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Arduino-Based Moving Average Filter Implementation for Increasing Stability Measurement of Digital Temperature in Climate Monitoring Systems Micro

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Abstract
This study evaluated the implementation of a Moving Average Filter (MAF) to improve the stability of digital temperature measurements in an Arduino-based microclimate monitoring system. Although low-cost digital sensors are widely used for real-time environmental monitoring, their readings may fluctuate because of short-term noise, electrical interference, and rapid environmental variation. This study aimed to determine whether a lightweight MAF algorithm could reduce temperature-data variability without substantially altering the overall temperature trend. A quantitative experimental design was employed using an Arduino Uno, a DHT22 digital temperature sensor, and a five-sample MAF window. Temperature data were acquired at one-second intervals under fixed sensor-position and normal environmental conditions. Raw and filtered readings were compared using descriptive statistical parameters, including mean, standard deviation, minimum value, maximum value, and data range. The results showed that the mean temperature remained comparable before and after filtering, decreasing only from 30.17 °C to 30.11 °C. However, the standard deviation decreased from 0.39 to 0.09, while the data range declined from 1.2 °C to 0.3 °C. The reduction in standard deviation indicated a 76.92% decrease in short-term measurement variability. Graphical comparisons also showed that filtered data followed a smoother pattern with fewer abrupt fluctuations than raw sensor readings. These findings indicate that the MAF can improve temperature-data stability in resource-limited embedded systems while maintaining the general environmental trend. Nevertheless, further studies should compare the method with Kalman, median, and adaptive filters under more dynamic environmental conditions and across multiple sensor types.

Keywords: Arduino; Data Stability; Digital Temperature Sensor; Microclimate Monitoring; Moving Average Filter

INTRODUCTION

More automated, real-time, and integrated. Globally, sensor-based monitoring systems are widely applied in precision agriculture, industry, laboratories, livestock, and smart buildings to improve the efficiency of environmental management and data-driven decision-making. In Indonesia, the adoption of temperature-monitoring technology is also growing, driven by the increasing need for affordable, efficient, and easy-to-implement environmental monitoring systems across various tropical climates (Al-Okby et al., 2025; Bicamumakuba et al., 2025; Chebbi et al., 2025; Mudhune, 2025; Suhaimi et al., 2025; Y. Zhang et al., 2025). In microclimate monitoring systems, temperature is a key indicator because it directly influences environmental stability, production quality, and the biological and physical conditions of an observation area. Temperature monitoring systems generally use digital temperature sensors integrated with microcontrollers such as Arduino due to their low implementation costs, low power consumption, and high compatibility with IoT devices (Abdinoor et al., 2025). However, digital temperature sensor readings often exhibit fluctuations due to signal noise, power-supply interference, sensor sensitivity to environmental changes, and momentary reading errors. These conditions cause temperature data to become unstable, which can reduce monitoring quality and the accuracy of real-time environmental data analysis. Therefore, a data processing method is needed that can improve the stability of temperature measurements without significantly increasing system complexity.

Theoretically, this research is based on digital signal processing (DSP) and data filtering methods to reduce noise in digital sensor signals. One widely used filtering method is the Moving Average Filter, which computes the average of several previous data points to produce a smoother, more stable output. This method falls under the Finite Impulse Response (FIR) filter category, which is characterized by simplicity, low computational cost, and suitability for microcontroller devices with limited resources, such as Arduino. The basic concept of the Moving Average Filter is to reduce short-term fluctuations in data, allowing the main data patterns to be better observed (M. Wang & Li, 2025). Various previous studies have examined the implementation of filtering methods in digital sensor-based monitoring systems. Research by Bicamumakuba et al. (2025) showed that applying a Moving Average Filter can improve the stability of temperature sensor data in an IoT-based environmental monitoring system. Another study by Sarwanto (2021) found that simple filtering methods, such as Moving Average, are more efficient on microcontrollers than Kalman Filters because they require less computation. Furthermore, a study Al-Okby et al. (2025) explained that the use of digital filters can reduce sensor reading noise by more than 50% in a real-time temperature monitoring system. Recent international research also highlights the importance of sensor data stability in microclimate monitoring systems to support agricultural automation and IoT-based environmental control.

