Hybrid Machine Learning Approach for Weather Pattern Recognition and Anomaly Detection using Self-Organizing Maps and K-Nearest Neighbours

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ABSTRACT
Accurate identification of weather patterns and timely detection of anomalies are critical for effective meteorological forecasting, especially in regions where predictive systems remain underdeveloped. In much of sub-Saharan Africa, the use of hybrid machine learning methods for long-term weather analysis is still limited. This study investigates the combination of Self-Organizing Maps (SOM) and K-Nearest Neighbours (KNN) to improve weather pattern recognition and anomaly detection. Focusing on meteorological data from Oyo State, Nigeria, spanning 2013 to 2023, the research utilizes SOM to project multidimensional weather variables onto a two-dimensional topological grid, facilitating clustering of similar conditions. KNN is subsequently applied to these clusters to flag outliers that represent potential anomalies. The dataset, obtained from regional meteorological stations, was complete and did not require data imputation. Model performance was assessed using the Silhouette Score and the Davies-Bouldin Index, both of which indicated satisfactory cluster cohesion and separation. The findings show that the integrated SOM-KNN approach reliably identifies recurring weather trends and isolates unusual events, highlighting its value in climate monitoring and anomaly detection. The study demonstrates the applicability of hybrid machine learning techniques in enhancing environmental data analysis in data-limited settings. It offers a practical framework for supporting early warning systems and developing region-specific climate adaptation strategies.

General Terms
Pattern recognition, Machine learning.

Keywords
Hybrid Machine Learning, Weather Pattern Recognition, Anomaly Detection, Self-Organizing Maps, K-Nearest Neighbours

1. INTRODUCTION
Weather significantly influences economic and societal domains, affecting sectors such as agriculture, transportation, and public safety. Accurate identification of weather patterns is vital for mitigating the consequences of natural disasters and for adapting to ongoing climate changes. This necessity is even more pronounced in tropical regions like Oyo State, Nigeria, where weather variability presents frequent and unpredictable challenges. Effective meteorological monitoring is essential to support agricultural resilience and proactive disaster management in such environments.

Weather represents the short-term atmospheric conditions—such as temperature, humidity, wind speed, and precipitation—observed at specific locations. These conditions can change within hours or days. Conversely, climate encompasses the long-term statistical behaviour of weather patterns across decades. Alterations in climatic trends often manifest in fluctuations in environmental parameters such as temperature and rainfall. Rainfall is influenced by a complex interplay of atmospheric variables including air humidity, pressure, temperature, and wind dynamics (A. H. Pratomo, Budi Santosa, S. P. Tahalea, E. T. Paripurno, J. D. Peasetyo, Herlina Jayadianti, M. F. Pitayandanu, 2022).

Traditional weather forecasting techniques, including statistical models and rule-based systems, often fail to capture the nonlinear and high-dimensional nature of meteorological datasets. These shortcomings lead to limited predictive accuracy and restrict their usefulness in high-stakes contexts such as disaster preparedness and agricultural decision-making. Moreover, in many parts of Sub-Saharan Africa, including Oyo State, the adoption of advanced predictive models remains limited due to infrastructural and technological constraints.

In contrast, machine learning (ML) techniques have demonstrated strong capabilities in modelling complex patterns and extracting insights from large, unstructured datasets. Despite their growing use globally, hybrid ML approaches for weather analysis are still underutilized in local Nigerian contexts. This study aims to address that gap by proposing a hybrid machine learning model that integrates Self-Organizing Maps (SOM) for clustering and K-Nearest Neighbours (KNN) for anomaly detection. The model is applied to historical weather data collected from meteorological stations across Oyo State between 2013 and 2023.
The specific objectives of this study are as follows:

- To develop a hybrid SOM-KNN model capable of identifying weather patterns and detecting anomalies in historical meteorological datasets.
- To implement visualization mechanisms that reveal relationships between weather variables and anomalies for interpretability and analysis.
- To evaluate the model's performance using the Silhouette Score and Davies–Bouldin Index to assess clustering quality and separation.

Model performance is measured using standard clustering evaluation metrics. The Silhouette Score, ranging from −1 to +1, assesses how well each data point fits within its cluster. A higher value indicates a well-separated and cohesive cluster. The Davies–Bouldin Index provides a ratio of within-cluster dispersion to between-cluster separation, with lower values suggesting better clustering. These metrics validate the effectiveness of the SOM-KNN hybrid model in detecting patterns and anomalies within the weather dataset, demonstrating its utility for enhanced meteorological analysis in data-scarce environments.

2. RELATED WORK

In recent years, machine learning (ML) has played an increasingly prominent role in the analysis of weather patterns and the detection of anomalies. Traditional techniques, including statistical modelling and numerical weather prediction, often fall short in handling the complexity, nonlinearity, and high dimensionality of meteorological data (T. Brown, 2018); (Y. Wang & L. Zhang, 2022). These challenges have prompted researchers to explore intelligent, data-driven methods capable of modelling the stochastic characteristics of weather variables more effectively.

