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Flatline Anomaly Detection in Automatic Weather Station Air Temperature Sensor Data Using LSTM Autoencoder

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Abstract: The quality of air temperature data from Automatic Weather Stations (AWS) is crucial for meteorological analysis, climatology, and early warning systems. However, flatline anomalies, a condition where sensor values tend to remain constant over a period of time, can degrade data quality and are often not optimally detected by conventional rule-based quality control (QC) methods. Previous research is also limited in specifically examining flatline detection, with most studies focusing on general anomalies and not integrating deep learning approaches with operational quality control systems. This study proposes a data-driven approach using a Long Short-Term Memory Autoencoder (LSTM-AE) combined with Level-1 QC. The novelty of this study lies in the use of a normal-only training scheme, anomaly threshold determination based on the reconstruction error distribution, and post-detection diagnosis to identify flatline characteristics. The methods include QC filtering, sliding window formation, model training, threshold determination, and anomaly detection. The results show stable model performance with an anomaly threshold value of 0.01177 (MSE). Of the 985,730 data windows, approximately 0.578% were detected as anomalies, indicating that flatline occurrences are relatively small but still significant to data quality. Most anomalies are short-lived and discontinuous, indicating localized sensor noise. This study demonstrates that LSTM-AE is effective as an adaptive flatline detection method and has the potential to be implemented as an automated QC module in AWS systems to improve data reliability.

Keywords: Air temperature data; Automatic Weather Station; Flatline anomaly; LSTM-AE; Quality control

Introduction

High-resolution air temperature data recorded by Automatic Weather Stations (AWS) is a crucial component in meteorological analysis, long-term climatology studies, and weather-based early warning systems (Sunusi, 2022; Wibawanty, 2022). The reliability of this data is heavily influenced by the performance of sensors operating continuously under various environmental conditions. In practice, AWS data quality often degrades due to sensor aging, environmental disturbances, and problems with the data acquisition system. Therefore, a robust quality control (QC) mechanism is required to ensure the consistency and validity of observations (Cerlini et al., 2020; Liu et al., 2024; Varet et al., 2016).

One of the key issues in AWS data is the emergence of sensor anomalies, particularly flatline anomalies, a condition where observed values tend to remain constant over a period of time due to decreased sensor response or recording system failure (Nsabagwa et al., 2024; Siregar et al., 2023). This condition results in the loss of natural variability in the data, particularly the diurnal cycle, which is a key characteristic of the surface temperature signal (Afif & Aly, 2023). If not properly detected, flatline anomalies can introduce bias in statistical analysis, disrupt derived parameter estimates, and reduce the accuracy of weather and climate prediction models (Ding, 2025; Gao et al., 2026).

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Therefore, flatline anomaly detection is a crucial aspect in maintaining the quality and reliability of meteorological data (Edkayasa & Yuliza, 2025; Lee et al., 2024).

In operational practice, meteorological agencies generally use rule-based QC methods, such as range checks, step checks, and flatline tests as initial filters (Farooq et al., 2025; Siregar et al., 2023). While these methods are effective in detecting extreme values or gross errors, rule-based approaches have limitations in capturing complex temporal dynamics and are less adaptable to variations in local environmental conditions, particularly in regions with unique characteristics such as tropical highlands (Akbar et al., 2024; Bashar & Nayak, 2025). As a result, subtle anomalies such as short-duration flatlines may go undetected, while certain normal conditions may be classified as anomalies (false positives) (Fitri, 2022; Irfan et al., 2025; Prada Wellyantama, 2021).