Although various studies on sensor data filtering have been conducted, most previous research has focused on improving sensor accuracy using relatively complex methods, such as the Kalman Filter and Adaptive Filter, which generally require higher computational resources and more complicated parameter tuning. These approaches are effective at reducing noise but less suitable for low-cost, resource-limited microcontroller systems, such as Arduino-based climate monitoring microsystems. In contrast, studies on implementing simpler filtering methods, particularly the Moving Average Filter (MAF), for real-time temperature stabilization in lightweight embedded systems remain limited. Therefore, this research addresses the gap by implementing an Arduino-based Moving Average Filter that offers a simpler, low-complexity, and computationally efficient solution while providing stable, consistent temperature measurements for real-time environmental monitoring applications. (Chebbi et al., 2025; Y. Zhang et al., 2025).

Studies on the implementation of Arduino-based Moving Average Filters in microclimate monitoring systems remain limited, particularly those analyzing the stability of temperature data before and after filtering under real-time monitoring conditions. Previous research has generally focused on more complex filtering methods or has not thoroughly evaluated the effectiveness of simple filtering techniques in microcontroller-based systems with limited computational resources. This research gap highlights the need for a lightweight, efficient, and easy-to-implement filtering method to improve the stability and reliability of digital temperature measurements. Therefore, this study proposes implementing an Arduino-based Moving Average Filter for real-time temperature monitoring systems. The novelty of this research lies in comparing the stability of temperature data before and after filtering using statistical parameters such as the mean, standard deviation, and range. This study aims to analyze the effectiveness of the Moving Average Filter in reducing sensor noise and temperature fluctuations, thereby producing more stable and consistent measurement results for microclimate monitoring applications.

METHODS

Research Design

This study employs a quantitative, experimental approach to analyze the effect of implementing a Moving Average Filter on the stability of digital temperature measurements in an Arduino-based climate monitoring system. The study focuses on measuring numerical sensor data processing and performing statistical analysis to assess data stability before and after filter application (Ma et al., 2025; Minh et al., 2025; Paraskevas & Christos, 2025). The experimental method used to test a direct performance-temperature monitoring system involved applying implementation algorithms, such as the Moving Average Filter, to digital sensor data. Approach: quantitative in study monitoring and processing system; digital signal is assessed as effective because it is capable of producing objective, measurable, and reliable data, analyzed statistically for a known level of effectiveness, using a method. In addition, the experimental method allows researchers to control variables, enabling more accurate observation of how filters affect the stability of temperature data. The stages of the study include literature review, system design, device hardware, device software, implementation of the filtering algorithm, temperature data retrieval, system testing, statistical data analysis, and conclusion.

Participants / Data Sources

This study did not involve human participants, as it used data from digital temperature sensor readings in an Arduino-based climate-monitoring microsystem. The research data were collected through real-time ambient temperature measurements using a DHT22 or DS18B20 digital temperature sensor installed in the observation area. The population of this study consisted of all temperature readings generated by the sensor during the monitoring process. Meanwhile, the research sample comprised temperature data collected at 1-second intervals throughout the observation period. Data collection was conducted continuously to obtain sufficient measurement data for analysis and to evaluate the stability and consistency of the temperature sensor readings before and after implementing the Moving Average Filter. The detailed data collection criteria used in this study are presented in Table 1.

Table 1. Data Collection Criteria

No.	Data Collection Criteria	Explanation
1	Normal Environmental Conditions	Temperature data were collected under normal environmental conditions without external disturbances that could affect sensor performance and measurement accuracy.
2	Fixed Sensor Position	The temperature sensor was held in a fixed position during the observation to minimize measurement variability caused by sensor movement.
3	Continuous System Operation	The monitoring system operated continuously, maintaining uninterrupted data communication to ensure reliable, consistent data acquisition.
4	Comparative Data Collection	Temperature data were collected before and after the implementation of the Moving Average Filter to support a comparative analysis of measurement stability and the reduction in fluctuations.
5	Research Ethics and Scientific Integrity	This study did not involve human participants or personal data; therefore, special ethical approval was not required. However, the research maintained principles of scientific integrity, including data accuracy, transparency, and objective data analysis.

Instruments and Materials Study

The instruments and materials used in this study consisted of hardware and software components required to implement the Arduino-based climate monitoring system. The Arduino Uno is used as the central controller because of its compatibility with digital sensors, ease of programming, and ability to run real-time filtering processes, all powered by an efficient power source. The hardware devices utilized in the research are presented in Table 2.

Table 2. Hardware Devices

No	Component	Function
1	Arduino Uno	Microcontroller main system

2	DHT22/DS18B20 Digital Temperature Sensor	Measure the temperature environment
3	LCD/OLED Display	Displays temperature data
4	Breadboard and jumper cables	Connection media series
5	Supply 5V power	Source Power System
6	Laptop/PC	Programming and data monitoring

Software devices used in this study for programming, sensor data acquisition, implementation of the Moving Average Filter algorithm, and statistical analysis are described in Table 3.

