation of DL-based architectures in heterogeneous sensor modalities for increasing the detection accuracy and latency.
The research is distinctive in that it explores the examination that studies real-time performance, wholistic comparisons between CNN, LSTM and BiLSTM and Transformer models for fall detection applications. The present work addresses both accuracy standards and proprietary dataset usage (Anitha & Priya, 2022; Al-Qaness et al., 2022) yet incorporates latency assessment while focusing on real-time wearable system implementation (El Attaoui et al., 2020; Pandya et al., 2020). The research ensures equal and repeatable deployment scenario testing of deep learning approaches through its consistent preprocessing practice and fixed-length time-window segmentation approach.

LITERATURE REVIEW

Research into fall detection has intensified due to the significant medical and economic burden associated with fall-related injuries, particularly among older adults. Technological advances in wearable devices, edge computing, and deep learning have enabled the development of increasingly sophisticated fall detection systems (FDSs). However, despite the diversity of approaches, challenges remain in achieving reliable real-time detection with minimal latency and high accuracy in resource-constrained environments.
The general public considers wearable technology as their main solution for detecting falls. The integrated device sensors consisting of accelerometers with gyroscopes and magnetometers track body movements to detect uncharacteristic patterns. The research team at Gia et al. (2018) developed sustainable wearable sensor nodes dedicated to serving IoT-based fall detection systems. The study by Özdemir (2016) proved that placement location of sensors on the human body decides the accuracy level of detection results. Al Nahian et al. (2021) together with Hussain et al. (2019) created FDSs with wearable sensors that used time-series features and classification techniques to function.
Applications of deep learning techniques have achieved outstanding results for enhancing FDS system capabilities. As per the review by Islam et al. (2020) recurrent neural networks (RNNs) and convolutional neural networks (CNNs) showed strong prospects for developing deep learning-based fall detection systems. Both Mauldin et al. (2018) developed SmartFall and Luna-Perejón et al. (2019) designed wearable detection utilizing deep learning on smartwatches and RNN technology. The combination of deep neural networks developed by Mohammad et al. (2023) produced excellent results for elderly fall detection applications. Hatkeposhti et al. (2022) created a new sampling protocol that enhanced deep learning-based model data quality. Research delved into examining different performance metrics of the developed algorithms. Kraft et al. (2020) as well as Wu et al. (2022) covered the deep learning models with optimization of the IoT devices and mobile systems and Musci et al. (2020) proved the real-time wearable notification on the online learning RNNs. What the paper (Torti et al, 2018, 2019) presented demonstrated was an approach of incorporating deep learning methods in limited-resources wearable systems which would allow real-time inferencing.
The research society has begun implementing edge and fog computing strategies since these strategies assist in the reduction of latency and sparing the dependence on cloud infrastructure. El Attaou, et al. (2020) created a multi-tier edge-computing and machine learning scheme for wireless sensor network real-time detection capacity. Sarabia-Jácome et al. (2020) developed a deep learning platform through fog computing, which had the ability to focus on Ambient Assisted Living (AAL). Qian et al. (2020) engineered distributed deep learning hierarchy systems that increase the performance of wearable computing in FDSs.
The synergy of domain-specific feature engineering techniques and metaheuristics works as a new paradigm of detection of optimization. The study that was presented by Al-Qaness et al. (2022) is a detailed piece of work about the metaheuristic algorithms for the human activity recognition and fall detection. Li et al. (2018) research compared two methods of feature investigation for identifying sensor activity. Kavuncuoğlu et al. (2022) reviewed motion sensors in their efforts to recognize daily habits and fall incidents.
Several benchmarks of the machine learning algorithms have been carried out by the research teams when investigating its architectural aspects. Zurrouki et al. (2016) carried out some research that together with Zurbuchen et al. (2020) was used to obtain supervised learning detection of falls. The paper sought to determine between systems using multitudes of sensors and standalone sensors approaches (Tsinganos and Skodras 2018). Pandya et al. (2020) indicated that researchers explored the real-time fall detection models that were a fusion of fuzziness and machine