Along with the development of deep learning methods, data-driven approaches such as Long Short-Term Memory Autoencoder (LSTM-AE) have begun to be widely used in time series anomaly detection (Varet et al., 2016) (Jo et al., 2025). This model is able to learn normal temporal patterns from data and identify deviations through reconstruction errors, without relying on fixed rules (Wei et al., 2024; Yahya et al., 2025). In addition, LSTM has the ability to capture long-term dependencies in time series data, making it very suitable for the analysis of meteorological data with seasonal and diurnal patterns (Bashar & Nayak, 2025; Liu et al., 2024; Tridaiana & Marzuki, 2023). This approach has proven to be more adaptive in dealing with the complexity of environmental data compared to conventional methods (Kanata et al., 2024; Karevan & Suykens, 2020).

However, existing research still has several important limitations. First, most studies categorize anomalies generally (such as bias, drift, and noise) without specifically targeting flatline anomalies, even though this type of anomaly has unique characteristics and directly impacts the loss of data variability (Kirichenko et al., 2024; Mardyansyah et al., 2024; Wahyusari et al., 2021). Second, the integration of operational QC procedures with deep learning approaches is still limited, so their implementation in real meteorological systems is not optimal (Al & Land, 2024; Setiyo, 2020). Third, studies applying a normal-only training scheme with data-driven anomaly threshold determination based on the distribution of reconstruction errors are still relatively limited, especially in the context of AWS data in tropical highland regions such as Indonesia (Afif & Aly, 2023; Fitri, 2022).

Furthermore, several studies in national journals indicate that AWS data quality issues, such as data loss, sensor instability, and measurement anomalies, remain significant issues in meteorological data processing in Indonesia (Bashar & Nayak, 2025; Prada Wellyantama, 2021). This demonstrates the urgent need for adaptive and data-driven QC methods to support more accurate climate and weather analysis.

Based on previous research, the novelty of this study lies in three main aspects. First, the development of an anomaly detection framework specifically focused on flatline anomalies using the LSTM-AE approach, rather than as part of a general anomaly. Second, the explicit integration of Level-1 Quality Control (QC) with a deep learning model, thus bridging meteorological operational practice with a data-driven approach. Third, the implementation of a normal-only training scheme with anomaly threshold determination based on the reconstruction error distribution, complemented by a post-detection diagnosis stage to characterize anomalies at various time scales.

This research is important because it directly addresses the practical need to improve AWS data quality, particularly in environments with high sensor vulnerability, such as tropical highlands. Improving the accuracy of flatline anomaly detection will contribute to the reliability of meteorological data, ultimately supporting climate analysis, improving the accuracy of weather predictions, and decision-making in weather-based disaster risk mitigation (Karevan & Suykens, 2020; Kiran, 2025).

Based on this, this study aims to: (1) develop an LSTM-AE-based flatline anomaly detection pipeline integrated with Level-1 QC, (2) determine anomaly thresholds in a data-driven manner based on the reconstruction error distribution, and (3) evaluate anomaly characteristics through post-detection diagnosis at various time scales.

This research is expected to contribute to the development of an adaptive automated quality control system to improve the quality and reliability of AWS air temperature data.

Method

This study uses a quantitative approach with time series analysis to detect flatline anomalies in air temperature data recorded by AWS. The method used combines rule-based Level-1 Quality Control (QC) with a deep learning approach using LSTM-AE trained normally-only. This approach enables the integration of operational QC practices with data-driven temporal pattern learning capabilities (Kiran, 2025; Li et al., n.d.; Wei et al., 2024).

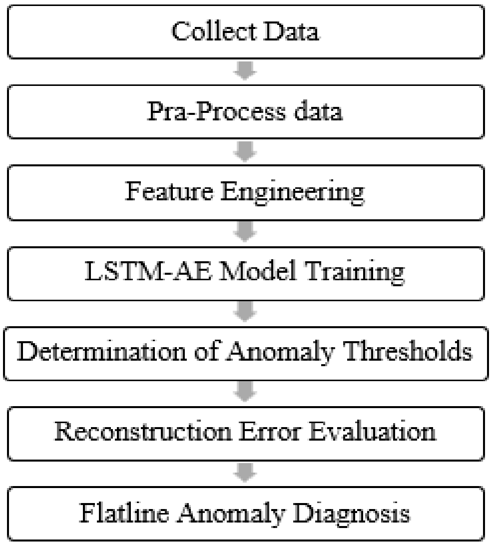


Figure 1. Research Method

In general, the research method (Figure 1) for flatline anomaly detection consists of the following stages: (1) Data collection, (2) Preprocessing, (3) Feature engineering, (4) LSTM-AE model training, (5) Anomaly threshold determination, (6) Reconstruction error evaluation, (7) Flatline anomaly diagnosis (González et al., 2024).

