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# ResQNet: Smart Emergency Response System

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**Abstract -** *ResQNet is a smart emergency response system designed to help users receive timely assistance when they are unable to manually request help during an emergency. The system brings together smartphone-based fall detection, emergency verification, priority-based alerting, and QR-based medical identification within a single response workflow. The fall detection component uses a rule-based sequential approach in which multiple motion conditions are considered in sequence rather than triggering an alert from a single acceleration threshold. This allows the system to distinguish potential falls from normal movements more carefully. For experimental evaluation, the fall-detection component was tested using the MobiFall Dataset v2.0, consisting of 630 trials from 24 subjects, including 288 fall trials and 342 activities of daily living. A simple acceleration-threshold method was also implemented as a baseline using the same evaluation procedure. ResQNet achieved an accuracy of 78.57%, sensitivity of 98.26%, specificity of 61.99%, precision of 68.52%, and an F1 score of 80.74%. The false-positive rate was 38.01%, compared with 78.36% for the threshold baseline. The results suggest that considering a sequence of motion states can reduce false detections while maintaining high sensitivity for fall detection on the evaluated dataset. The evaluation also shows the potential of combining fall detection with verification, medical identification, and emergency alerting as part of a broader emergency response system.*

**Key Words: ResQNet, Emergency Response System, Fall Detection, Smartphone Sensors, Accelerometer, Gyroscope, False Alarm Reduction, Emergency Escalation, Medical Identification.**

## 1. INTRODUCTION

Emergencies such as falls, accidents, or sudden health problems can occur without warning. In such situations, getting timely help can be difficult when the affected person is unable to make a call or press an emergency button. This becomes particularly important when a person is alone or temporarily unable to communicate. A useful emergency-response system therefore needs to do more than simply detect an unusual event; it should also support verification, provide relevant information, and help initiate an appropriate response. Smartphones provide a practical platform for this type of system because they are widely available and contain sensors that can capture changes in body movement. Smartphone-based fall-detection approaches have used motion data to identify patterns associated with falls and other activities [6], [12]. Systems such as FallAlarm have also explored combining smartphone-based fall detection with positioning and emergency assistance [7]. These approaches demonstrate the potential of smartphones for emergency detection, but distinguishing an actual fall from normal activities involving sudden movement remains a challenge. A common approach is to use acceleration thresholds to identify a possible fall. Although threshold-based detection is simple and computationally lightweight, sudden movements during everyday activities can produce acceleration patterns similar to those observed during a fall [6], [12]. The way a smartphone is carried or positioned can also affect the sensor measurements and, consequently, detection performance. For this reason, relying on a single acceleration event may result in unnecessary alerts. Considering a sequence of motion conditions can provide additional context before a fall is treated as a genuine emergency.

Detecting a possible fall is only one part of an emergency response process. Once an emergency is identified, the system may need to verify the event, determine its priority, provide the user's location, and make relevant medical information available to an authorized responder. Previous emergency response research has examined the use of location information to support assistance during emergency situations [8]. At the same time, access to personal health information requires appropriate protection because medical records contain sensitive information. Existing studies have investigated fine grained access control for personal health records [9], secure sharing of electronic health records [10], and broader access control mechanisms for healthcare information systems [11]. Motivated by these challenges, this work presents **ResQNet, a smart emergency response system that combines fall detection, emergency verification, alert generation, and QR-based medical identification within a single workflow**. The fall-detection component follows a rule-based sequential approach in which multiple motion conditions are examined rather than triggering an alert from a single acceleration threshold. The system is designed to verify a possible emergency before proceeding with the response process, helping reduce unnecessary alerts while retaining the ability to respond to genuine events. The QR-

based component provides a controlled way for an authorized responder to access relevant medical information without placing the complete patient information directly inside the QR code.