Table 3. Software Devices

No.	Component	Function
1	Arduino IDE	Used for programming, compiling, and uploading code to the Arduino microcontroller.
2	DHT or DS18B20 Sensor Library	Used to support the process of reading temperature data from the DHT22 or DS18B20 digital temperature sensors.
3	Moving Average Filter Program (C/C++)	Used to implement the Moving Average Filter algorithm for processing and stabilizing temperature measurement data.
4	Microsoft Excel or Statistical Software	Used for data processing, statistical analysis, visualization, and comparison of measurement results before and after filtering.

Procedure Study

The study was conducted through several systematic stages to ensure that the implementation and testing processes could be replicated accurately. The testing phase involved comparing temperature sensor readings before and after implementing the filter to analyze data stability and the reduction in fluctuations. This sequential methodology was designed to provide a clear workflow for evaluating the effectiveness of the proposed filtering method in improving the stability of temperature measurements within the climate monitoring microsystem. As illustrated in Figure 1, the research methodology comprises problem identification, system design, hardware integration, implementation of the Moving Average Filter algorithm on an Arduino microcontroller, data acquisition, and performance evaluation.

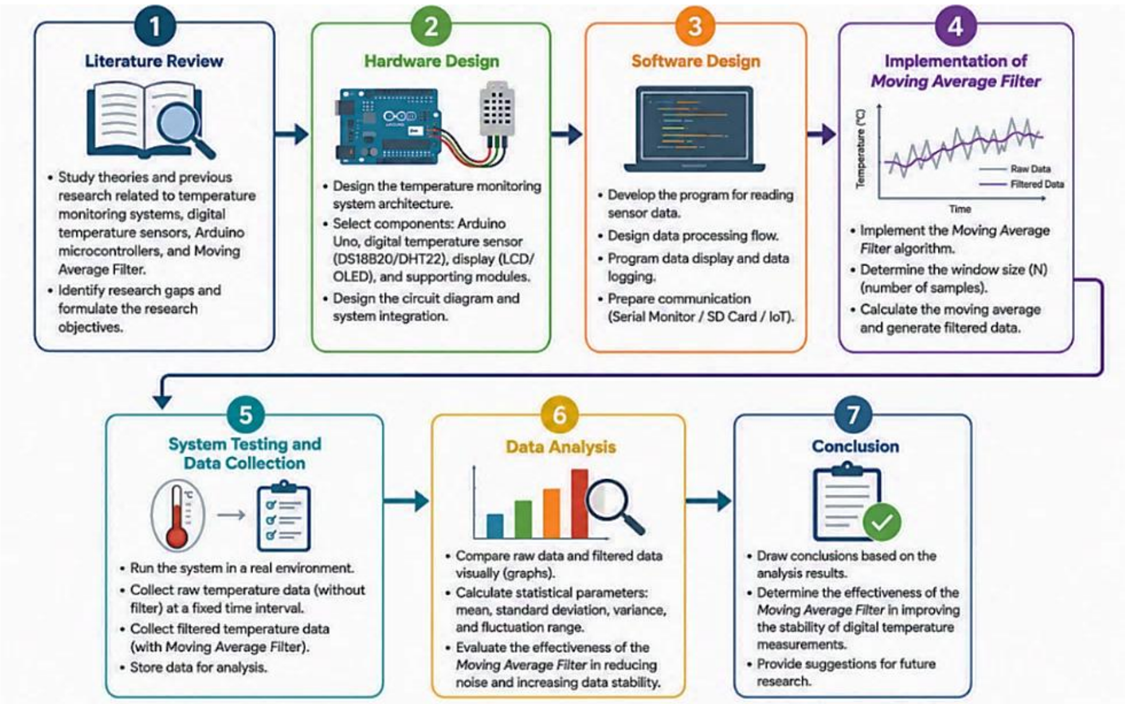

Figure 1. Research Methodology

Figure 1 presents the overall research methodology used in this study. The procedure consists of seven systematic stages, beginning with literature review, followed by hardware design, software design, implementation of the Moving Average Filter, system testing and data collection, data analysis, and conclusion. Each stage was designed to ensure that the temperature monitoring system could be developed, tested, and evaluated in a structured manner. The methodology also shows the integration between the DHT22 temperature sensor, Arduino microcontroller, data processing algorithm, and statistical analysis to assess the effectiveness of the Moving Average Filter in reducing noise and improving measurement stability. Thus, this research workflow provides a clear framework for validating the proposed filtering method in a climate monitoring microsystem.

