Experimental Investigation of Smartphone MEMS Accelerometers Under Simulated Temperature and Humidity Changes for Long-Term SHM Programs

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**Abstract.** Smartphone sensing technology offers a new and next-generation system for structural health monitoring (SHM) of civil structures. Among smartphone built-in sensors, the tri-axial MEMS accelerometer is an appropriate and affordable choice for vibration monitoring with successful applications to real-world large-scale structures such as bridges and high-rise buildings. However, the implementation of a long-term SHM program via the smartphone sensing technology is a big challenge. One of the critical issues is the impact of environmental changes, particularly ambient temperature, on both the civil structure being monitored and the smartphone MEMS sensors. Under such circumstances, it is challenging that variability in measured accelerations is caused by structural changes or sensor performance variations. To investigate the impacts of temperature and humidity on smartphone MEMS sensors and their applications to long-term SHM programs, this research implements an experimental study and assesses extreme environmental conditions of such sensors. In this investigation, a smartphone is placed and fixed in different areas with various temperatures ranging from –25⸰C to 40⸰C and the humidity levels varying from 28% to 96%. To indicate the capabilities of machine learning for dealing with the challenges regarding MEMS sensors under varied environmental conditions, three unsupervised outlier detectors in terms of discriminative models are introduced and compared to identify conditions that the smartphone MEMS sensors are significantly influenced by extreme environmental changes. Results demonstrate that extreme cold and warm temperatures critically impact the performance of the smartphone MEMS sensor.

**Keywords:** Structural Health Monitoring, Smartphone Sensing Technology, Micro-Electro-Mechanical System, Accelerometer, Temperature, Humidity

1. Introduction

Structural health monitoring (SHM) has increasingly integrated innovative sensing technologies and advanced computational algorithms based on artificial intelligence and machine learning to enhance the reliability and functionality of civil structures [1-3]. Among these technologies, smartphone sensing offers a promising and practical system for monitoring of large-scale civil structures, especially bridges [4]. Smartphones are equipped with various built-in sensors, including accelerometers, gyroscopes, and GPS, which can be effectively utilized to monitor and assess the structural integrity of civil infrastructures. Beyond their ubiquitous sensing capabilities, smartphones also enable wireless data communication through the Internet of Things (IoT), facilitating real-time data transfer and remote monitoring. Another advantage of smartphone sensing technology is its ability to capture both vibration and vision data in both mobile and fixed measurement schemes, providing flexible and scalable options for SHM [4].

The tri-axial micro-electro-mechanical system (MEMS) accelerometer embedded in smartphones provides a practical solution for vibration monitoring by recording acceleration time histories in the lateral, longitudinal, and vertical directions. Most smartphone accelerometers are based on capacitive MEMS technology. These sensors, initially designed for consumer electronics to detect orientation changes and motion, typically offer sensitivity levels ranging from 1 to 3 mg. Although not as sensitive as high-end accelerometers, this sensitivity is sufficient for capturing larger amplitude vibrations, making them particularly effective in applications where extreme precision is not the primary requirement. The application of smartphone MEMS accelerometers in SHM primarily focuses on monitoring vibrations and movements of structures to detect potential damage or to extract dynamic features such as modal properties [4]. Due to their moderate sensitivity, these accelerometers are especially well-suited for large civil structures like bridges and high-rise buildings, where environmental loads such as wind and traffic induce noticeable vibrations. This capability highlights the potential of smartphone-based MEMS accelerometers as cost-effective tools for SHM in large-scale infrastructure monitoring.

Smartphone applications for SHM can be categorized into two primary schemes: mobile measurements and fixed measurements. Mobile measurement involves the use of smartphones carried by individuals, vehicles, or drones, offering flexible and ad-hoc monitoring capabilities that can cover extensive areas without the need for permanent installations. This approach is particularly effective for rapid assessments following events such as earthquakes or storms, where vibration data, images, or videos are collected to evaluate structural conditions swiftly. In contrast, fixed measurement utilizes smartphones that are securely attached to the structure's surface, functioning similarly to traditional contact-based sensors. This method enables continuous data collection from specific points, providing detailed insights into structural responses over extended periods. Fixed measurements are ideal for long-term monitoring, capturing time-dependent variations that can indicate gradual changes or emerging damage in the structure. Both schemes offer unique advantages: mobile measurements provide rapid, flexible deployment for emergency assessments, while fixed measurements ensure consistent, long-term monitoring for in-depth structural analysis. Together, they represent versatile strategies for enhancing SHM through the practical integration of smartphone sensing technology [4].