The main contributions of this work are as follows:

1)**A rule-based sequential fall-detection approach** that considers multiple motion states instead of relying only on an isolated acceleration threshold.
2)**An emergency verification and response workflow** that connects fall detection with alert generation and escalation.
3)**A QR-based medical identification mechanism** that allows relevant patient information to be retrieved by an authorized responder during an emergency.
4)**An experimental evaluation of the fall-detection component** using 630 trials from the MobiFall Dataset v2.0, consisting of 288 fall trials and 342 activities of daily living, with comparison against a simple acceleration-threshold baseline.
5)**An analysis of false detections across different daily activities**, providing a more detailed view of detector behavior than overall accuracy alone.

## 2. RELATED WORK

Research on emergency assistance and fall detection has developed around several related areas, including access to medical information, healthcare information management, smartphone-based fall detection, and real-time notification. These studies provide useful components for emergency systems, but they address different stages of the overall response process.

Balbudhe et al. [1] proposed a QR-code-based emergency information sharing system intended to help first responders and law-enforcement personnel quickly obtain information such as vehicle details, medical history, emergency contacts, and nearby hospital information. The system also uses Google Maps to support hospital identification. Its main purpose is rapid information retrieval and identification during an emergency, while automatic detection of an emergency is outside its primary scope. The authors identify automated emergency notifications as a possible future extension.
Healthcare information systems have also focused on organizing patient information and controlling access to it. Kshirsagar et al. [2] presented an AI-integrated hospital management system with role-based access for administrators, doctors, and receptionists. The system manages patient details, appointments, laboratory results, and prescriptions and also includes an AI-based chatbot for user interaction.

Mungane et al. [3] developed an integrated hospital management system covering patient registration, appointment scheduling, doctor availability, and access to healthcare information for different users. Their work emphasizes centralized healthcare management and protection of patient information. These systems are useful for managing medical information, but their main focus is hospital administration rather than detecting an emergency and initiating a response when the patient cannot request help.

Smartphone sensing has been investigated more directly for automatic fall detection. Harari et al. [4] developed online smartphone-based fall detection system using accelerometer and gyroscope measurements together with a regularized logistic regression model. Their prospective study involved 23 participants over 2,070 days and recorded 37 real-life falls. The system detected 27 of these falls, giving a sensitivity of 73.0%, while reporting specificity above 99.9%. In addition to fall detection, the system stored contextual information such as location and activity and provided real-time notifications through an online platform. This work demonstrates that smartphone sensors can be used for real-time fall monitoring outside controlled laboratory conditions, while also showing the importance of evaluating detection systems using real-life events.

Habib et al. [5] provided a broader review of smartphone-based fall detection and prevention systems. Their study examined different sensing technologies, detection approaches, communication methods, and applications and identified practical challenges associated with smartphone-based fall detection. In particular, the review discusses issues related to sensor placement, device positioning, usability, and the differences between controlled experiments and practical deployment. These observations are important because a fall detector that performs well under controlled conditions may behave differently when the smartphone is used during normal daily activities.

**ResQNet differs in scope by combining these separate aspects into an emergency-response workflow**. Smartphone based motion sensing is used as one possible trigger, after which the detected event passes through verification before an emergency response is initiated. The system also provides QR based access to medical information and a priority-based escalation mechanism. Unlike the systems discussed above, the focus is not only on detecting a fall or storing medical information, but on connecting detection, verification, and response within the same workflow. However, the experimental evaluation presented in this paper is specifically limited to the fall-detection component. The MobiFall dataset is therefore used to evaluate the detector, while the other ResQNet components are described as implemented system functionality rather than as components validated by the MobiFall experiment.

## 3. SYSTEM ARCHITECTURE

ResQNet is organized as a sequence of connected stages that takes the system from detecting a possible emergency to

deciding how it should be handled. The smartphone acts as the main sensing device and provides accelerometer and gyroscope readings when monitoring is enabled. The acceleration magnitude is calculated from the three sensor axes as A = sqrt(x^2 + y^2 + z^2)

These readings are processed by the fall-detection module using five movement states: Normal Activity, Free Fall, High-Impact Event, Post-Impact Inactivity, and Possible Emergency. A possible emergency is identified only when the required sequence of movements occurs, rather than from a single sudden change in acceleration.