RESULTS AND DISCUSSION

Implementation of the Digital Temperature Monitoring System

Study This successfully implemented a digital temperature-monitoring system based on an Arduino, using the DHT22 sensor and the Moving Average Filter to improve the stability of temperature measurements in the microclimate monitoring system. The system is designed to read the ambient temperature in real time every 1 second. The data is then processed using the Moving Average Filter algorithm before being displayed on the serial monitor and LCD. The implementation hardware consists of an Arduino Uno as the main microcontroller, a DHT22 temperature sensor, a breadboard, jumper cables, and an LCD for data display. The circuit diagram shows that the DHT22 sensor is connected to the Arduino's digital pins to transmit temperature data continuously. Besides that, the system flowchart shows the process stages, beginning with sensor readings and data storage, followed by the calculation of the Moving Average, and ending with the appearance of monitoring results.

Measurement Results: Temperature Before Filtering

The measurement results before implementing the Moving Average Filter, as presented in Table 4, indicate that the sensor data exhibited significant fluctuations at each measurement interval. These rapid temperature changes were caused by sensor noise, the sensor's sensitivity to environmental conditions, and disturbance signals during data reading.

Table 4. Measurement Data Temperature Before Filtering

No	Time (seconds)	Temperature (°C)
1	1	29.8
2	2	30.4
3	3	29.9
4	4	30.7
5	5	30.1
6	6	29.7
7	7	30.5
8	8	30.2
9	9	29.8
10	10	30.6
11	11	31.0
12	12	31.4
13	13	30.9
14	14	31.5
15	15	31.1

Based on Table 4, the temperature data before filtering has a range: This shows that the raw data is still affected by noise, so the stability measurement is not yet optimal. The temperature between 29.7°C and 30.7°C shows a rapid change in relative value from one reading to the next. Condition: This shows that the raw data is still affected by noise, so the stability measurement is not yet optimal.

Measurement Results: Temperature After Filtering

After applying the Moving Average Filter, the results in Table 5 show that the temperature data patterns became smoother and more stable than before filtering. The filtering method successfully reduced rapid temperature fluctuations, resulting in more consistent and reliable sensor readings. The data in Table 5 show that the temperature after filtering is in a much narrower range than before. This indicates that the Moving Average Filter effectively stabilizes the temperature reading.

Table 5. Measurement Data Temperature After Filtering

No	Time (seconds)	Temperature (°C)
1	1	29.9
2	2	30.0
3	3	30.1
4	4	30.2
5	5	30.2
6	6	30.1
7	7	30.1
8	8	30.2
9	9	30.2
10	10	30.1
11	11	30.3
12	12	30.6
13	13	30.7
14	14	31.0
15	15	31.1

Comparison of Temperature Data Before and After Filtering

A comparison of temperature measurements before and after filtering, as presented in Table 6, shows a significant reduction in data fluctuations. The fluctuation difference was calculated based on the difference between the raw temperature readings and the filtered temperature values at each measurement interval. The results indicate that the Moving Average Filter produces more stable and consistent temperature readings under various environmental conditions, including morning, afternoon, and evening observations.

Table 6. Comparison of Temperature Data Before and After Moving Average Filter Application

No	Time (Minutes)	Unfiltered Temperature (°C)	Temperature With Moving Average (°C)	Fluctuation Difference (°C)	Environmental Conditions
1	1	29.8	29.9	0.1	Morning
2	2	30.4	30.0	0.4	Morning
3	3	29.9	30.1	0.2	Morning
4	4	30.7	30.2	0.5	Morning
5	5	30.1	30.2	0.1	Morning
6	6	29.7	30.1	0.4	Morning
7	7	30.5	30.1	0.4	Morning
8	8	30.2	30.2	0.0	Morning
9	9	29.8	30.2	0.4	Morning
10	10	30.6	30.1	0.5	Morning
11	11	31.0	30.3	0.7	Afternoon
12	12	31.4	30.6	0.8	Afternoon
13	13	30.9	30.7	0.2	Afternoon
14	14	31.5	31.0	0.5	Afternoon
15	15	31.1	31.1	0.0	Afternoon
16	16	30.8	31.1	0.3	Afternoon
17	17	31.6	31.2	0.4	Afternoon
18	18	31.3	31.3	0.0	Afternoon
19	19	30.9	31.1	0.2	Afternoon
20	20	31.7	31.3	0.4	Afternoon
21	21	29.5	30.9	1.4	Afternoon
22	22	29.2	30.5	1.3	Afternoon