Data was obtained from the AWS network operated by the Meteorology, Climatology, and Geophysics Agency (BMKG). Figures 2 and 3 show the AWS location and a view of the research field located in the Dieng Plateau, Central Java, at an altitude of approximately 2,000 m above sea level (Rohmah & Utomo, 2024; Wahyusari et al., 2021).

Figure 2. Location of Automatic Weather Station (AWS) in the Dieng Plateau, Central Java https://awscenter.bmkg.go.id/

Figure 3. Field view of the Automatic Weather Station (AWS) on the Dieng Plateau, Central Java

This region experiences extreme daily temperature fluctuations and high humidity, making it representative for sensor health studies in tropical highland environments. The data spans the period from January 2022 to December 2024 with a temporal resolution of minutes to hours.

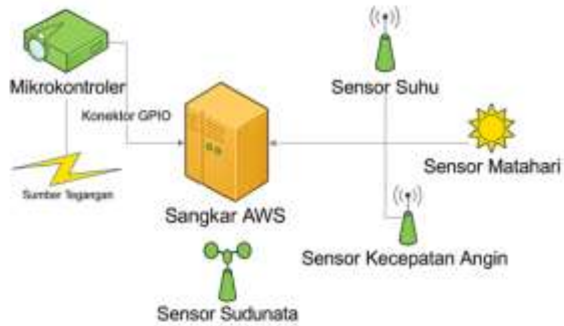


Figure 4. Sensor configuration in the AWS system

Figure 4 illustrates the sensor configuration in the AWS system. The primary variable in this study is air temperature (TA), while solar radiation (SR) and wind speed (WS) are used as supporting variables in the QC and anomaly diagnosis stages (Azad et al., n.d.; Wang et al., 2025). All data is standardized in the Western Indonesian Time (UTC+7) and obtained through the official AWS transmission system in accordance with meteorological data quality assurance standards (Angela et al., 2023; Kirichenko et al., 2024; Raihan & Ahmed, n.d.).

After data collection, the next stage is data processing, applying Level 1 QC to filter out data that is unsuitable for use in model training (Issn & Issn, 2025; Kim et al., 2020). Level 1 QC is performed using a rule-based approach commonly used in meteorological operational practice, including range checks, step checks, and flatline checks (Costa et al., 2021; Isnianto et al., 2012; Yuniarto & Septiadi, 2020). Data that passes Level 1 QC is then preprocessed by aligning time intervals and eliminating duplications. Air temperature values are then normalized to the 0–1 range using the min-max normalization method to improve numerical stability and accelerate the convergence process of the deep learning model (Faybishenko et al., n.d.; Kirichenko et al., 2024).

The third stage, capturing temporal characteristics, involves forming air temperature data into sequences using a sliding window technique (Tridaiana & Marzuki, 2023). Each window represents a sequential sequence of observations that serve as a single input sample for the model. This approach enables LSTM-AE to learn the diurnal patterns and short-term fluctuations that are the primary characteristics of the air temperature signal (Givnan et al., 2022). The model is trained using a normal-only training scheme, so only data that has passed Level-1 QC and does not contain any indication of anomalies is used as training data. The training period is selected during a relatively stable sensor operational phase so that the learned representation reflects the normal state of the system (Kanata et al., 2024). This strategy is commonly used for error reconstruction-based anomaly detection, when explicitly labeled anomaly data is not available (Attribution & Republic, 2009).