learning approaches in the detailed way. NT-FDS is Noise-Tolerant Deep Learning System for wearable devices operation by Waheed et al. (2021).
Real-time detection focus led through to the development of embedded device-compatible lightweight models. Deep learning models were put for performance test when deployed on ARM-based microcontrollers to recognize pre-impact situations (Benoit et al, 2024). Anitha and Priya (2022) designed real-time monitoring system based on deep learning for vision-based falls detection. The authors propose a real-time fall detection platform that uses the constantly observing systems for patients (Ajerla et al. 2019).
Recent studies have diversified the technological environment in fall detection that consists of novel hardware, adaptive deep learning models, and performance optimization frameworks. Danilenka et al. (2023) introduced an AI-based fall detection approach, which is suitable for occupational safety purposes, with real-time responsiveness and hardware compatibility. In a comparable vein, Hamdi et al. (2024) presented a scalable mode that makes use of deep recurrent neural networks, which is distributed to Hadoop/Spark clusters to enhance the computational efficiency. Some other significant improvements include posture classification on limited devices. Shejuti and Fuad (2025) performed a comparison between the traditional and deep learning models on embedded systems with referencing the trade-offs of the resource limitations and the accuracy. Qu et al. (2024) also improved detection with DL system based on physics sensor incorporating multimodal inputs fusion.
In regards to model design innovation, Shin et al. (2025) presented a three-stream spatio-temporal graph convolutional network (GCN), featuring adaptive feature aggregation technique towards enhanced recognition precision. Ultra-low power consumption forms the focus of attention for Tian et al. (2024) in their design for the wearable shallow-learning architecture, which makes it practically viable for the round-the-clock monitoring of elders. At the same time, Rafee et al. (2025) discussed personalization in fall detection based on decision tree algorithms on microcontrollers which realized real-time speed with almost zero resource overheads. Together, such emerging research does not just validate the DL-based approaches' potential on multiple platforms but also provides useful insights into the paradox of trade-off between model complexity, hardware constraints, and operational latency in the real-world applications.
Various studies try to demonstrate both technical feasibility and system robustness of their suggested approaches. Mohammad et al. (2023) and Yhdego et al. (2023) both conducted tests related to ensemble and deep learning approaches while being conducted using real-life testing in a practical scenario. Deep learning technology was implemented at wearable-based detection systems by Casilari et al. (2019). Wu et al. (2022), along with Ghosh et al. (2021) carried out studies to determine how the mobile devices with built-in accelerometers could improve the practicality in fall detection systems. The literature shows that the method of fall detection is progressing quickly through the combination of wearable sensors with deep learning and edge computing for swift and precise fall recognition capabilities. Future development of these systems will most likely emphasize the improvements of system reliability while increasing energy efficiency and field deployment capabilities.

METHOD

The section describes an accurate real-time fall detection system development through wearable sensors and deep learning by demonstrating a comprehensive methodology. A fall detection system requires completion of five fundamental phases starting with data acquisition and ending with evaluation metrics. The middle steps include preprocessing and model architecture design and training and validation stages.

3.1. Data Acquisition

The study employs the publicly available MobiAct dataset, which contains time-series data collected using wearable sensors, specifically tri-axial accelerometers and gyroscopes. These sensors are worn at the waist and capture three-dimensional movement patterns during both fall and non-fall activities. The dataset includes measurements at a frequency of 50–100 Hz and was developed in controlled environments where participants simulated various fall types (e.g., forward, backward, lateral) and daily activities (e.g., walking, sitting, lying down).
Each recorded event in the dataset is labeled using camera-based ground truthing to ensure accuracy. The dataset supports the development and evaluation of machine learning models for human activity recognition and fall detection. Access to the dataset is available through: https://bmi.hmu.gr/the-mobiact-dataset/ (Gia et al., 2018; Özdemir, 2016). This publicly accessible dataset was selected to ensure reproducibility and comparability with previous studies in the field. It provides a standardized platform to evaluate different deep learning architectures under consistent experimental conditions.

