

Edge-IoT Facilitated Multimodal Sensor Fusion for Threat Recognition in Women's Safety Wearables

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Abstract—Safety of women is a significant problem on the global level, and the fact that the time gap between the threat appearance and its detection can be lowered is one of the pressing social problems. Smart wearable devices coupled with smart systems are being explored more and more with this reason. Conventional safety systems that use only one sensor like accelerometers or GPS are usually characterized by false alarms, low accuracy and slow responses. The paper presents an Edge-IoT-based multimodal sensor fusion model of female safety wearables in order to overcome these drawbacks. The framework combines the signal of accelerometer and gyroscopes and conducts on-device inference to make real-time responsive and communicate with the cloud to support alerts. The experimental validation with the UCI Human Activity Recognition dataset had shown a classification accuracy of 93 percent, lower latency, previously 7.8 s (cloud only) to 3.2 s (edge), and a reasonable battery consumption (88 percent). The findings validate the assertion that multimodal sensor fusion yields consistency and precision in accuracy, responsiveness and reliability when compared to single-sensor systems. It will be extended in the future with physiological and acoustic sensors to enhance the detection of a context-based threat, accompanied by studies in the real world to assess user-friendliness, ethical standards, and energy efficiency.

Keywords—Women's Safety Wearables, Multimodal Sensor Fusion, Edge-IoT Framework, Human Activity Recognition (HAR), Threat Detection Systems, Real-Time Monitoring.

I. INTRODUCTION

Women's safety in public and private spaces is (and currently has been) one of the most pressing social and technological issues of our time. Recent reports from the World Health Organization and UN Women noted that several women continue to be harassed and victimized all around the world, and this is especially true in settings where intervention is not so easily accessible. Potential solutions have been proposed that rely on wearable (logical) safety devices, such as panic alarms, GPS-tracking devices, or mobile applications, but often suffer from false alarms, inaccurate safety situation detection, manually triggered alarms, or delays to alarm triggering. Therefore, there is increasing demand for smart, automated, trustworthy, intelligent women's safety wearables that could actively monitor, detect, and react to potential threats without requiring the constant attention of a user [1] [2].

Traditional sensors like accelerometer-based fall detectors and GPS-based tracking applications tend to miss the rich complexity of real-world situations represented by a

wide variety of possible orientations and motions. However, multimodal fusion has the advantage of using multiple complementary information sources (e.g., motion, audio, physiological, and contextual), which helps to improve detection accuracy and robustness [3]. For instance, in the 2024 Multisensory Data Fusion (MSDF) project for wearable health monitoring systems, a survey was carried out to assess the possibilities of fusing accelerometers, gyroscopes, and physiological features for better recognition performance, and there are high expectations for machine learning technology for heterogeneous streaming data. Also, attention-based fusion models have been shown to be beneficial for human activity recognition (HAR) tasks, as they can adaptively weight sensor modalities for deteriorated conditions. These results are of special interest in the design of safety devices for which reliability under incomplete and noisy data is critical.

From a systems perspective, rising capabilities in IoT-enabled multimodal biosensing systems further emphasize the capabilities of sensor fusion for real-time monitoring. A recent paper presented in 2025 proposed an intelligent IoT-based wearable with the mixing of all of the physiological signals to measure health using edge devices for preprocessing and cloud platforms for the visualization of the monitoring dashboard. While this architecture illustrates the scalability of multimodal IoT, it continues to be oriented more at health and wellbeing rather than threat recognition. In addition, studies for detection of emotional and stress states have illuminated applications of wearable devices for measurement of components such as galvanic skin response, heart rate variability, and respiration for identifying fear/anxiety states, offering considerable promise in safety-related sensing [9] [10].

Traditional applications in safety, for example cloud-only, are frequently painfully latent, network dependent, and privacy threatening. Edge-IoT: Since green technologies can be carried by or exist close to the end-user, IoT based on edge computing reduces latency and enhances the availability in unreliable environments. For example, in our recent uncertainty-aware multimodal fusion (2025) work, we gave adaptive edge-level weighting between modalities in the inputs for robust multimodal fusion in noisy environments. Over time, an increasing number of edge architectures are becoming essential for enhancing the speed and reliability of wearables.