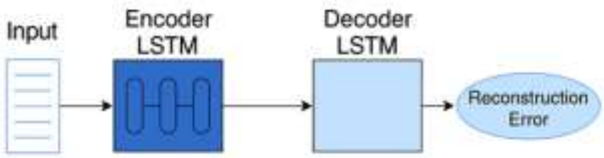


Figure 5. LSTM-AE architecture

Figure 5 shows the training stage of an LSTM-AE model with air temperature (TA) as the primary variable. The architecture consists of an LSTM encoder and an LSTM decoder to reconstruct the input sequence. The model is trained by minimizing the Mean Squared Error (MSE) between the original signal and the reconstructed result. The stability of the training curve is used as an indicator of the success of learning normal temporal patterns (Kirichenko et al., 2024).

The fifth stage, the anomaly threshold, is determined data-drivenly based on the distribution of reconstruction errors in the training data. The threshold value is set using the $\mu + 3\sigma$ statistical criterion of the MSE of normal data. Data segments with reconstruction error values exceeding this threshold are classified as anomalies, as a conservative approach to suppress false positives (Liu et al., 2024).

The final stage is the evaluation and diagnosis of flatline detection. Segments detected as anomalies are then analyzed to determine the characteristics of the flatline (Afif & Aly, 2023). Diagnosis is performed by calculating the local variance of temperature over a specific time window. A flatline is indicated when the variance approaches zero, indicating a loss of sensor response to atmospheric variations (Siregar et al., 2023). Diagnostics are visualized on various time scales (hourly to daily) to evaluate the duration and nature of anomalous events (Jasra et al., 2025).

Result and Discussion

In this section, the research results are discussed in an integrated manner to demonstrate the relationship between data preprocessing, flatline anomaly detection results using the LSTM-AE method, and anomaly characteristics in AWS air temperature data.

Figure 6 displays the first and last 20 rows of preprocessing results from the AWS used in the study. The data consists of 12 main variables, including observation time (Time), battery voltage (Battery), lithium reserve voltage (Lithium), rainfall (RR), wind direction (WD), wind speed (WS), air pressure (PA), air temperature (TA), solar radiation (SR), and additional indicators in the form of reference sensors (TA T107, TS T107) and frost status (Frozen Dew).

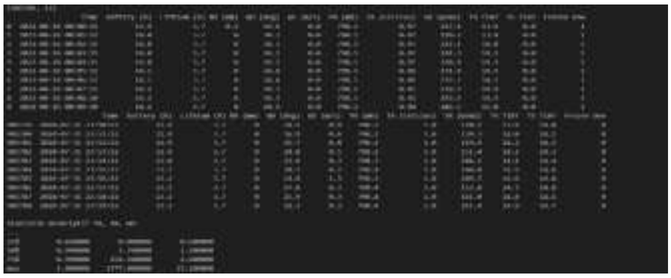
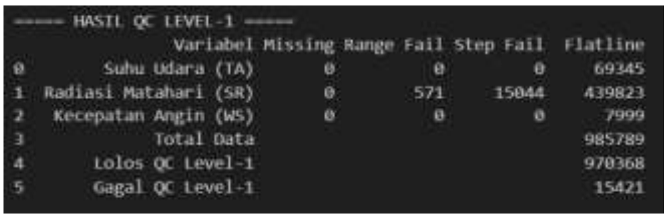


Figure 6. AWS data pre-processing results display

Two segments (10 rows) of data are displayed for different periods, namely August 16, 2022, and July 31, 2024, which represent nighttime conditions in the Dieng Plateau. In both segments, the air temperature (TA) ranges from 0.92 to 1.00 (normalized scale), indicating cool conditions consistent with local climate characteristics. Solar radiation (SR) is relatively low (139 - 246 W/m²), corresponding to the evening before morning, while wind speed (WS) ranges from 0.0 to 1.8 m/s, indicating calm to light winds. Battery and lithium voltage are within a safe range (12.9 - 14.0 V), indicating stable sensor power supply. Figure 7 shows the results of QC level-1 with variables of air temperature (TA), solar radiation (SR), wind speed (WS), and displays the total QC level-1 data.