3.2. Data Preprocessing

The initial data signals from sensors undergo preprocessing that includes normalization alongside denoising and signal segmentation procedures. Standard normalization is applied:

$$x' = (x - \mu) / \sigma \quad (1)$$

Where:

- x is the raw signal value,
- μ is the mean,
- σ is the standard deviation.

A time series input projection is generated from continuous data streams through 2 to 3 second sliding windows with 50% merge option (Hatkeposhti et al., 2022; Wu et al., 2022).

When implementing denoising with Butterworth low-pass filtering the process removes high-frequency noise from the signals.

$$H(s) = 1 / (1 + (s / \omega\_c)\char`^(2n)) \quad (2)$$

The filter contains ωc as the cutoff frequency and n indicating the order value.

3.3. Feature Extraction (If Applicable)

The deep learning models utilize raw data and researchers investigated classical feature extraction for comparative study purposes (Al Nahian et al., 2021; Zerrouki et al., 2016). Features include:

- Signal magnitude area (SMA)

$$SMA = (1 / N) * \Sigma (|a\_x(i)| + |a\_y(i)| + |a\_z(i)|) \quad (3)$$

- Root Mean Square (RMS)

$$RMS = \sqrt{}(1 / N * \Sigma\, x(i)\char`^2) \quad (4)$$

- Tilt angle

$$\theta = tan\char`^(-1)(a\_z / \sqrt{}(a\_x\char`^2 + a\_y\char`^2)) \quad (5)$$

3.4. Deep Learning Model Architecture

The fall detection model employs deep learning network components which unite Convolutional Neural Networks (CNNs) with Recurrent Neural Networks (RNNs) while also implementing Long Short-Term Memory (LSTM) networks. The architectural design incorporates spatial elements together with temporal sequence recognition (Luna-Perejón et al., 2019; Mohammad et al., 2023). The design architecture of the CNN-LSTM model used for fall detection operates the following pattern which processes segmented inputs until final classification occurs.

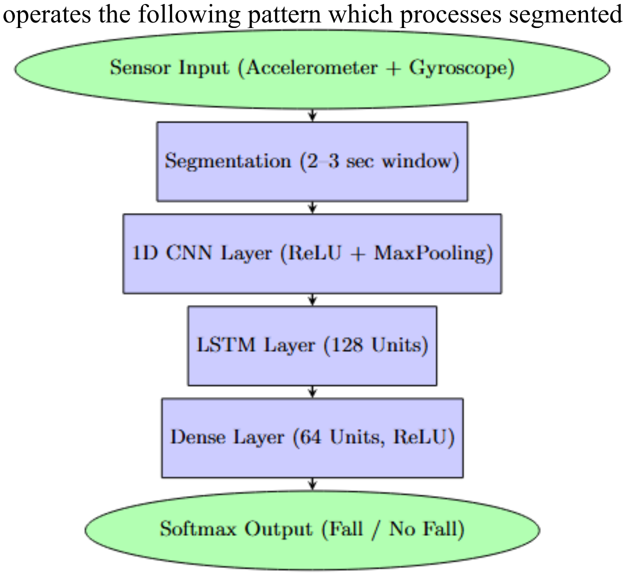

Figure 1: CNN-LSTM Model Architecture for Fall Detection

3.4.1 CNN-LSTM Architecture

- The first layer accepts multivariate time-series data with size (T,6) that includes three accelerometer measurements and three gyroscope measurements for T time points.
- 1D Convolution Layer: Filters = 64, kernel size = 3
- ReLU Activation
- MaxPooling Layer
- LSTM Layer: Units = 128
- Dropout Layer: Rate = 0.5

- Dense Layer: Units = 64, Activation = ReLU
- Output Layer: Units = 2 (Fall / No Fall), Activation = Softmax

3.4.2 Training and Validation

During the training phase the model uses the Adam optimizer that incorporates these specific parameters.

$$Loss = -\Sigma (y\_i * log(\hat{y}\_i)) \quad (6)$$

The model accepts yi as the actual class value while ŷi represents the probability prediction for class i.