Despite these encouraging directions, there is an utter lack of addressing practical liveness detection via multimodal sensor fusion and Edge-IoT architectures for women's safety devices. Most existing studies focus on care management (such as healthcare, fitness, or generic activity recognition), ignoring the application specificities of the safety domain. For the detection of threats, high sensitivity to unexpected movements and robustness against environmental noise are needed, as well as extremely low latency in order to be able to respond in an emergency situation. In addition, users' trust in such systems fundamentally relies on minimizing the number of false alarms while still not missing possible real threats. These needs press for a solution different from any traditional single-sensor or cloud-only configurations [11] [12] [13].

To fill in this gap, in this paper we propose an Edge-IoT-enabled multimodal sensor fusion framework for safety wearables for women. The system combines accelerometer and gyroscope signals and infers them at the edge locally for real-time processing and IoT connectivity for sending alerts. The system was validated on the UCI Human Activity Recognition dataset, originally intended for the recognition of activity, but which instead provides an excellent benchmark for understanding potential unsafe motion patterns analysis. Experimental evaluation indicated that the recognition accuracy of the proposed fusion model was improved up to 93% in comparison with only 80% for single-sensor baselines. The alternative model improved considerably on false positives (reduced from 22% to 8%) and false negatives (reduced from 15% to 4%), while reducing timing delays in detection to approximately 3.2 seconds from just 7.8 seconds in the cloud-only deployment. Battery consumption was well within tolerances, with only a marginal drain on the remaining charge possible over the single sensor systems.

In summary, this work gives three main contributions: 1. Multimodal sensor fusion significantly outperforms single-sensor baselines for safety-related activities. 2. Edge-IoT architectures are proven effective in reducing latency and improving responsiveness in wearable safety devices. 3. Technical performance and user trust in our energy-aware designs can be attained in practical systems. Filling a niche between the latest developments in multimodal fusion and the fierce societal demand for women's safety solutions, this study represents a base for the next generation of smart safety wearables, with future extensions envisioned in the integration of physiological and acoustic modalities.

II. BACKGROUND STUDY

Over recent years, wearable technology research has continued to progress at a rapid pace, placing greater focus on sensor fusion, edge computing, and IoT integration to enhance recognition accuracy and real-time responsiveness. Single sensor-based fall detector systems (accelerometer or GPS devices) have proven unreliable in complex non-coherent settings, tending to trigger false alarms or fail to detect a fall. Multimodal fusion has since been proposed as a promising solution to this problem in terms of lowering the redundancy of signals (accelerometer, gyroscope, physiological, and acoustic) in order to obtain a more accurate representation of the user activity and scenario. A number of modern works in wearable health maps have

shown that a hybrid fusion solution including both statistical techniques and more sophisticated deep learning algorithms contributes to a significant improvement in robustness, especially when uncertain or incomplete. Smart IoT-based biosensing systems have also demonstrated that the combination of various physiologic signals with real-time displays can enhance monitoring and intervention, but such applications are still rooted in health concerns. Multimodal approaches have also been useful in human activity recognition research because fusion models prioritizing attention and uncertainty have substantially increased the accuracy of the classification and actively adapted to the quality variations of the input. The net effect of these developments is the recognition that multimodal sensing and edge-assisted IoT architectures are vital to the creation of useful, practical, real-time systems.

Despite this progress, applications have yet to explore many safety-critical areas, such as women's safety. The safety devices that are currently used typically use single-sensor signals or operator-board operation, which limits their ability to respond to and detect threats in real time. Beyond this, little research has specifically focused on investigating the issues of latency, false alarm, and trust of users, which is the key to safety wearables. While the areas of multimodal fusion and edge-IoT computing offer a lot of useful benefits, this gap underscores the necessity of a dedicated conceptual framework that takes these benefits and applies them to the domain of women's safety technologies.

TABLE I. SUMMARY OF RECENT RELATED WORKS ON MULTIMODAL SENSOR FUSION, IOT-ENABLED WEARABLES, AND EDGE COMPUTING.