===== HASIL QC LEVEL-1 =====

	Variabel	Missing	Range Fail	Step Fail	Flatline
0	Suhu Udara (TA)	0	0	0	69345
1	Radiasi Matahari (SR)	0	571	15044	439823
2	Kecepatan Angin (WS)	0	0	0	7999
3	Total Data				985789
4	Lolos QC Level-1				970368
5	Gagal QC Level-1				15421

Figure 7. QC level-1 results display

Of the total QC Level-1 data, 985,789 observation data were generated, of which 970,368 data (98.4%) met the Level-1 Quality Control (QC) criteria, while 15,421 data (1.6%) did not meet these criteria. The most dominant non-conformity to the Level-1 QC criteria occurred in the solar radiation (SR) variable, which was characterized by 439,823 flatline events and 15,044 step fail events. Furthermore, the air temperature (TA) variable recorded 69,345 flatline events, followed by wind speed (WS) with 7,999 flatline events. No missing data or non-conformity to the physical measurement limits (range check) were found for the three variables, indicating that the sensors were still operating within a reasonable measurement range. However, the dominance of flatline events indicates the presence of sensor response disturbances that could potentially affect the quality of the observed data variability.

Figure 8. Heatmap of the percentage of data not suitable for training (QC Level-1)

Figure 8 shows the percentage of data that failed QC or flatlined for the TA variable per month. In 2023, the percentage remained relatively stable at <5%, while in 2024, there were significant spikes in May (35%), June (51.5%), and July (29%). These spikes are suspected to be related to sensor degradation or environmental disturbances such as frost, which frequently occurs during the dry season in the Dieng Plateau.

===== DATA TIDAK LAYAK TRAINING PER BULAN =====

	tahun	bulan	total_data	tidak_layak_training	persen_tidak_layak (%)
22	2024	6	42930	22127	51.54
21	2024	5	44478	15549	34.96
23	2024	7	44125	12832	29.08
17	2024	1	44347	3300	7.44
19	2024	3	35567	2599	7.31
20	2024	4	42954	2982	6.94
2	2022	10	43582	2832	6.50
18	2024	2	32424	1638	5.03
3	2022	11	41978	1969	4.69
4	2022	12	43776	1961	4.48
6	2023	2	40041	1669	4.17
9	2023	5	43453	1754	4.04

Figure 9. Data not suitable for training (May–July 2024)

Figure 9 shows the dominance of flatlines in SR, reaching over 400,000 cases, significantly higher than TA and WS. This indicates that solar radiation sensors are most susceptible to disruption, possibly due to extreme weather conditions or sensor technical issues.

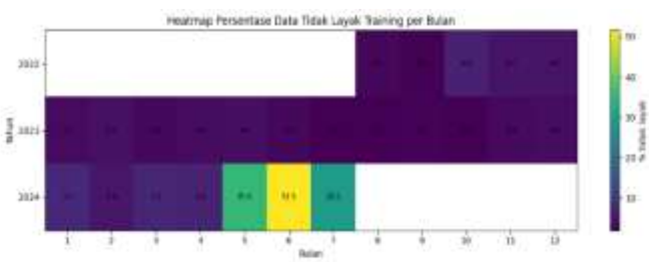


Figure 10. Heatmap of Percentage of Data Not Suitable for Training per Month

Figure 10 reinforces the heatmap findings, with June 2024 having the highest percentage (51.54%), followed by May (34.96%) and July (29.08%). This pattern indicates seasonal sensor degradation, necessitating special attention in AWS sensor maintenance.