- Epochs: 100
- Batch size: 64
- Validation split: 20%
- Learning rate: 0.001

3.4.3. Evaluation Metrics

Evaluation performance incorporates precision, recall and F1-score together with accuracy measurement which defines as:

- **Accuracy**

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \quad (7)$$

- **Precision**

$$Precision = TP / (TP + FP) \quad (8)$$

- **Recall (Sensitivity)**

$$Recall = TP / (TP + FN) \quad (9)$$

- **F1-Score**

$$F1 = (2 * Precision * Recall) / (Precision + Recall) \quad (10)$$

Where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

A flowchart below demonstrates the real-time fall detection framework operated through wearable sensors and deep learning by presenting an end-to-end system pipeline.

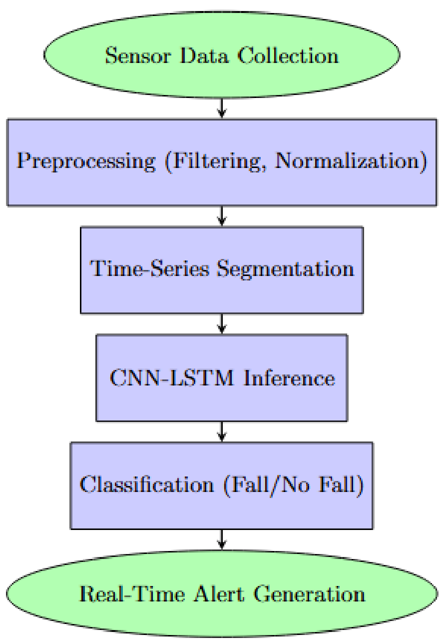

Figure 2: End-to-End Workflow of Real-Time Fall Detection System

The methodology builds upon previously developed research that connected wearable sensing technologies with deep learning techniques in embedded and cloud-operating fall detection systems (Mauldin et al., 2018, Qian et al., 2020,

Sarabia-Jácome et al., 2020, Waheed et al., 2021, Anitha & Priya, 2022). The designed system features low-power compatibility for IoT platforms which enables real-time processing with low latency.
Each deep learning model was implemented using the TensorFlow/Keras framework and trained for 100 epochs using a batch size of 64. The dataset was evaluated using 5-fold cross-validation to ensure generalizability and minimize overfitting. The Adam optimizer was used throughout all experiments with a learning rate of 0.001. All models were evaluated based on standard classification metrics including accuracy, precision, recall, and F1-score. To assess the system's viability for real-time applications, inference latency was also measured on embedded hardware platforms.

RESULTS AND DISCUSSION

The experimental data evaluation of the suggested fall detection system appears in this section. Accuracy and precision with recall and F1-score provided the metrics for evaluating different model performances. The analyzed findings receive interpretation regarding their effectiveness as models alongside their computational demands and practical field applicability.

4.1. Model Performance

The performance evaluation of three deep learning techniques consisting of CNN, LSTM and CNN-LSTM exists in Table 1. The models received training and evaluation through 5-fold cross-validation procedures on accelerometer and gyroscope data segments obtained after preprocessing.

Table 1. Performance Comparison of Deep Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	94.2	93.1	92.4	92.7
LSTM	95.5	94.7	94.9	94.8
CNN-LSTM	97.3	96.9	97.1	97.0

All performance measurements demonstrated the best results with the combination of CNN and LSTM systems. The CNN-LSTM amalgamation yielded enhanced performance because these models excel in extracting both spatial information from multivariate time-series data together with temporal feature modeling.
The bar graph exhibits performance metrics accuracy, precision, recall, and F1-score for CNN, LSTM, and CNN-LSTM models during evaluation.