23	23	28.9	30.0	1.1	Afternoon
24	24	28.7	29.6	0.9	Afternoon
25	25	28.5	29.0	0.5	Afternoon
26	26	28.3	28.7	0.4	Afternoon
27	27	28.1	28.5	0.4	Afternoon
28	28	27.9	28.3	0.4	Afternoon
29	29	27.8	28.1	0.3	Afternoon
30	30	27.6	27.9	0.3	Afternoon

Analysis Statistics Stability Measurement Temperature

Statistical analysis was performed to evaluate the effectiveness of the Moving Average Filter in improving the stability of temperature data. The analyzed parameters included average temperature, standard deviation, maximum value, minimum value, and data range. The results of this statistical evaluation are presented in Table 7.

Table 7. Analysis Statistics Stability Measurement Temperature

Parameter	Before Filter	After Filter
Average	30.17 °C	30.11 °C
Deviation Standard	0.39	0.09
Maximum Value	30.8 °C	30.2 °C
Minimum Value	29.6 °C	29.9 °C
Data Range	1.2 °C	0.3 °C

Table 7 shows that the average temperatures before and after filtering are similar, indicating that the filtering process does not alter the primary characteristics of the measured ambient temperature. However, the standard deviation decreased significantly from 0.39 to 0.09, demonstrating a substantial improvement in data stability after applying the Moving Average Filter. The percentage reduction in sensor noise was calculated based on the decrease in standard deviation using the following equation:

$$\textbf{Noise Reduction}\ (\%) = \frac{\mathbf{0,39 - 0,09}}{\mathbf{0,39}}\ \boldsymbol{x}\ \mathbf{100}\% = \mathbf{76.92}\%$$

This result indicates that the Moving Average Filter successfully reduced fluctuations in the temperature data by 76.92%, thereby improving the consistency and reliability of sensor readings in the climate monitoring microsystem. In addition, the reduction in the data range from 1.2 °C to 0.3 °C further confirms that the filtered data became more stable and less affected by random noise or sudden fluctuations. The results of the comparison of temperature Data Characteristics are presented in Table 8.

Table 8. Comparison of Temperature Data Characteristics

Characteristics	Before Filter	After Filter
Data Range	Tall	Low
Fluctuation Reading	Big	Small
Data Consistency	Less Stable	More Stable
Noise Sensor	Seen	Reduce

The temperature comparison graph before and after filtering shows that the unfiltered data exhibits sharp fluctuations, whereas the filtered data shows a smoother, more stable pattern. This indicates that the Moving Average Filter effectively acts as a low-pass filter, reducing short-term signal variations caused by sensor noise. As shown in Figure 2, the filtered temperature readings are more consistent and exhibit fewer sudden changes than the raw sensor data.