Figure 11. Example of Air Temperature (TA) Time Series for 14 Days

Figure 11 displays the normalized air temperature pattern, with blue markers indicating data points that are unsuitable for training. While most of the data follows a normal diurnal pattern, there are flatlines and anomalous segments marked as unsuitable for training. This identification is important to ensure that the LSTM-AE model is trained only on anomaly-free data.

```
Jumlah total data: 985789
Jumlah data training (normal-only): 901031
Persentase data training: 91.4 %

Data training & deteksi telah disimpan.
```

Figure 12. Results of Training and Detection Data Division

Figure 12 shows the results of data partitioning and storage in the context of machine learning modeling, specifically for model training purposes. A total of 985,789 samples were available, representing the entire dataset before being partitioned into training and detection subsets. 91.4% of the total samples were allocated as training data using the normal-only scheme.

```
Periode TRAINING dipakai dari: 2023-08-01 00:01:28 sampai 2023-10-30 23:59:27
Jumlah data training: 121454
Rata-rata TA (training) : 0.798
Std dev TA (training)   : 0.181

Shape X_train : (121395, 60, 1)
Shape X_detect: (985730, 60, 1)

Ringkasan sliding window:
      jenis  jumlah_data  window_size  jumlah_window
0  training       121454           60         121395
1    deteksi       985789           60         985730
```

Figure 13. Feature engineering parameters for training data for the period August–October 2023

Figure 13 presents the training data period selected for feature engineering, from August 1, 2023, at 00:01:28 to October 30, 2023, at 23:59:27. This period was selected to ensure that the model was trained using data that represented the system's stable operational state. The total number of data included in the training period was 121,454 samples, with an average TA (Training Attribute) value of 0.798 and a standard deviation of 0.181. These statistics indicate that the training data has relatively moderate variation, making it suitable for use in developing a learning representation-based model.

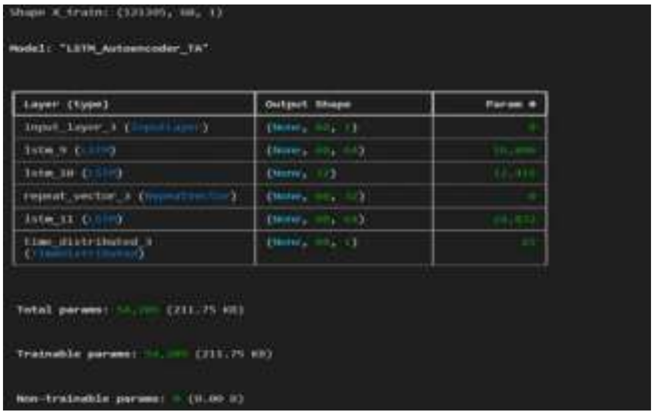


Figure 14. LSTM-AE Model Architecture

The model architecture in Figure 14 shows the LSTM-AE configuration designed to learn latent representations of the temporal patterns of TA variables. The encoder extracts important features from the input sequence, while the decoder reconstructs the sequence from a 32-neuron latent representation. The RepeatVector layer ensures that the latent representation is expanded into a full sequence before entering the decoder. With a total of 54,209 parameters, the model has sufficient capacity to learn non-linear patterns while remaining efficient, reducing the risk of overfitting. This architecture is proven effective based on the reconstruction performance shown in the training curve.