Capacitive MEMS sensors used in smartphones are sensitive to environmental conditions, particularly temperature and humidity [5-8]. The sensitivity of the accelerometer can vary with temperature due to changes in the mechanical properties of the silicon elements within the MEMS sensor, potentially leading to errors in acceleration measurement. Temperature fluctuations induce thermal expansion or contraction in the MEMS material, causing internal stress that may misalign its internal structures. Over time, this can result in long-term damage or calibration shifts, impacting the accuracy and reliability of the measurements. Another critical issue associated with ambient temperature is bias drift or zero-point drift, where the accelerometer's resting output deviates from its calibrated zero value. This shift introduces errors in acceleration readings even when the smartphone is stationary, leading to inaccurate vibration measurements. Regarding humidity, if moisture penetrates the sensor package, it can cause corrosion of electrical components or alter the mass of the microstructures, both of which affect the sensor's accuracy. In capacitive smartphone MEMS sensors, elevated humidity levels can introduce moisture into the dielectric medium between the capacitive plates, altering the capacitance and, consequently, the sensor output. These environmental influences underscore the importance of robust calibration and environmental compensation techniques for reliable SHM applications using smartphone-based MEMS sensors.

Temperature and humidity also impact the **materials and structural properties** of civil structures, leading to variations in sensor readings [9-15]. Although these sensor readings can be attributed to structural changes induced by environmental conditions (i.e., temperature and humidity), the overlap between structural behavior and the performance of MEMS accelerometers may cause misleading or inaccurate measurements [16,17]. In such cases, it becomes crucial to understand the influence of environmental factors on smartphone sensors to accurately interpret the data and ensure that the measurements reflect true structural changes rather than environmental-induced variations. To address this challenge, machine learning algorithms can be leveraged to develop advanced solutions for distinguishing between structural responses and sensor-induced anomalies. Unsupervised outlier and anomaly detection models, acting as discriminative mechanisms, can effectively identify unreliable MEMS sensor readings that are influenced by extreme environmental conditions. This approach enhances the reliability of smartphone-based SHM by filtering out environmentally induced noise, allowing for more accurate structural assessments.

Generally, machine learning-assisted discriminative models can be categorized into two main types: statistical models and neural network models. Statistical models are rooted in the principles of statistical learning theory [18], while neural network models are derived from artificial neural networks (ANNs), encompassing both shallow and deep learning architectures [19]. One significant advantage of discriminative models is their ability to automatically detect outliers without requiring prior knowledge of environmental conditions. In other words, these models rely solely on sensor records of structural responses to identify anomalous samples that may be influenced by environmental changes. This capability enhances the robustness of SHM systems by filtering out sensor noise and isolating genuine structural responses, even in the presence of fluctuating environmental factors.

To address the challenges posed by environmental effects on smartphone MEMS accelerometers, this study implements an experimental program consisting of lab-scale investigations under controlled conditions to analyze and detect the impacts of extreme environmental changes on sensor performance. A smartphone, along with a digital temperature/humidity recorder, is employed to record tri-axial acceleration time histories in the lateral, longitudinal, and vertical directions, as well as corresponding temperature and humidity values. The experimental program considers five controlled environmental conditions, ranging from freezing to extremely warm temperatures. During each test, the smartphone is placed horizontally on rough surfaces and securely fixed with double-sided adhesive to prevent movement, ensuring that any recorded accelerations are solely influenced by environmental changes rather than external excitations. In total, the program includes 40 test measurements across the defined environmental scenarios. To detect unreliable performance of the smartphone MEMS accelerometer under these conditions, three unsupervised outlier detection models are proposed and compared. These models aim to identify anomalous sensor readings resulting from extreme environmental influences, contributing to enhanced reliability of smartphone-based SHM applications.