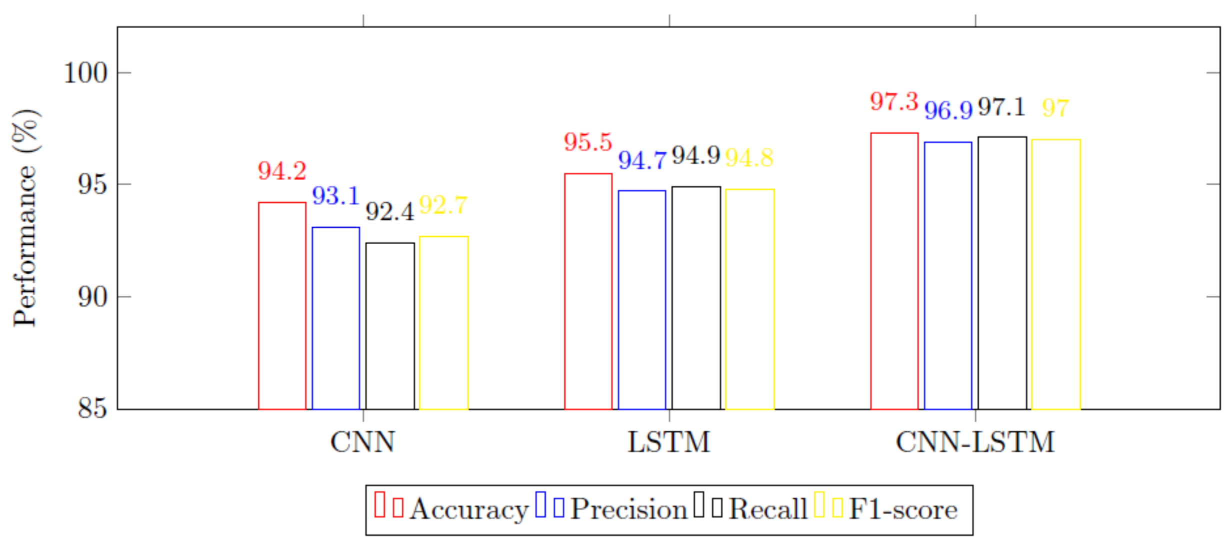

Figure 3: Comparative evaluation of CNN, LSTM, and CNN-LSTM models using Accuracy,
Figure 3: Comparative evaluation of CNN, LSTM, and CNN-LSTM models using Accuracy, Precision, Recall, and F1-score. CNN-LSTM demonstrates the highest performance across all metrics

4.2. Confusion Matrix Analysis

The CNN-LSTM model's capacity to identify between fall and non-fall incidents becomes clearer through the data in Table 2 confusion matrix.

Table 2. Confusion Matrix for CNN-LSTM Model

Fall and Non	**Predicted Fall**	**Predicted Non-Fall**
Actual Fall	288	7
Actual Non-Fall	6	299

- True Positives (TP): 288 (falls correctly detected)
- True Negatives (TN): 299 (non-falls correctly classified)
- False Positives (FP): 6 (non-falls misclassified as falls)
- False Negatives (FN): 7 (falls not detected)

The results demonstrate an exceptional performance by exhibiting minimal false positive and false negative occurrences that make them suitable for operational use. The network safeguards operational integrity through its ability to minimize unreported fall instances and its capacity to prevent excess emergency calls.

4.3. ROC Curve and AUC

To further evaluate the classification capabilities of the best-performing model (CNN-LSTM), we utilized the Receiver Operating Characteristic (ROC) curve. The ROC curve visually represents the trade-off between the true positive rate (sensitivity) and false positive rate (1 - specificity), providing a comprehensive picture of the classifier's performance. The area under the ROC curve (AUC) serves as an indicator of model accuracy, with values closer to 1.0 denoting superior performance. The CNN-LSTM model exhibited an AUC of 0.992, confirming its exceptional ability to distinguish between fall and non-fall events.