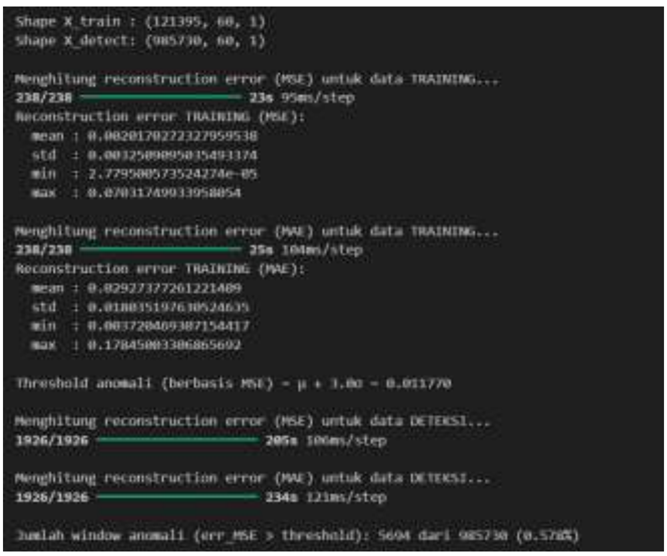


Figure 15. Results of Anomaly Detection Based on Reconstruction Error

Based on Figure 15, the reconstruction error MSE value for the training data has an average (μ) of 0.002017 with a standard deviation (σ) of 0.003251, and a minimum and maximum value of 2.78×10^{-5} and 0.0703, respectively. Consistent results were obtained for the MAE metric, with μ = 0.02973, σ = 0.01803, min = 0.00870, and max = 0.17845. This distribution illustrates that during the normal pattern learning phase, the model generally produces low and stable reconstruction errors.

Based on the MSE statistics for the normal (training) data, the anomaly threshold was determined using the μ + 3σ rule, resulting in a threshold value of 0.011770. The three standard deviations criterion was chosen to highlight events that fall outside the normal error distribution and to limit the false positive rate in time series scenarios that are at risk of local variation. The MSE-based threshold was chosen because this metric is more sensitive to large deviations at one or more points within the sequence window, which is relevant for the purpose of detecting abnormal events. A flatline is a condition where the temperature value does not change over time. Indications of a flatline are analyzed by calculating local variance within the time window.

$$Var(T_{t..t+n}) = \frac{1}{n}\sum_{i=1}^{n}(T_i - \bar{T})^2 \quad (1)$$

Flatline is indicated when:

$$Var(T_{t..t+n}) \approx 0 \quad (2)$$

Variation near zero indicates the sensor has stopped responding or a failure has occurred in the data recording system.

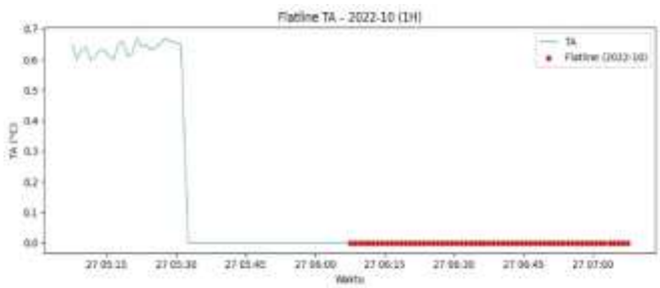


Figure 16. Flatline anomalies of air temperature (AT) per 1 h

Figure 16 displays the normalized TA values on October 27, 2022, showing a flatline anomaly in air temperature between 05:15 and 07:00. The blue line represents the dynamics of air temperature, while the red line marks the segment detected as a flatline, a condition where the temperature value remains constant for a certain duration.

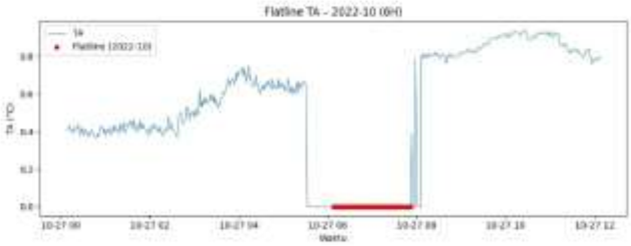


Figure 17. Flatline anomalies of air temperature (ta) per 6 h

Figure 17 displays a normalized air temperature (TA) time series in the range 0–1, with the horizontal axis representing the observation time (October 27, 2022, 00:00–12:00) and the vertical axis showing the TA value. The blue plot represents the air temperature dynamics, while the red dots mark segments detected as flatlines, i.e., conditions where the temperature value remains relatively constant over a certain duration.