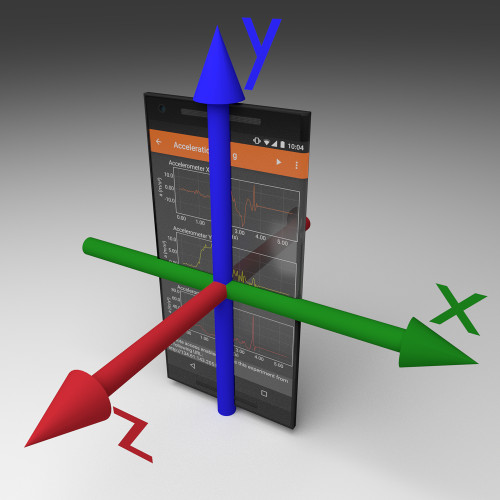
1. Experimental program

The experimental program was conducted using a smartphone and a digital temperature/humidity recorder, as illustrated in Fig. 1(a) and (b), respectively. A third-party app called “phyphox” [20] is utilized to record and transmit the measured acceleration time histories along the *x*-, *y*-, and *z*-axes, corresponding to the lateral, longitudinal, and vertical directions, respectively. Fig. 2 provides a vertical view of the smartphone, indicating these directional axes.

|  |  |
| --- | --- |
| **(a)** | **(b)** |

**Fig. 1**. (a) The smartphone contributed in the experimental program, (b) the digital temperature/humidity recorder

The experimental procedure involved a total of 40 test measurements under various controlled environmental conditions, as detailed in Table 1. Representative examples of the recorded acceleration time histories are presented in Figs. 3–5, corresponding to the test numbers 10, 16, 24, and 36. The environmental conditions during these tests included temperatures of –23.4°C, 5.6°C, 22.2°C, and 41°C, with humidity levels of 42%, 38%, 96%, and 29%, respectively. These instances highlight the variation in acceleration responses under different thermal and humidity settings, showcasing the sensitivity of the smartphone MEMS accelerometer to environmental fluctuations.



**Fig. 2**. The vertical view of the smartphone coordination including the lateral (*x*), longitudinal (*y*), and vertical (*z*) axes

**Table 1**. Controlled environmental conditions

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Test conditions | Temperature (⸰C) | | Humidity (%) | | Test no. |
| Min | Max | Min | Max |
| Extremely cold and dry | -8.7 | -23.4 | 38 | 43 | 1 – 10 |
| Cold and moderately humid | 2.1 | 8.4 | 32 | 58 | 11 – 20 |
| Extremely hot and humid | 22.2 | 29.7 | 70 | 96 | 21 – 26 |
| Mild and dry | 20.6 | 21.2 | 33 | 35 | 27 – 30 |
| Extremely warm and dry | 27.6 | 41.0 | 28 | 40 | 31 – 40 |



**Fig. 3**. Lateral acceleration time histories in the test numbers 10,16, 24, and 41



**Fig. 4**. Longitudinal acceleration time histories in the test numbers 10,16, 24, and 41



**Fig. 5**. Vertical acceleration time histories in the test numbers 10,16, 24, and 41

1. Unsupervised Anomaly Detectors

Detecting outliers in sensor data affected by extreme environmental conditions is crucial for maintaining the reliability and accuracy of measurements, especially in applications such as SHM, where precise sensor readings are vital. This section introduces and compares three unsupervised outlier detection models including isolation forest (IF), robust random cut forest (RRCF), and one-class support vector machine (OCSVM) for identifying critical anomalies in data collected from smartphone MEMS sensors under extremely cold and warm temperatures.

A key advantage of these models is their ability to detect outliers without requiring direct environmental (temperature or humidity) data for modeling. Instead, they rely solely on the statistical properties and distribution of the sensor readings to distinguish anomalies from normal conditions. This capability simplifies deployment and enhances robustness in scenarios where environmental measurements are either unavailable or impractical to collect, making them highly effective for smartphone-based SHM applications.

* 1. Isolation Forest (IF)

The IF model lies in an unsupervised outlier detection technique based on the principles of tree-based ensemble learning[21]. Unlike conventional algorithms that attempt to model normal data distributions to identify anomalies, IF detects anomalies by directly isolating them through random partitioning of the dataset. The core idea behind this approach is that anomalies are rare and exhibit distinctive characteristics compared to normal observations, making them easier to isolate through random splits. The fundamental principle of this technique is that an anomaly can be isolated faster than a normal observation due to its rarity and uniqueness. The process of isolation is akin to splitting a dataset into partitions, and the goal is to construct a series of trees (decision trees) that isolate each point.