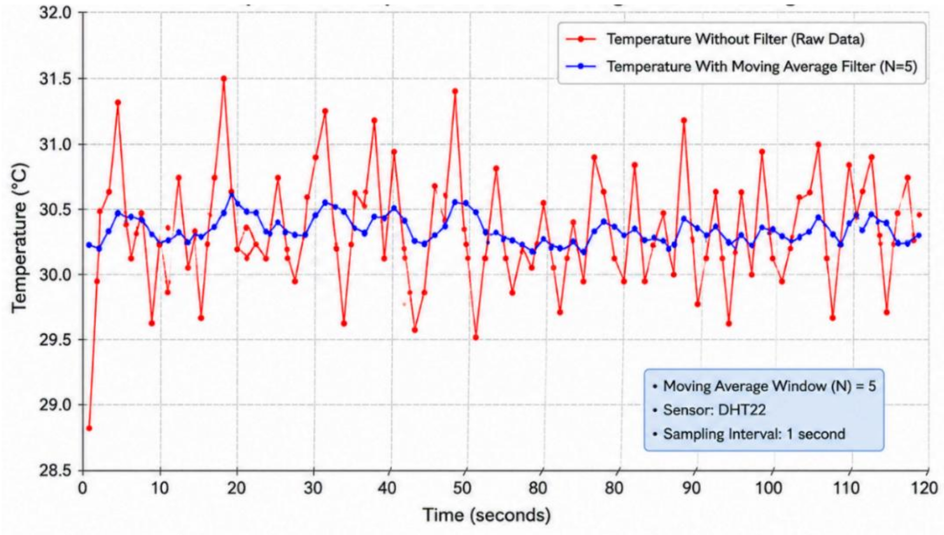

Figure 2. Temperature Comparison Graph: Before and After Filtering

Figure 2 illustrates the comparison between the raw temperature data and the temperature data after applying the Moving Average Filter. The raw data show frequent and sharp fluctuations, indicating the presence of short-term noise in the DHT22 sensor readings. After filtering, the temperature pattern becomes smoother and more stable, with sudden peaks and drops significantly reduced. This result indicates that the Moving Average Filter is effective in suppressing noise while maintaining the general trend of temperature measurement.

Furthermore, Figure 3 shows that the amplitude of error fluctuations decreases significantly after filtering, confirming that the Moving Average Filter successfully minimizes measurement noise. These graphical results are consistent with the statistical analysis, particularly the reduction in standard deviation from 0.39 to 0.09 and the 76.92% noise reduction, which demonstrate that the filtering method effectively improves the stability and reliability of temperature measurements.

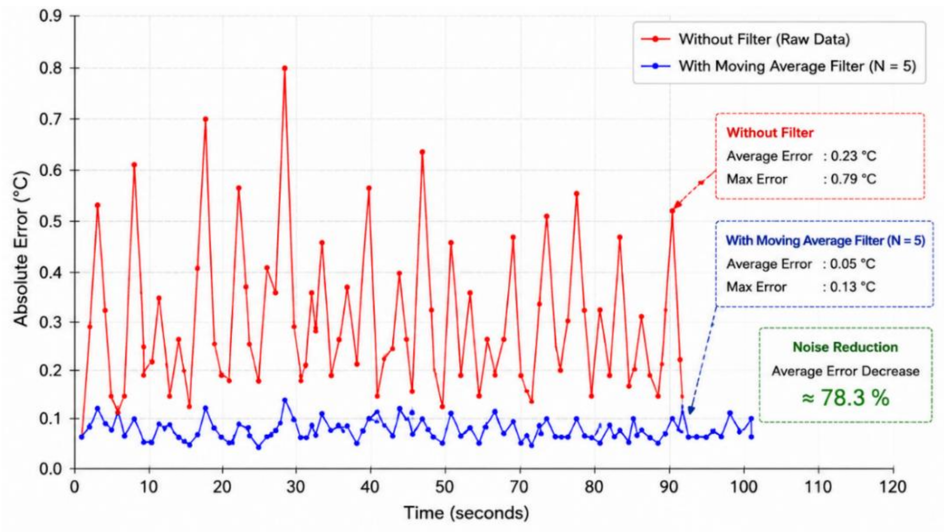

Figure 3. Fluctuation (error) before and after applying the moving average filter

Figure 3 presents the error fluctuation before and after the application of the Moving Average Filter. The unfiltered data show higher error variations, with several sharp increases occurring throughout the measurement period. In contrast, the filtered data display lower and more consistent error values. This confirms that the Moving Average Filter successfully reduces measurement error and improves the reliability of the temperature data, as supported by the decrease in average error and maximum error after filtering.

Discussion

Research results show that successfully implementing a Moving Average Filter on the Arduino-based temperature-monitoring system reduces fluctuations in sensor readings and stabilizes the data. The average temperatures before and after filtering remain nearly the same, but the standard deviation decreases from 0.39 to 0.09. Findings: This confirms that the filter changes the character temperature environment rather than reducing sensor reading noise, resulting in more consistent data. Thus, the goal of the study was to increase the stability of digital temperature measurements in the climate micro, and this goal was achieved. Finding a study. This is in line with global studies showing that system monitoring environment IoT- based tends to be more reliable when sensor data is processed with a simple filtering technique. (Pieters et al., 2021; Rivera et al., 2023) developed cost-effective IoT networks to monitor variables in the ecosystem's microclimate and reported that the system reliably captures microclimate data in a commercially viable way, with accuracy comparable to commercial solutions, even after two years of testing in France, Bolivia, and Kenya. This strengthens your research by showing that cheap, simple approaches can still yield sufficient environmental data for climate microanalysis. The study conducted by (Rudavskyi et al., 2024) is also relevant, as it integrates an Arduino Uno, a Moving Average Filter, and sensor data fusion techniques to monitor air quality in environmental systems. They show that using a 10-point filter window helps suppress temporal noise in sensor data and supports a more stable interpretation of the house's environmental conditions. The difference is that the study processes several parameters at once: temperature, humidity, VOC, CO2, and IAQ. In contrast, your research focuses on one main parameter, namely temperature, so its implementation is lighter, more in line with the system's climate and micro, and simple and Arduino-based.