After a possible emergency is detected, ResQNet moves to a verification stage. The user can confirm the event or cancel it if the detection was incorrect. If the user confirms the emergency, or does not respond within the given time, the system continues with the emergency response process. Alerts are then handled according to the configured priority of the emergency contacts.

The system also provides a QR-based medical identification feature. The QR code stores a token rather than directly displaying the user's medical information. When an authorized responder scans the code, the token is checked by the backend before the related medical information is retrieved.

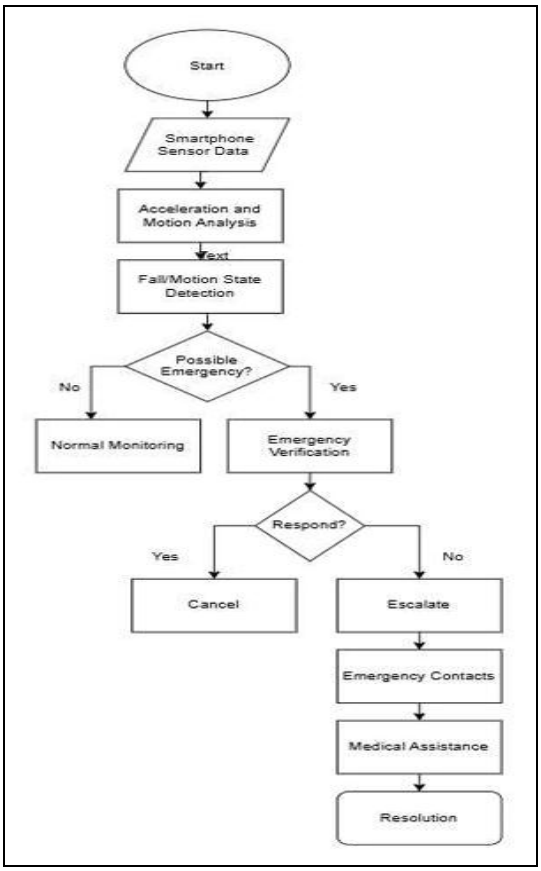



**Fig 1:** Overall Workflow

## 4. DATASET

The fall-detection component of ResQNet was evaluated using the **MobiFall Dataset v2.0** [6], a publicly available smartphone-sensor dataset containing recordings of falls and activities of daily living. The dataset provides motion information collected from smartphone sensors, including accelerometer and gyroscope measurements, making it suitable for evaluating smartphone-based fall-detection approaches.

For the experiments reported in this work, **630 trials from 24 subjects** were evaluated, consisting of **288 fall trials and 342 activities of daily living (ADL)**. The trials were processed using the same pipeline used for the ResQNet evaluation. The fall trials include four fall categories, while the ADL trials represent everyday movements that can produce changes in smartphone motion.

## 5. METHODOLOGY

ResQNet follows a sequential approach in which a possible emergency is first detected, then verified before an alert is raised. The methodology combines smartphone-based sensing with verification and emergency-response mechanisms. The main stages of the system are described below.

### A. Emergency Data Collection

When monitoring is enabled, the smartphone continuously provides accelerometer and gyroscope readings. The accelerometer records movement along the three axes, while the gyroscope provides information about changes in device orientation. The acceleration magnitude is calculated as

$$A = \text{sqrt}(x^2 + y^2 + z^2)$$

These sensor readings form the primary input for the fall detection module.

### B. Fall Detection

Instead of declaring a fall whenever the acceleration crosses a fixed threshold, ResQNet evaluates the order in which different motion events occur. The detector uses five states: Normal Activity, Free Fall, High-Impact Event, Post-Impact Inactivity, and Possible Emergency. A sudden reduction in acceleration is first considered as a possible free-fall event. This must be followed by a high-impact movement and a period of reduced activity before the system considers the event a possible emergency. This state-based approach helps distinguish a possible fall from isolated movements that may produce similar sensor readings.