Isolation mechanism is comprised of random partitioning, tree construction, and isolation path length. In the first step, i.e., random partitioning, each tree in the forest is constructed by recursively splitting the data at randomly chosen feature values. These random splits create partitions that progressively isolate data points. During the tree construction, the IF starts from the roof node to select a random feature to determine a random split value within the range of this feature. The process continues recursively, which splits the data into smaller and smaller subsets until each point is isolated in its own node, or a stopping condition (like tree depth) is met. Eventually, in the isolation path length step, the key insight is that anomalies, being few and different, are easier to isolate and will typically require fewer splits (resulting in shorter paths in the tree). In contrast, normal points tend to require more splits (resulting in longer paths) because they are part of dense regions of the data.

Given the measured RMS values of the acceleration time histories of a tri-axial smartphone MEMS sensor **,** where is the total number of test measurements and denotes the number of measurement directions, i.e., =3, the IF considers the path length from the root node to the terminal node. Having considered isolated in a tree, where , this length is a measure of how anomalous is. The shorter the path, the more likely it is that is an outlier. Accordingly, the outlier score for is computed as:

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|  |  | (1) |

where is the average path length (i.e., the number of splits required to isolate ) over the trees in the forest and is the average path length of an unsuccessful search in a binary search tree, which is defined as follows:

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| --- | --- | --- |
|  |  | (2) |

where stands for the harmonic number, which approximates the average path length of random binary trees. The anomaly score ranges between 0 and 1. Using a fraction () anticipating the potential outliers in the dataset, the IF can measure a threshold for decision-making. In this regard, it sorts the outlier scores in descending order and then selects the score at the -quantile as the threshold. If the outlier score exceeds this threshold, the IF detects the sample regarding this score as an outlier.

* 1. Robust Random Cut Forest (RRCF)

RRCF is an extension and adaptation of the IF technique, which was designed to enhance outlier detection in streaming data environments and datasets with complex structures. RRCF not only maintains the efficiency and simplicity of IF in handling large datasets but also improves its ability to adapt dynamically to changes in the data distribution [22]. Although the variability in the acceleration RMSs is not complex, this study incorporates RRCF to compare it with other unsupervised outlier detectors.

RRCF builds upon the principles of IF by utilizing a collection of binary trees (i.e., random cut trees) to isolate points. Along with the main steps of IF, RRCF follows two additional steps of dynamic tree structure and co-dispersion. The rationale behind the dynamic tree structure is that trees in RRCF can adjust over time, accommodating new data points and forgetting old ones, which helps maintain model accuracy over time. Moreover, the co-dispersion is a measure used in RRCF to quantify how outlying a point is relative to others within the tree structure. It assesses the impact of removing a point on the structural integrity of the forest, providing a robust anomaly score.

As mentioned, the isolation process in RRCF is similar to that in IF but includes mechanisms for dynamically adjusting tree nodes. Similar to IF, RRCF performs random cuts to isolate data points. Each cut is made by selecting a random feature and a random threshold within the range of that feature. As new data points arrive, they are incorporated into the forest, potentially causing rebalancing of the trees. The outlier score for each point is calculated based on its co-dispersion, which measures the degree to which its removal would decrease the average path length in the tree as follows:

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|  |  | (3) |

where denotes the number of trees; is the forest (trees) constructed by RRCF; and is the dispersion of point in tree expressed as follows:

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|  |  | (4) |

where represents the change in the path length of the node when point is removed from the tree. The co-dispersion value is the outlier score for RRCF. This technique also follows the same threshold determination strategy as IF. Therefore, any co-dispersion value over the threshold is detected as outlier.