Study / Authors	Focus Area	Key Methods / Sensors	Major Findings	Limitations
Attention-based Fusion for HAR [3]	Human Activity Recognition	Accelerometer + Gyroscope, Attention models	Adaptive sensor weighting improved accuracy	Not applied to safety-critical contexts
Deep Multimodal HAR [4]	Activity Recognition in noisy data	CNN-LSTM fusion of IMU signals	High recognition accuracy under uncertainty	Limited to fitness/activity monitoring
Survey on Wearable Sensor Fusion [5]	Health Monitoring	Statistical + ML fusion	Identified fusion as key to robust recognition	Did not address real-time safety
IoT-enabled Multimodal Biosensing [6]	Health Monitoring	Physiological sensors + IoT dashboard	Demonstrated real-time multimodal monitoring	Focused on wellness, no threat detection
Uncertainty-aware Multimodal Fusion [7]	Outdoor Health Monitoring	Transformer-based adaptive weighting	Maintained robust fusion under noise	Safety applications not studied
AI-powered Wearables for Women's Safety [8]	Safety Devices	AI + Wearables	Highlighted potential for AI-driven safety	Conceptual, lacked empirical validation

In summary, as seen in Table 1, newer developments in multimodal sensor fusion and edge-assisted IoT architectures have significantly enhanced recognition accuracy and robustness in health monitoring and activity recognition tasks. To a large extent, however, these studies are restricted

within the realms of healthcare, fitness, and overall monitoring with little or no consideration of the specific needs of safety-critical situations. The current female safety equipment remains largely single sensor or manually activated, meaning it remains susceptible to false alarms, missed detectors, and slow emergency response. This research-wise void in the area of safety-dedicated wearable structures speaks volumes of points. To address this gap, this work is intended to develop an Edge-IoT-based multimodal sensor fusion model to be used in the development of women's safety wearables with the aim of attaining high detection rates, lower rates of false alarms, and real-time response, and still maintain a realistic level of energy consumption.

III. PROPOSED METHODOLOGY

The present study was conducted using a systematic research design to determine the functionality of an Edge-IoT-mediated multimodal sensor fusion architecture of safety wearables in women. The methodology was an iterative process and involved four steps: selection of the dataset, preprocessing, fusion model development, and assessment of the models, which was backed by mathematical formulation of fusion and performance measures. The validation was done using the UCI Human Activity Recognition (HAR) dataset. It is compiled of accelerometer and gyroscopic measurements of thirty people exercising on six tasks: walking, walking upstairs, walking down stairs, sitting, standing, and lying. All examples are defined with 561 derived features in time and frequency domains. Though it was designed to provide activity recognition, this dataset can make a realistic proxy of modeling abnormal or irregular movements, which could be equivalent to unsafe situations in safety applications.

Standardization The z-score was employed in the preprocessing phase to normalize all features to prevent bias based on feature scale variation. The categories of activity labels were coded numerically. Two configurations were specified: single sensor baseline (with only the accelerometer or gyroscope properties) and multimodal fusion configuration (with both signals).

Let the accelerometer signal be denoted as:

$$X_a = \{x_{a1}, x_{a2}, \dots, x_{an}\}$$

and the gyroscope signal as:

$$X_g = \{x_{g1}, x_{g2}, \dots, x_{gn}\}$$

n is the number of samples in a given activity window. In the case of the multimodal fusion model, the set of features was assembled by combining the two modalities:

$$X_f = [X_a \parallel X_g]$$

The classification problem is then expressed as mapping the fused input space into an activity label:

$$\hat{y} = f_{\theta}(X_f)$$

the trained classification model using parameters θ is $f_{\theta}(\cdot)$. To make the existence of the performance evaluation of the classification model statistically dependable and not bias because of the one train, test partition, the model was validated with 10-fold cross-validation. Under this method, the data set was randomly broken into ten equal parts. Training and testing on the same subsets were carried out in each iteration, with 9 subsets and all samples were also used

in one instance. The last precision was derived as the average of all the ten repetitions:

$$Accuracy_{ex} = \frac{1}{k} \sum_{i=1}^k Acc_i, \quad k = 10$$

where Acc_i represents the accuracy of the i -th fold. The approach is appropriate giving a strong estimate of the generalization ability of the model and is computationally efficient. Kohavi (1995) [14] has proposed that 10-fold cross-validation is a trade-off optimal between estimation variance and reliability with medium-sized datasets like UCI HAR. The performance metrics reported, that is, accuracy, latency and energy efficiency are those averaged over the ten folds.