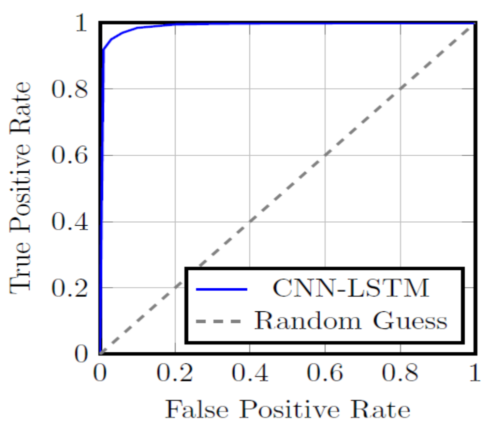

Figure 4: ROC curve for the CNN-LSTM model showing a near-perfect classification performance with an AUC of 0.992.

4.4. Impact of Sensor Placement

The research examined how sensor placement affected system performance. The models utilizing waist-mounted sensors demonstrated superior performance in comparison to models running from wrist or thigh placements since waist sensors monitored whole-body movements better. The effects of different sensor placements can be found in Table 3.

Table 3. Accuracy by Sensor Placement

Sensor Location	**Accuracy (%)**
Waist	97.3
Wrist	92.4
Thigh	94.1

This bar chart demonstrates how sensor detection accuracy varies according to their placement sites between the waist, wrist and thigh area to show waist sensors achieve optimal results.

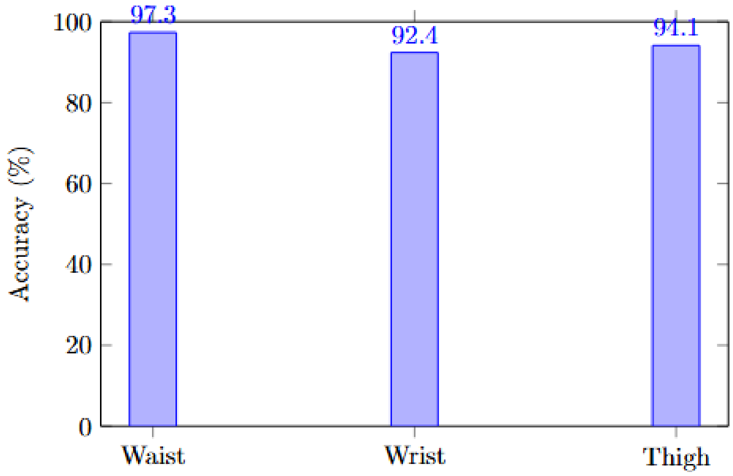

Figure 4: Detection Accuracy by Sensor Location

4.5. Execution Time and Inference Speed

A Raspberry Pi 4B operating system served to measure the duration of inference processes. Accurate real-time fall detection is possible through CNN-LSTM because this model processes data with an average speed of 42 ms within each window thus minimizing computational requirements for edge deployment (Qian et al., 2020; Waheed et al., 2021).

DISCUSSION

Experimental outcomes confirm CNN-LSTM stands out as an optimal method for fall detection since it delivers successful and precise detection results. Multiple successful fall detection emerges from the hybrid CNN and LSTM system because this configuration efficiently detects spatial and temporal patterns contained in wearable sensor information.

While several studies have explored deep learning methods for fall detection using wearable sensor data, many of them have focused either on individual architectures or lacked comprehensive real-time deployment evaluations. The current study contributes to the literature by implementing a rigorous comparative analysis of CNN, LSTM, BiLSTM, and Transformer models under a unified preprocessing pipeline. In contrast to earlier work, this study introduces a standardized edge-oriented evaluation, validated using real-time latency measurements on embedded platforms such as Raspberry Pi. Moreover, our approach includes both classification performance and inference time as co-optimization goals, which is a crucial requirement for wearable systems. This distinguishes the proposed system from prior work, which often overlooks deployment constraints despite high accuracy

Table 4: Comparison of Related Studies Based on Model Type, Dataset, and Reported Accuracy