* 1. One-Class Support Vector Machine (OCSVM)

OCSVM is a specialized version of the support vector machine (SVM) that is suitable for the problem of outlier detection. The primary objective of OCSVM is to distinguish the normal data from all other possible outliers which do not belong to this normal class [18]. This approach is particularly useful when the dataset has a majority of normal instances and the outliers are not well-defined or known a priori. The objective of OCSVM is to find a function that is positive for regions with high density of points and negative for the rest. This function is used to capture regions in the input space where the probability density of the data is high. OCSVM involves transforming the data into a higher-dimensional space (feature space) using a kernel function. This transformation is key to the ability of OCSVM to handle complex data structures. Gaussian kernel is among the most applicable function in OCSVM utilized here.

The OCSVM model attempts to separate the data from the origin in a high-dimensional feature space by maximizing the margin, while penalizing instances that fall on the wrong side of the hyperplane. The optimization problem can be stated as follows [16]:

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|  |  | (5) |

subject to

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|  |  | (6) |
|  |  | (7) |

In Eq. (5), is the weight vector normal to the hyperplane; stands for slack variables that allow for the soft-margin formulation;represents the offset of the hyperplane from the origin; and denotes a parameter that controls the trade-off between the margin size and the misclassification rate. The optimization problem of OCSVM can be solved in a dual form using the Lagrange multiplier function:

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|  |  | (8) |

subject to:

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| --- | --- | --- |
|  |  | (9) |
|  |  | (10) |

where are the Lagrange multipliers; and denotes the kernel function, evaluating the dot product in the transformed feature space. As explained, OCSVM operates by finding a hyperplane in a high-dimensional space (i.e., mapped by a kernel function) that separates the normal data points from the origin with maximum margin, which can effectively encapsulate the normal data in a decision boundary. The aim is to isolate all the normal data on one side of the hyperplane while minimizing the volume of the space enclosing the data. The decision function for this goal is defined as:

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|  |  | (11) |

where (.) represents the sign function in mathematics, which is commonly used to determine the sign of a real number. On this basis, the actual value of the decision function , which is the distance of from the hyperplane, can be used to derive an outlier score. In practical terms, the decision function provides a measure of how far a data point lies from the boundary of the normal class region. To make these scores more interpretable, the outlier score of OCSVM for outlier detection can be derived as follows:

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|  |  | (12) |

The same threshold determination strategy as IF and RRCF can be used to make a boundary for decision-making. Thus, the outlier score exceeded the threshold is detected as outlier.

1. Results and Discussions

Based on the measured acceleration time histories, it is evident that the vertical accelerations are influenced by temperature and humidity changes. This observation is particularly noticeable when comparing Fig. 5 and Figs 3 and 4, where distinct variations in acceleration amplitudes are visible under different environmental conditions. To further evaluate the impacts of various temperature and humidity levels, this section first analyzes the recorded acceleration time histories and then develops the corresponding unsupervised outlier detectors. The variations in temperature and humidity associated with the forty test measurements are illustrated in Fig. 6. To link the acceleration responses with their respective environmental conditions, the root-mean-squared (RMS) value of each acceleration response is computed for each test, resulting in 40 RMS values for each directional axis (lateral, longitudinal, and vertical). These RMS values provide a quantitative measure of the vibration intensity under varying environmental settings. Fig. 7 presents these RMS values, ordered according to the test measurements listed in Table 1, highlighting the relationship between environmental variations and acceleration responses.



**Fig. 6**. The temperature and humidity records during the experimental program



**Fig. 7**. Effects of temperature and humidity changes on the lateral (a), longitudinal (b), and vertical (c) RMS values of the measured accelerations of the smartphone MEMS accelerometer

The RMS values of the lateral acceleration, as depicted in Fig. 7(a) exhibit noticeable spikes around the test numbers 10 and 36, which correlate with periods of extreme cold and warm temperatures, respectively. In contrast, the longitudinal acceleration RMS values presented in Fig. 7(b) show smaller variations, with a distinct spike around the test 36, indicating sensitivity primarily to warm temperatures. The vertical acceleration RMS values, shown in Fig. 7(c), display the most significant variability among the three directions, with pronounced spikes in the first test condition and particularly around the tests 8–10, where the extremely cold temperatures of –18.5°C, –20.8°C, and –23.4°C were recorded. Furthermore, a substantial spike is observed at the test 35, corresponding to an extremely warm temperature of 41°C. These observations clearly demonstrate that the vertical RMS values are the most sensitive to temperature fluctuations, especially under extreme environmental conditions. This suggests that the accuracy and stability of the smartphone MEMS accelerometer are considerably affected during periods of very cold or very warm weather.