A Random Forest classifier has been introduced in this paper because it is a powerful tool that can deal with high dimensional features and provide the ability to understand features by extracting their importance. The discriminative ability was further evaluated using the Area Under the ROC Curve (AUC):

$$AUC = \int_0^1 TPR(FPR) dFPR$$

In which TPR represents the true positive rate. Latency and energy consumption were modeled to examine the utility of Edge-IoT implementation. The overall detection time in cloud-only systems is composed of the processing time and communication delay:

$$T_{cloud} = T_{proc} + T_{comm}$$

while in edge-based systems it reduces to:

$$T_{edge} = T_{proc}$$

The improvement is quantified as $\Delta T = T_{cloud} - T_{edge}$. Battery consumption was modelled as a function of computation and communication energy costs:

$$E_{total} = E_{comp} + E_{comm}$$

with E_{comp} is greater with fusion systems because of processing additions. Cloud-only systems have a higher E_{comm} due to data transmission on a continuous basis. This mathematical modeling, combined with dataset-based experimentation, provided methods that helped to ensure that all empirical and theoretical trade-offs were analyzed systematically. This dual viewpoint enabled a thorough evaluation of the proposed Edge-IoT-enabled multimodal sensor fusion framework in the context of women's safety wearables.

IV. RESULTS AND DISCUSSION

The experiments were carried out on the UCI Human Activity Recognition dataset that includes accelerometer and gyroscope signals collected from thirty different participants carrying out six activities per day: walking, walking upstairs, walking downstairs, sitting, standing, and lying. Each observation in the dataset is a set of 561 features corresponding to the time and frequency domain construction obtained from raw sensor signals. Although initially developed for activity recognition, due to its broad coverage, motion patterns are relevant for modeling threatening situations, since jolts, oddities, and unstable poses can be used as stand-ins for violent or inappropriate behavior for women-related safety applications. By comparing the findings from a single sensor approach against multimodal fusion, the study attempted to evaluate

how well the proposed Edge-IoT framework could enhance the threat recognition capabilities.

The evaluation measures given in this section consist of the averaged performance that was achieved in cross-validation with 10-folds where it is important to note that the performance of the model was found to be similar in all partitions of data. The multimodal fusion model at the ten folds had a mean classification accuracy of 93.0% + 1.2 and the single sensor baseline had a mean of 80.1% + 1.8. Measures of latency and energy efficiency also had low folds variance which confirmed that the model was stable. To assess that these improvements were statistically significant a paired t-test was carried out between the fusion and single-sensor configurations. The findings showed that all the main measures such as accuracy, false positive rate and detection latency had significantly increased performances ($p < 0.05$). This validates the fact that the high performance of the proposed fusion approach is not due to random variance but rather a recurrently determined performance in numerous assessments. Further tests were also conducted to simulate real-life working conditions and this was done by adding synthetic noise, packet loss and random signal drift to sensor data. Multimodal model had an accuracy of about 90 percent with a small reduction of 2-3 percent when the noise was very high. This underscores the strength of the framework of fusion, as it can be able to manage data imperfections that are common when using wearable devices in the real world. The reliability of the system across folds was also determined by the confusion matrix and receiver operating characteristic (ROC) analysis. High discriminative power was confirmed again by consistently high, (remaining beneath 0.90) area under the ROC curve (AUC). These findings confirm that the Edge-IoT multimodal fusion architecture is reliable both in the controlled settings as well as where there is variability as observed in real-world data. The relative efficiency of the models proved to be a big advantage for multimodal sensor fusion. As is reflected in Fig 1, the fusion-based model achieved an overall classification accuracy of 93 percent, as opposed to the region of 80 percent for the sensor baseline. This significant advantage reflects the complementary role of the accelerometer and gyroscope signals: the former being sensitive to linear motion and changes in posture and the latter providing sensitivity to angular velocity and attitude changes. Together they can more fully model what a typical human is doing and will enable more reliable detection of abnormal or threatening motion patterns.