### C. Emergency Verification

A detected event is not immediately treated as a confirmed emergency. Once the fall-detection conditions are satisfied, the system presents a verification step to the user. The user can confirm the emergency or cancel the alert if the detection was incorrect. If the user does not respond within the specified time, the event is allowed to proceed to the next stage. This step provides an additional check before an emergency alert is generated.

### D. Decision and Alert Generation

After verification, the system determines the appropriate response based on the available event information. The emergency alert contains relevant context such as the reason for the alert, the user's location, and the current status. The notification process follows the priority assigned to the emergency contacts. If the situation requires further assistance, the response can proceed to the next level of escalation.

### E. Medical Identification and Response Support

ResQNet also provides a QR-based medical identification mechanism to support responders during an emergency. The QR code contains a token linked to the user's medical record rather than storing the medical details directly. When the code is scanned, the backend validates the token before retrieving the associated information. This allows relevant medical information to be accessed without exposing the complete record through the QR code itself.

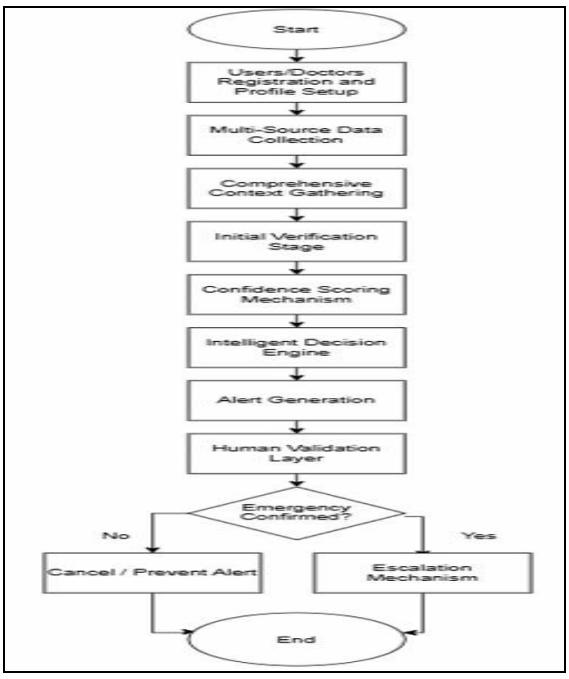



**Fig 2:** Overall system methodology and emergency-response workflow

### F. Fall-Detection Evaluation

The fall-detection component was evaluated using the selected dataset trials containing falls and activities of daily living. The same preprocessing and decision procedure was applied to the evaluated trials. For comparison, a simple acceleration threshold method was implemented as a baseline. Both approaches were evaluated using trial-level predictions, where a trial was classified as a fall if at least one analysis window produced a fall trigger. Accuracy, precision, sensitivity, specificity, F1-score, and false-positive rate were then calculated to compare the two approaches.

## 6. EVALUATION PROTOCOL

**Preprocessing and Evaluation Setup:** The recorded accelerometer and gyroscope signals were first extracted from the MobiFall Dataset v2.0 trials. The gyroscope measurements were converted from radians per second to degrees per second where required. Since the sensor streams could contain different timestamps, the measurements were aligned using nearest-neighbor timestamp matching. The aligned signals were then resampled to 20 Hz to provide a common sampling rate for evaluation. A rolling window of 5 seconds, corresponding to 100 samples at 20 Hz, was used for fall detection. The same preprocessing procedure was applied to both ResQNet and the acceleration-threshold baseline to ensure a fair comparison. Each trial was classified as a fall if at least one analysis window produced a valid fall trigger; otherwise, it was classified as an activity of daily living. The resulting trial level predictions were then used to calculate the confusion matrix and the reported accuracy, precision, sensitivity, specificity, F1-score, and false-positive rate.