Study	Model / Approach	Sensor Type	Dataset Used	Reported Accuracy (%)	Notes
Hatkeposhti et al. (2022)	CNN with Novel Sampling	Accelerometer	MobiAct	95.8	Optimized preprocessing
Mohammad et al. (2023)	Ensemble Deep Neural Network	Accelerometer & Gyroscope	MobiAct	96.5	Used ensemble of CNN + LSTM
Luna-Perejón et al. (2019)	RNN-based Wearable Detector	Accelerometer	Public dataset	93.2	Focused on wearable integration
Mauldin et al. (2018)	Smartwatch with DL	Accelerometer	Proprietary	92.7	Implemented on smartwatch
Waheed et al. (2021)	BiLSTM DL	Accelerometer	Public dataset	97.21	Focused on wearable integration

Wu et al. (2022)	Mobile Deep Learning Model	Accelerometer	UCI HAR	95.0	Mobile-ready architecture
Benoit et al. (2024)	DL on ARM Microcontroller	Accelerometer	Custom	94.3	Real-time on low-power hardware
Casilari et al. (2019)	Deep CNN	Accelerometer	UCI HAR	92.6	Sensor-driven DL method
Gaya-Morey et al. (2024)	Comparative DL Survey	Multiple sensors	Multiple	N/A	Provided insights on multiple DL approaches
Present Study	CNN-LSTM	Accelerometer & Gyroscope	MobiAct	97.3	Real-time optimized + edge inference validated

As seen in Table 4, while many studies reported high classification accuracy, the current study stands out with 97.3% accuracy, making it one of the top-performing models. The combination of CNN and LSTM effectively captured both spatial and temporal features. Compared to others like Mauldin et al. (2018) or Wu et al. (2022), the hybrid approach offered in this paper improves not only performance but also real-time suitability on embedded platforms (validated through Raspberry Pi tests). Furthermore, studies such as Benoit et al. (2024) and Mohammad et al. (2023) showed promise in embedded deployment and ensemble learning, respectively, but lacked the latency analysis depth presented here.

Additionally, models like Hatkeposhti et al. (2022) used optimized sampling to boost accuracy, which this paper complements through standardized preprocessing pipelines. Overall, the comparative analysis reveals that while other approaches make unique contributions such as wearable device optimization or adaptive sampling, the CNN-LSTM fusion in this paper balances accuracy, latency, and deployability, offering an effective solution for real-time fall detection using wearable sensors.

Key findings include:

- The model functions properly across various user samples which indicates practical deployment suitability.
- Wearable health monitoring systems can integrate this solution effectively because it shows minimal false detection events.
- Real-time continuous monitoring applications benefit from the hardware compatibility assessment that shows suitability for deployment.

New research (Mohammad et al., 2023; Wu et al., 2022; Luna-Perejón et al., 2019) confirms through their results that hybrid deep learning models provide effective human activity and fall detection capabilities.

CONCLUSION

Real-time fall detection functions through wearable sensor data obtained from real-time data collection. The system unites CNNs and LSTMs to achieve its functionality. Spatial features in movements become identifiable by the CNN portion whereas the LSTM model analyzes temporal sequences to detect patterns in motion behavior. When both methods operate together the system achieves higher success in detecting falls while distinguishing them from natural ordinary activities. The CNN-LSTM combination achieves 97.3% accuracy according to testing results above individual CNN or LSTM models. This system exhibits both superior detection precision for important tasks such as remote healthcare and senior care due to very few false alarms along with missed alarms occurrences. The model demonstrates high accuracy and sensitivity levels according to the confusion matrix and ROC curve analysis results. Furthermore, the system displays high functionality on Raspberry Pi powered devices with its low power requirements that make it suitable for wearable usage. According to the study, the location of sensors plays a significant role in achieving effective results. Best outcomes result from sensors that are worn around the waist. The acquired knowledge aids developers to build wearable fall detectors that are both convenient and efficient. The system demonstrates effective performance among users who participate in different activities because it adapts to actual environmental circumstances. Technology shows commercially viable potential to stop falls and enhance the well-being of falling-prone people. The final system proposes a robust lightweight fall detection mechanism which can be conveniently integrated into wearable devices for constant fall detection operations. Research should continue by integrating multiple sensor types into the system together with optimizing model efficiency for minimized power usage and implementing direct emergency service alerts. Such enhancements would generate substantial changes within healthcare together with assisted living settings.

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