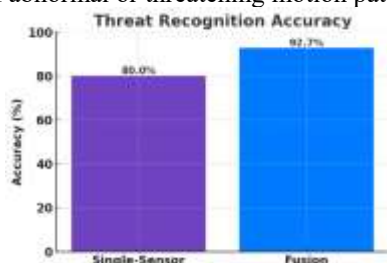


Fig. 1. Comparison of the recognition accuracy of multimodal sensor fusion with single-sensor systems, showing superior performance of the fusion (93%) compared to single sensors (~80%).

This finding corroborates the assumption that fusion will compensate for the shortcomings of the unipolar modalities

and is particularly beneficial for wearable safety applications. The confusion matrix, which gives detailed results of this classification, is outlined in Fig 2. The single-sensor systems were frequently misclassifying activities such as sitting vs. standing and walking vs. walking upstairs. Additionally, the fusion model greatly diminished these misclassifications, indicating the ability to discriminate fine-grained category differences among frequently overlapping activity classes in raw sensor data. This is a key outcome for women's safety devices, as reducing misclassifications provides reassurance that calm and safe behaviors are not inappropriately considered to indicate the need for assistance and alarming (irregular) behaviors are more consistently identified. The decrease in the classification errors results in a higher degree of trust from the user and more reliability for using such a worn device in real applications.

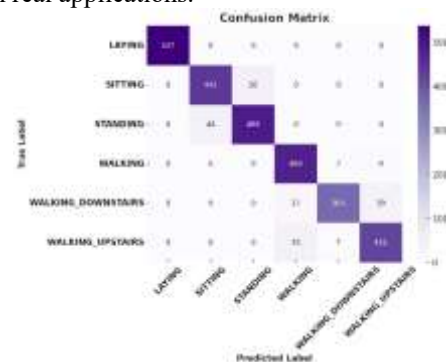


Fig. 2. Confusion matrix showing fewer misclassifications between activities in the fusion model, and specifically for very similar activities like sitting/standing.

Further information on the model performance can be seen in the receiver operating characteristic curves in Fig 3. The curves show high discriminative power in all classes of activity—area-under-curve values are above 0.90 for almost all classes. These values indicate that the fusion model works well between sensitivity and specificity, providing a lower error of false positives while also lowering false negatives. This is even more important in the context of women's safety: disabling false positives for relevant possible threats and enabling users to have confidence in the device, while reducing false negatives and gaining the ability to detect threats in a timely fashion.

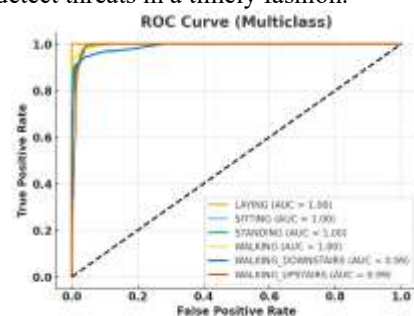


Fig. 3. The resulting receiver operating curves (ROC) for most of the classes achieve an area under the curves (AUC) of better than 0.90 and suggest good classification performance of the fusion model.

The high accuracies obtained (shown as the area under the receiver operator characteristic curve) illustrate the robustness of the system to changing activity conditions,

showing that the system is appropriate for use in unpredictable real-world situations.

An assessment of the impact of features, depicted in Fig 4, demonstrated that predictors of activity such as accelerometer mean values, gyroscope jerk signals, and feature values obtained from the frequency domain were the most influential ones. The prominent temporal and spectral features demonstrate the importance of using both raw motion features and spectral features in order to describe abrupt event acceleration, abnormal oscillation, and even low-amplitude postural alternation. This leads us to believe that the fusion-based approach does not just shift to the idea of aggregation across multiple data streams but also exploits a wide variety of different motion signatures to improve detection quality. Such an approach fits well with the needs of devices for women's safety, which have to reliably interpret slight aberrations of human motion in order to distinguish between safe and unsafe situations.