Regarding the influence of humidity, RMS values in all three directions, i.e., lateral, longitudinal, and vertical, show some degree of fluctuation. However, the most significant changes in RMS values appear to be driven more by temperature extremes rather than humidity levels. Even during the period between the tests 20–30, where humidity peaks are observed, the increases in RMS values are relatively moderate compared to the abrupt changes recorded during extreme temperature events. This indicates that while humidity has some impact, temperature variations are the dominant factor affecting the sensor performance.

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**Fig. 8**. Outlier detection for evaluating the performance of the smartphone MEMS accelerometer under extreme environmental (temperature) conditions: (a) IF, (b) RRCF, and (c) OCSVM

The direct and manual analysis of measured acceleration responses to identify the impacts of environmental conditions may be neither straightforward nor practical, particularly for long-term SHM programs. To address this challenge, machine learning techniques offer automated and efficient solutions for continuous and long-duration monitoring projects. Based on this premise, the proposed outlier detection models are applied to evaluate the reliability of the smartphone MEMS accelerometer under extreme temperature variations. In this context, the term outlier is defined as a condition where the MEMS accelerometer is significantly influenced by temperature changes, resulting in abnormal sensor readings. Fig. 8 presents the outlier detection results obtained from the three proposed techniques; that is, IF, RRCF, and OCSVM. These methods were applied to the RMS values of the lateral, longitudinal, and vertical accelerations, represented as .As illustrated in the figure, all three unsupervised outlier detectors successfully identified changes in the MEMS sensor performance during the extremely cold and warm temperature conditions corresponding to the test numbers 10 and 36, respectively.

However, the IF and RRCF methods exhibited some false detections, likely due to the influence of lateral and longitudinal accelerations, which have shown less correlation with temperature variability compared to the vertical acceleration. This misidentification suggests that IF and RRCF are more sensitive to noise in the less temperature-sensitive axes, leading to occasional false positives. In contrast, the OCSVM method demonstrated more reliable outcomes than the other two techniques. As shown in Fig. 8(c), the majority of outlier scores during the first set of test conditions (the tests 1–10), which correspond to extremely cold temperatures, were correctly identified as outliers. Additionally, the hottest condition recorded during the test 36 was accurately detected as an outlier by OCSVM. These findings indicate that OCSVM is more robust in distinguishing true environmental-induced anomalies in the acceleration data, particularly when vertical RMS values dominate the temperature-related variations.

1. Conclusions

Due to the critical influence of environmental conditions on the reliability and accuracy of long-term SHM, this study evaluated the effects of temperature and humidity on the acceleration time histories recorded by a smartphone MEMS accelerometer. To achieve this objective, an experimental program was designed and conducted under various controlled temperature and humidity conditions. To automatically detect anomalies in the MEMS accelerometer performance caused by extreme environmental variations, three unsupervised outlier detection models, i.e., IF, RRCF, and OCSVM, were proposed and compared. These models were utilized as discriminative mechanisms to identify unreliable measurements resulting from severe environmental changes, enhancing the reliability of sensor-based SHM applications. The main conclusions of this study can be summarized as follows:

1. The sensitivity of the smartphone MEMS accelerometer to extreme temperatures (both cold and warm) is evident from the emergence of sudden spikes in RMS values under these conditions.
2. When the smartphone is horizontally attached to a surface, the vertical acceleration measured by the MEMS accelerometer shows the most significant changes in response to extremely cold and warm temperatures.
3. In short-term monitoring projects, humidity has minimal impact on the performance of smartphone MEMS accelerometers unless moisture penetrates the smartphones, potentially causing corrosion of electrical components or altering the mass of the microstructures.
4. Leveraging machine learning significantly enhances the reliability of MEMS sensing technologies. In this context, various unsupervised outlier detection methods can be effectively used to identify abnormal performance of MEMS sensors.
5. Among the proposed unsupervised outlier detectors, the OCSVM method outperforms both the IF and RRCF technique. This indicates that outlier detectors with more complex algorithms tend to produce more reliable outputs.

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