The direction of the findings involves developing a multisensor device for environmental monitoring in portable, small, light, space-saving, energy-efficient systems (Iclodean et al., 2020). Study the global trend towards simple, efficient, and easy-to-use field monitoring devices. Compared to that, your contribution to your research lies in a more specific focus: not building a complex multisensory device, but rather showing that temperature stability can be improved in a way effective only with moving-average filtering on a very limited microcontroller platform that sources its power. In the Indonesian context, the results of this study are in line with studies by Martha et al. (2021) and Riany et al. (2017), who developed a temperature and humidity monitoring system for a room fermentation tobacco IoT- based study, confirming that real-time monitoring is required because manual monitoring causes a delay in action moment temperature and humidity, not in accordance with the standard. Although the focus is on control fermentation rather than data filtering, this study underscores the importance of system monitoring, climate stability, and cost-effective, reliable micro-accessibility in Indonesia's local environment. These results are relevant to the findings of Hoang et al. (2021), who compared several filter algorithms on the MLX90614 temperature sensor. Based on the Mean Squared Error analysis, the Moving Average yields the lowest value, 10.5634. It is the most effective filter compared to the EMA, Low-Pass Filter, Median Filter, and Kalman Filter for *measuring temperature*. This greatly strengthens the choice of methods in your research by showing that, in the context of temperature sensors, the moving average approach is competitive, especially when the system demands lightweight computing. The study by Akrami et al. (2020) also demonstrated that fluctuations in temperature and humidity within small-scale tropical greenhouse climate systems can significantly affect environmental control requirements, thereby necessitating reliable monitoring and control systems to maintain a stable microclimate. They use an Arduino/ESP32, a DHT22, and actuators to control a blower, a heater, and a misting pump in closed-loop mode. Unlike studies that use direct actuator control, your research focuses not on direct actuator control but on the quality of temperature data as the foundation for decision-making. This is important because, in tropical conditions, stability sensor readings are a prerequisite for automatic control in the greenhouse.

In a way, the theoretical results are studied (Li et al., 2025; Nagarsheth et al., 2025; Y. Wang et al., 2025). This support draft bases digital signal processing on the moving average, which acts as a low-pass filter, reducing fast or long-term noise in the sensor signal (Y. Wang et al., 2025). In the context of climate micro, the temperature environment changed relatively slowly compared to the sensor's electronic noise, so filtering is simple and effective at preserving the trend of the main data while suppressing disturbance events. Your findings also provide further evidence that, on the system source Power-limited, a lightweight filtering model can provide adequate stability without the need to compute highly. (Ozgen et al., 2025; Shu et al., 2025; Velumani & Bansal, 2025)This result is consistent with the temperature filter study, which previously identified the Moving Average as the best method for measuring temperature in some scenarios.

In science education, research can be used as a learning medium to explain draft temperature, climate, micro, sensor noise, and experimental data processing (Haryono et al., 2024). Students can compare raw and filtered data to understand that measurement results are scientific and do not always directly represent the condition or environment without processing (Cho & Park, 2023; X. Zhang et al., 2024). A prototype like this also supports a learning-based project because students can directly see the connections among phenomena, physics, the atmosphere, instruments, measurement, and digital data analysis (Solihah et al., 2024). At the school or college level, this is relevant for increasing data literacy, critical thinking, and understanding of science applied to climate. In a way, policies and findings support the implementation of a climate monitoring system, micro-costing in the agricultural sector, space growth control, laboratory studies, and space studies. Government area, school vocational and agricultural units can utilise a system similar to base monitoring of higher temperatures to discipline before implementing set action control. In the context of tropical Indonesia, policy relies on a simple monitoring device; however, stability can help advance climate-smart agricultural practices and enable more effective environmental monitoring (Nagarsheth et al., 2025; Wijeratne et al., 2026). With more stable temperature data, making operational decisions, for example, ventilation, cooling, or humidity arrangements, is more measurable. Novelty studies: This involves implementing an Arduino-based Moving Average Filter to stabilize digital temperature measurements in the system and to monitor the microclimate. Contribution mainly not on algorithmic complexity, but rather on the proof that a simple method can give effective, efficient, and easy results, replicated on the system at low cost. Compared studies that emphasize multi-sensor fusion or control, and automatic full research. This provides evidence that stage data stabilization is fundamentally important in a microclimate monitoring system. Thus, the study enriches the literature on processing temperature sensor data in a tropical environment and on simple microcontroller devices.