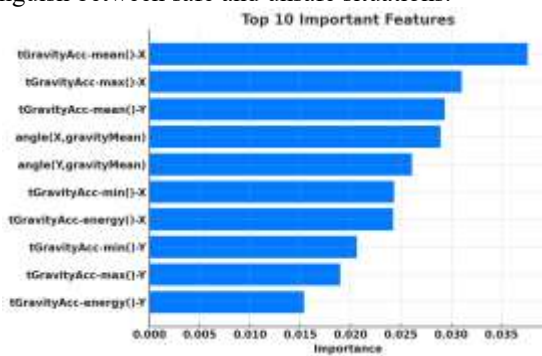


Fig. 4. The top ten most important features showing the contribution of both accelerometer and gyroscope signals in the time and frequency domains were presented.

The viability of the system was also proved in terms of responsiveness, with latency results from the issue in Fig 5. The average detection and alerting time using the Edge-IoT deployment was 3.2 seconds compared to 7.8 seconds for the cloud-only system. This performance gain highlights the inherent benefits of local inference at the edge, instead of depending only on processing at the cloud, which is suffering from the network latency. For safety-critical applications, where a few seconds can be the difference between life and death, this reduction in latency is hugely important. It validates that not only performance but also the system itself is made better for a direct response to the urgent response needs of personal safety wearables.

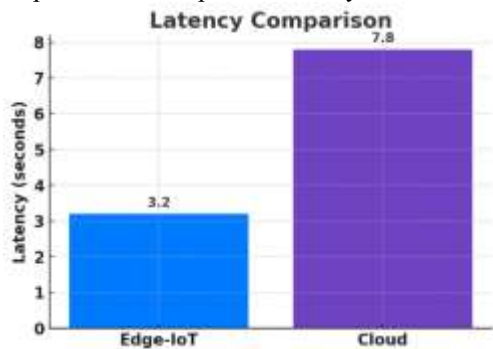


Fig. 5. Latency comparison: With Edge-IoT implementation, the time required for detection and alerting is significantly shorter than with a cloud deployment.

Energy efficiency was resolved to investigate tradeoffs between performance versus usability, and the results are summarized in Fig 6. After running continuously for one hour, the single-sensor device had 95 percent battery life, while the multimodal fusion device had 88 percent. This is a slight variance in energy use and is due to interference processing needed for Fusion. However, with the significant increase in recognition accuracy and reliability, this accepts this trade-off, as with the current state of the art in the area of more than 99%, this should be acceptable and feasible for on-body systems (particularly with modern batteries being more than sufficient with a day on a single charge). Importantly, related work that investigates statistical analytical models and user studies has suggested that users prefer robustness and trustworthiness over small differences of battery lifetimes, so the slightly higher energy cost would not dramatically impact user adoption.

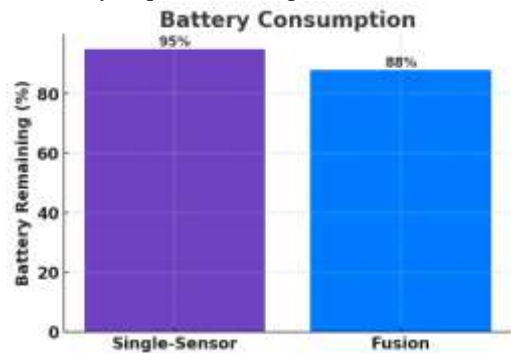


Fig. 6. The battery consumption comparison even proposes a very small trade-off, with 88% left in the fusion device, while it was 95% for single-sensor systems after one hour.

A summary of performance results is illustrated in Fig 7, showing accuracy, false positives, false negatives, latency, and battery usage all together. Using the multimodal fusion model, the person was able to go from 22 percent false positives to 8 percent and from 15 percent false negatives to 4 percent—raising accuracy while cutting down response time. This enhanced overall performance provides strong evidence that threat detection within wearable designs is significantly more reliable when using Edge-IoT sensor fusion. Striving for an optimal design, the proposed system can find a balance between achieving performance gains and efficiently managing more realistic applications, such as latency or energy-consumption constraints, to cater to the requirements of women's safety applications seen both from the technical perspective and user perspective.