The dataset-based experiment evaluates the **fall-detection component** of ResQNet. Other system functions, including emergency verification, QR-based medical identification, and alert escalation, were evaluated separately as system features and are not included in the dataset-based classification results.

## 7. RESULTS AND DISCUSSION

### A. Overall Fall-Detection Performance

The fall-detection performance of ResQNet was evaluated against a simple acceleration-magnitude threshold baseline using the same 630 MobiFall trials and preprocessing procedure. The baseline classified a trial as a fall when the acceleration magnitude exceeded 14.0 $m/s^2$ at any sample. ResQNet used the sequential finite-state detection logic described in Section V.

The evaluation resulted in 283 true positives, 212 true negatives, 130 false positives, and 5 false negatives. The

corresponding performance measures are presented in Table I.

TABLE I. OVERALL PERFORMANCE OF THE RESQNET FALL-DETECTION MODULE

| Metric | Threshold Baseline | ResQNet |
|---|---|---|
| Accuracy | 57.46% | **78.57%** |
| Precision | 51.80% | **68.52%** |
| Sensitivity | **100.00%** | 98.26% |
| Specificity | 21.64% | **61.99%** |
| F1-score | 68.25% | **80.74%** |
| False-positive rate | 78.36% | **38.01%** |

ResQNet achieved an accuracy of 78.57%, compared with 57.46% for the threshold baseline. Although the baseline achieved 100% sensitivity by detecting all 288 fall trials, this came at the cost of 268 false-positive trials among the 342 ADL trials. ResQNet detected 283 of the 288 fall trials, resulting in 98.26% sensitivity, while reducing false-positive trials to 130. This increased specificity from 21.64% to 61.99% and reduced the false-positive rate from 78.36% to 38.01%. The F1-score also improved from 68.25% for the baseline to 80.74% for ResQNet.

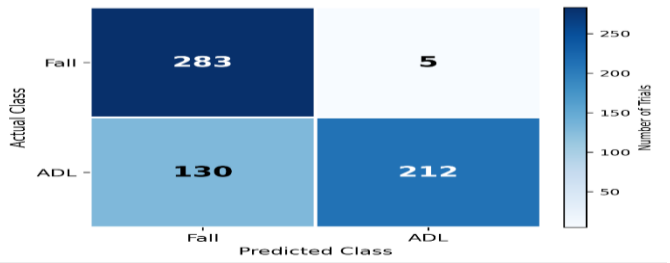



**Fig. 3:** Confusion Matrix

The confusion matrix in Fig. 3 provides a direct view of these results. The detector correctly classified 283 fall trials and 212 ADL trials, while 5 falls were missed and 130 ADL trials were incorrectly classified as falls.

### B. Performance Across Fall Types

To determine whether the detector's performance was consistent across different types of falls, the detected fall trials were further grouped according to their fall category. The results are shown in Table II.

TABLE II. FALL DETECTION PERFORMANCE BY FALL TYPE

| Fall Type | Detected | Total | Recall |
|---|---|---|---|
| FKL | 72 | 72 | 100.00% |
| FOL | 71 | 72 | 98.61% |
| BSC | 70 | 72 | 97.22% |
| SDL | 70 | 72 | 97.22% |
| Overall | 283 | 288 | 98.26% |

The detector achieved 100.00% recall for FKL trials. FOL trials achieved 98.61% recall, while BSC and SDL trials each achieved 97.22%.

The five missed falls occurred in FOL, BSC, and SDL trials. These missed cases indicate that some fall movements may not produce the complete sequence of motion conditions required by the detector.