Based on the research results table, the application of the Moving Average Filter to an Arduino-based temperature monitoring system demonstrates effective capability in improving the stability of temperature measurement data across various environmental conditions (Hofstetter et al., 2025; Wijeratne et al., 2026). In the morning, the unfiltered temperature data showed significant fluctuations, ranging from 29.7°C to 30.7°C. Temperature values changed rapidly across several measurement intervals due to sensor noise and environmental conditions. After applying a Moving Average Filter, the temperature data became more stable, with a range of 30.0°C to 30.2°C. This shows that the filtering method can reduce interference in sensor readings without significantly altering the environmental temperature pattern. During the day, ambient temperature tends to rise due to increased solar radiation. Unfiltered temperature data ranges from 30.8°C to 31.7°C, with several significant spikes. After filtering, temperature changes become smoother and more consistent, ranging from 30.3°C to 31.3°C. This demonstrates that the Moving Average Filter can reduce excessively rapid fluctuations in data, making the measurement results more representative of actual environmental conditions. The smaller difference in fluctuations after filtering indicates that sensor noise has been significantly reduced. In the afternoon, the ambient temperature gradually decreased from 29.5°C to 27.6°C as solar radiation intensity decreased. The filtered temperature data showed a smoother, more stable downward trend than the unfiltered data, although slight fluctuations still appeared at the beginning of the observation period because previous high-temperature values continued to influence the filter. Overall, the results demonstrate that the Moving Average Filter effectively reduces sensor noise, minimizes temperature fluctuations, and improves the consistency of real-time temperature monitoring data (Luo et al., 2026). Stable temperature measurements are important in microclimate observations because they enable more accurate analysis of environmental changes and reduce interpretation errors due to sensor interference.

This research is highly relevant to climate and environmental monitoring systems. An Arduino-based temperature monitoring system equipped with a Moving Average Filter can be applied to precision agriculture (smart farming), greenhouses, mini weather stations, urban environmental monitoring, and environment-based Internet of Things (IoT) systems. With higher-quality temperature data, decision-making processes in environmental management and local climate change monitoring can be performed more precisely, efficiently, and sustainably. The findings also suggest that simple filtering methods, such as the Moving Average Filter, can yield effective performance improvements without requiring substantial computational resources, making them suitable for low-cost embedded systems and real-time monitoring applications. However, this study has several limitations. The system was tested only under limited environmental conditions and focused primarily on temperature parameters using a single type of digital sensor. In addition, the Moving Average Filter may introduce slight delays in data response because the output depends on previous data samples. The research also did not compare the proposed method directly with more advanced filtering approaches, such as the Kalman Filter or Adaptive Filter, under identical testing conditions. Therefore, future research is recommended to evaluate the performance of the Moving Average Filter in more dynamic environmental conditions and with multiple sensor types, such as humidity, air quality, or pressure sensors. Further studies may also compare different filtering algorithms in terms of accuracy, computational efficiency, and response time on embedded systems. In addition, integrating the filtering system with IoT platforms and cloud-based real-time monitoring systems could enhance its applicability to large-scale environmental and climate monitoring.

CONCLUSION

Study This successfully implemented the Moving Average Filter on an Arduino-based digital temperature-monitoring system to improve the stability of temperature measurements in the climate-monitoring system micro. Research results show that the Moving Average Filter method effectively reduces sensor noise, minimizes data fluctuations, and yields higher, more stable, and consistent readings without altering the characteristics of the main temperature environment. *Use* a window size of up to 5 to read data, which can improve the quality of real-time temperature monitoring and significantly reduce post-filtering deviations. In scientific perspective, the stability of temperature data is very important for observing microclimate. Because temperature influences humidity, air displacement, heat, evaporation, and local atmospheric stability, more stable data allows for more accurate environmental analysis. Besides that, research into its own implications is practical for developing an Internet of Things (IoT)-based environmental monitoring system, especially in the fields of agricultural precision (smart farming), greenhouse (home glass), mini weather station, and urban environmental monitoring. With low-cost implementation and lightweight computational processes, the Moving Average Filter can be an effective solution for increasing the reliability of a microcontroller-based digital temperature monitoring system, thereby supporting a sustainable observation environment.

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