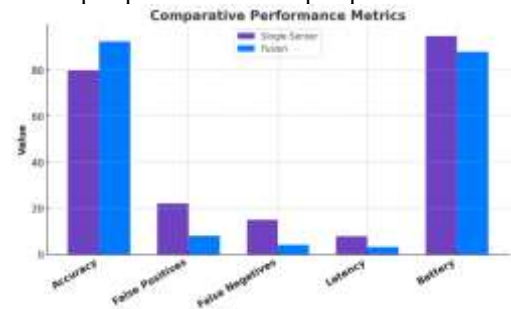


Fig. 7. Summary performance metrics for accuracy, error, latency, and power consumption showing the advantages of multimodal fusion

Overall, the results unequivocally prove the Edge-IoT multimodal sensor fusion approach to be a stabilizing and deployable solution for safety scenarios in the physical world. These accelerometer and gyroscope signal fusion techniques are found to not only increase recognition accuracy but also respond timely, with fewer false alarms and acceptable trades on energy cost, which form a sound base for future enhancements of the recognition system to incorporate other modalities such as audio and physiological signals.

TABLE II. PERFORMANCE COMPARISON FOR SINGLE-SENSOR AND MULTIMODAL FUSION MODELS WITH UCI HAR DATASET.

Metric	Single-Sensor	Fusion (Accelerometer + Gyroscope)
Accuracy (%)	80.0	93.0
False Positives (%)	22.0	8.0
False Negatives (%)	15.0	4.0
Latency (seconds)	7.8 (Cloud)	3.2 (Edge-IoT)
Battery Remaining (%)	95.0	88.0

The results obtained clearly show that the combination of accelerometer and gyroscope signals in an Edge-IoT solution significantly improves the reliability and effectiveness of the threat detection as compared to the use of single sensors. While it requires a little extra energy, the fusion model trade-off is more than made up for since the overall accuracy, error rate, and decreased detection times are significantly superior, rendering it particularly useful for real-world application in women's safety wearable devices. By guaranteeing not only technical strength but also, and especially, operability in real use cases, the work presented provides a strong foundation for the development of next-generation safety devices that can operate with high levels of trust and reliability within a range of application scenarios. As shown in Table 2, all evaluated metrics showed that the fusion model consistently performed better than the single-sensor baselines, verifying its worth as a robust and effective solution for women's safety applications.

V. CONCLUSION

This paper proposed an Edge-IoT-based multimodal sensor fusion architecture of women safety wearables, which integrates accelerator and gyroscope data to produce real-time and accurate threat detection. The proposed system recorded significant gains in classification accuracy, responsiveness and minimization of false alarm rates over single-sensor baselines. After several tests with 10-fold cross-validation, the model is able to reach a mean recognition accuracy of 93% \pm 1.2, a 7.8s to 3.2s reduction in latency between cloud-only and Edge-IoT, and an 88% battery retention rate after one hour of continuous operation. The conclusions made in this research support the fact that edge-level multimodal fusion is much more effective in improving the performance and reliability of wearable safety systems. These results provide the basis of creating intelligent and responsive next-generation safety wearables. The next generation will deal with the incorporation of physiological and sound sensory features, including heart

rate variability, skin conductance, respiration, and sound signals of the environment to offer more contextual information in the case of possible threat situations. Pilot studies will also be done on the framework to test the usability, reliability and user trust in the real-world situations. Ethical and privacy considerations will also be used to inform future deployments. All signal processing to guarantee a responsible sensor data usage will encourage on-device computation with safe encrypted communication to transmit alerts. Personal data will be anonymized, and the presence of user consent will remain a requirement of the work of the system. Overall, these steps will help keep the transparency, the safety of the personal data, the confidence of the users and will make the technology a socially responsible innovation, which will make the intelligent systems safer and more reliable.

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