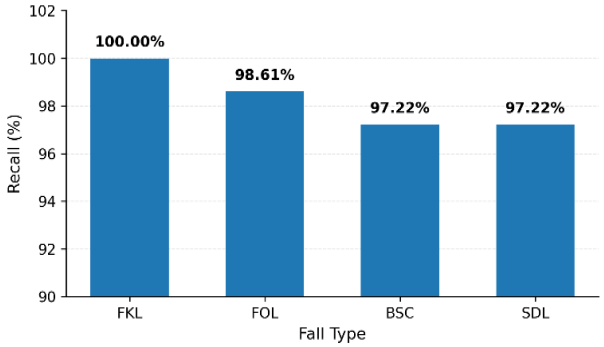



**Fig. 4**. Recall of ResQNet across the evaluated fall types.

Figure 4 shows the relatively consistent recall across the four fall categories. The results support the use of the sequential motion-state approach for detecting different types of falls in the evaluated dataset.

### C. False-Positive Analysis Across Activities of Daily Living

Since unnecessary emergency alerts are an important concern in an automatic emergency-response system, false-positive behavior was analyzed separately for the ADL categories. Table III presents the number of incorrectly detected trials and the corresponding false-positive rate

TABLE III. FALSE-POSITIVE RATE ACROSS ACTIVITIES OF DAILY LIVING

| Activity | False Positives | Total Trials | FP Rate |
|---|---|---|---|
| WAL | 7 | 9 | 77.78% |
| CSI | 32 | 54 | 59.26% |
| STN | 30 | 54 | 55.56% |

| | | | |
|---|---|---|---|
| STU | 30 | 54 | 55.56% |
| CSO | 27 | 54 | 50.00% |
| STD | 1 | 9 | 11.11% |
| JOG | 1 | 27 | 3.70% |
| JUM | 1 | 27 | 3.70% |
| SCH | 1 | 54 | 1.85% |

For clarity, the activity codes used in Table III are defined as follows: WAL – walking, CSI – car step-in, STN – stairs down, STU – stairs up, CSO – car step-out, STD – standing, JOG – jogging, JUM – jumping, and SCH – sitting on a chair. Table III presents the number of incorrectly detected trials and the corresponding false-positive rate.

The false positives were concentrated in a few activity categories. WAL produced false detections in 7 of 9 trials, while CSI, STN, STU, and CSO produced false detections in 50% or more of their evaluated trials. In comparison, the false-positive rates for STD, JOG, JUM, and SCH were considerably lower.

The distribution suggests that activities involving sudden changes in movement or device orientation are more difficult for the detector to distinguish from falls. Stair movement and car entry or exit, for example, can contain acceleration and orientation changes that resemble individual stages of a fall. This explains why evaluating only the overall accuracy would not provide a complete picture of the detector's behavior.

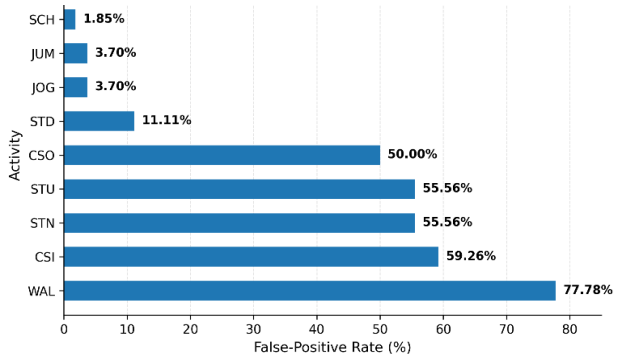



**Fig. 5.** False-positive rate across activities of daily living.

### D. Trigger Timing

The timing behavior of the detector was examined for the correctly detected fall trials. For the **283 detected fall trials**, the mean time from the beginning of the recorded trial to the detector trigger was **3.754 s**. The median was **3.700 s**, with observed values ranging from **1.600 to 6.100 s** and a standard deviation of **0.681 s**.

This measure represents the time from the beginning of a recorded trial to the first detector trigger. **It should not be interpreted as the physical fall-detection latency**, because the evaluated dataset does not provide precise annotations for the actual onset of each fall. A true detection-latency measurement would require synchronized annotations indicating the start of the fall event.

### E. System-Level Functional Verification

The dataset experiment evaluates the fall-detection component of ResQNet. Other implemented functions were therefore evaluated separately through functional tests rather than being included in the classification metrics.