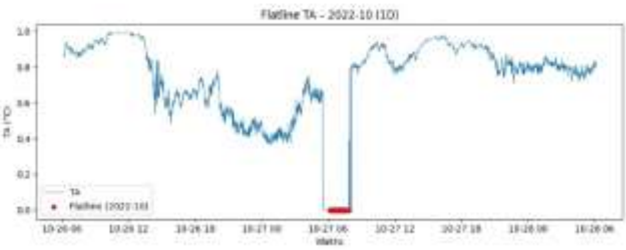


Figure 18. Flatline anomalies of air temperature (TA) per 1 day

Figure 18 displays a normalized air temperature (TA) time series in the range 0–1, with the horizontal axis representing the observation time (October 26–28, 2022) and the vertical axis showing the TA value. The blue plot represents the air temperature dynamics, while the red dots mark segments detected as flatlines, i.e., conditions where the temperature value remains relatively constant over a certain duration. The presence of flatline segments in this time range indicates potential disturbances in the quality of the air temperature data that need to be identified in the QC process.

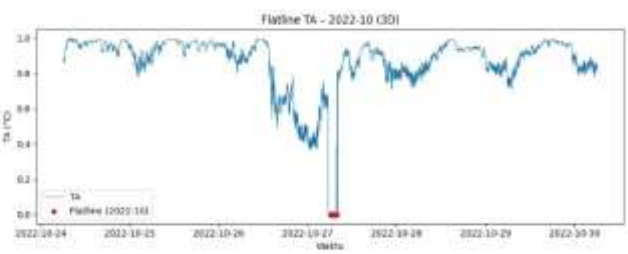


Figure 19. Flatline anomalies of air temperature (TA) per 3 days

Figure 19 displays a normalized air temperature (TA) time series on a scale of 0–1, with the horizontal axis representing the observation time (October 24–30, 2022) and the vertical axis the TA value. The blue plot represents air temperature dynamics, while the red dots mark segments detected as flatlines, which are conditions where the temperature value remains relatively constant over a certain duration. The presence of flatline segments that occur over a period of several days indicates potential quality issues with air temperature data that need to be identified during the quality control process.

Conclusion

This study demonstrates that the proposed LSTM-AE approach is effective in adaptively detecting flatline anomalies in AWS air temperature data, in line with the research objective of developing a data-driven anomaly detection system integrated with Level-1 QC. Of the total 985,730 data windows, 0.578% were identified as anomalies, which, although relatively small, have a significant impact as they have the potential to reduce the natural variability of the data and cause bias in meteorological analysis.

The main contribution of this research lies in the detection approach that specifically targets flatline anomalies, the integration of operational QC procedures with deep learning methods, and the application of a normal-only training scheme with data-driven anomaly threshold determination.

However, this study has limitations because it was only conducted in one geographic location (the Dieng Plateau) and focused on one type of anomaly. Therefore, further research is needed to test the generalizability of the method across different environmental conditions, sensor types, and anomaly types.

Overall, the proposed approach shows strong potential to be implemented as an automated quality control module in AWS systems to improve the reliability of meteorological data.

Author Contributions

Conceptualization, S., S. S., M., and D. H.; methodology, S., S. S; software (LSTM-AE model), S.; validation, S., S. S.; formal analysis, S., S. S.; investigation, S., S. S.; data curation, S.; resources, S., S. S.; writing-original draft, S., S. S.; writing-review and editing, S. S., M., and D. H.; visualization, S.; supervision, S. S.; scientific advice/input, S. S., M., and D. H.; All authors have read and approved the final version of the submitted manuscript.

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Conflicts of Interest

The authors declare that there are no conflicts of interest in this research. The entire process, from data collection and analysis to manuscript writing, was conducted independently without any external influence that could influence the results or interpretation of the research.

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