TABLE IV. FUNCTIONAL VERIFICATION OF RESQNET

| Test Case | Result |
|---|---|
| QR Generation | Successful |
| QR Scanning | Successful |
| Token Validation | Successful |
| Patient Identification | Successful |
| Revoked QR Detection | Successful |
| QR Validation | Successful |
| Unsupported Media Type | Successful |

The functional tests confirmed that the tested QR-based medical-identification operations completed successfully. These results demonstrate that the implemented functions operated as expected for the tested cases. They should not, however, be interpreted as clinical validation, a security audit, or evidence of real-world responder performance.

### F. Discussion

The evaluation shows that the main strength of the current ResQNet detector is its ability to identify falls. A sensitivity of 98.26% was obtained, with 283 of the 288 evaluated fall trials detected. Performance was also similar across the four evaluated fall categories, with recall ranging from 97.22% to 100.00%.

The main limitation is the number of false positives. The 130 incorrectly classified ADL trials resulted in a specificity of 61.99% and a false-positive rate of 38.01%. The activity-level analysis shows that these errors are concentrated in particular movements rather than being evenly distributed across all normal activities. This provides a clear direction for further refinement of the motion-state conditions and decision logic.

## 8. LIMITATIONS AND FUTURE WORKS

The evaluation of ResQNet has several limitations that should be considered when interpreting the reported results. The fall-detection experiment was conducted using the MobiFall Dataset v2.0, which contains recorded smartphone sensor data. Although the dataset provides a useful basis for evaluating the detector, it does not fully

represent the range of conditions that may occur when a smartphone is used during everyday activities.

A major limitation observed during the evaluation is the number of false-positive detections. ResQNet achieved high sensitivity for the evaluated falls, but some activities of daily living produced motion patterns that were interpreted as possible falls. The false positives were particularly noticeable in activities involving sudden movements or changes in body position. Further refinement of the state-transition conditions may therefore be required to improve the distinction between genuine falls and normal activities.

Another limitation concerns the reported trigger timing. The measured value represents the time from the beginning of a recorded trial to the first detector trigger. It does not represent the actual physical fall-detection latency because the dataset does not provide precise annotations for the onset of each fall. A more accurate latency evaluation would require synchronized information identifying the exact beginning of the fall event.

The current experimental evaluation also focuses mainly on the fall-detection component. The QR-based medical identification, verification, alerting, and escalation features were functionally tested separately rather than evaluated together as a complete real-world emergency scenario.

Future work will focus on reducing false-positive detections by refining the sequential detection logic and testing the system with more varied sensor recordings. Further evaluation using real-world data would help determine how the detector performs under different smartphone positions, movement patterns, and usage conditions. Future experiments can also include synchronized fall-onset annotations to measure actual detection latency. In addition, an end-to-end evaluation of detection, verification, alert delivery, QR-based identification, and emergency escalation would provide a more complete assessment of the ResQNet system.

## 9. CONCLUSION

ResQNet was developed as a smartphone-based emergency response system that connects automatic fall detection with emergency verification, alert generation, escalation, and QR-based medical identification. Instead of making a decision from a single acceleration value, the fall-detection component considers a sequence of movement conditions involving free fall, impact, and post-impact inactivity.

The evaluation on the MobiFall Dataset v2.0 showed that ResQNet detected 283 of the 288 fall trials, resulting in a sensitivity of 98.26%. The system achieved an overall accuracy of 78.57%, a precision of 68.52%, a specificity of 61.99%, and an F1-score of 80.74%. The results also showed that false positives remain a challenge for certain activities of daily living, particularly those involving abrupt or transitional movements.

Overall, the results indicate that the sequential detection approach can identify a high proportion of falls while reducing unnecessary triggers compared with relying on isolated acceleration events. However, the current evaluation is based on recorded sensor data and separate functional testing of the supporting emergency-response components. Further real-world testing and refinement of the detector are therefore required before evaluating its performance in practical emergency situations.

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