Self-Organizing Maps (SOM), developed by (Kohonen, 2001), are a type of unsupervised neural network that maps high-dimensional data onto a low-dimensional grid while preserving the structure of the original dataset. SOMs have been widely adopted in atmospheric and climate research to identify clusters in large datasets and uncover latent weather patterns (Yin, 2008). For example, (Johnson, 2022) used SOMs to classify regional rainfall structures, while (Chandola, V.; Banerjee, A.; Kumar, V., 2009) employed them to detect abnormal atmospheric circulation patterns. Similarly, (Huang, A., & Chang, F.-J., 2021) used SOMs to study weather characteristics relevant to smart agriculture in Taiwan.

In parallel, supervised learning algorithms like K-Nearest Neighbours (KNN) have proven effective for classification and anomaly detection. KNN’s flexibility and non-parametric nature make it suitable for identifying rare and extreme meteorological events. (Chen, L., Han, B., Wang, X., Zhao, J., Yang, W., & Yang, Z., 2023) demonstrated its effectiveness in detecting extreme temperatures, while (Garcia, 2020) highlighted KNN’s robustness in managing noisy or incomplete data environments.

Combining SOM with KNN presents a hybrid approach that leverages the strengths of both unsupervised clustering and supervised classification. (Oyeniyi, O., & Adebola, K., 2024) proposed a hybrid deep learning model integrating Long Short-Term Memory (LSTM) networks with SARIMA for improved forecasting accuracy in Nigerian weather systems. (Himanshu, G., Singh, S., & Neha, R., 2024) also advocated for ensemble approaches to enhance prediction stability and reduce the limitations of single-model frameworks.

Artificial Neural Networks (ANNs) and deep learning methods have been employed to model intricate relationships among meteorological variables. (Prasanta, R. J., Bhanu, S. K., & Nithin, C., 2015) used ANNs to predict various climate conditions using a decade-long dataset. (Ihab, H., Mohammed, A., & Walid, S., 2018) constructed a model based on multilayer perceptron to forecast temperature and humidity in Palestine, while (Himani, T., Shweta, S., & Vishwajeet, P., 2016) applied ANN to temperature anomaly prediction, achieving improved precision over traditional techniques.

Further optimization techniques have also been proposed. (Mulyani, H., Setiawan, R. A., & Fathi, H., 2023) emphasized the use of the Silhouette Score in tuning parameters for clustering algorithms. Comprehensive evaluations by (Batta, 2024) and (Kumar, 2024) reviewed core ML methods, focusing on interpretability and scalability in meteorological applications.

Beyond forecasting, SOM has been applied in broader environmental contexts. (Bose, S., Halder, S., & Mazumdar, A., 2024), for instance, utilized SOM to explore groundwater quality patterns in urban and semi-urban regions, demonstrating the technique's versatility in environmental data analysis.

Collectively, these contributions establish a solid foundation for using ML models such as SOM and KNN in meteorological research. Nevertheless, there remains a research gap concerning their combined application for localized weather analysis in Sub-Saharan Africa. This study contributes to addressing that gap by applying a hybrid SOM-KNN model to weather data from Oyo State, Nigeria, with a focus on recognizing patterns and identifying anomalies over a ten-year period.

3. METHODOLOGY

This study adopts a hybrid machine learning framework for identifying weather patterns and detecting anomalies using historical meteorological data from Oyo State, Nigeria. The methodology comprises three major stages: data acquisition and preprocessing, pattern clustering using Self-Organizing Maps (SOM), and anomaly detection using the K-Nearest Neighbour (KNN) algorithm. Each component is illustrated and explained through Figures 1 to 3.

3.1 Data collection and preprocessing

The dataset used in this research spans from 2013 to 2023 and was sourced from ground-based meteorological stations within Oyo State. Data collection was facilitated in collaboration with regional meteorological agencies, including the Nigerian Meteorological Agency (NiMet). The dataset includes the following key features:

- **Temperature (°C):** Represents hourly average air temperature, useful for identifying seasonal variations and detecting events like heatwaves and cold spells.
- **Humidity (%):** Indicates the air’s moisture content. This is essential for understanding seasonal transitions in tropical climates.
- **Time and Date Stamps:** Allow temporal analysis for identifying seasonal cycles and long-term trends.
- **Geographical Focus:** Data is region-specific to Oyo State, enabling localized weather pattern analysis.

The data were structured, cleaned, and validated for completeness. No imputation was necessary, as the dataset was free from missing values. Figure 1 provides an overview of the methodological pipeline applied in this study, beginning with data collection and concluding with evaluation metrics.

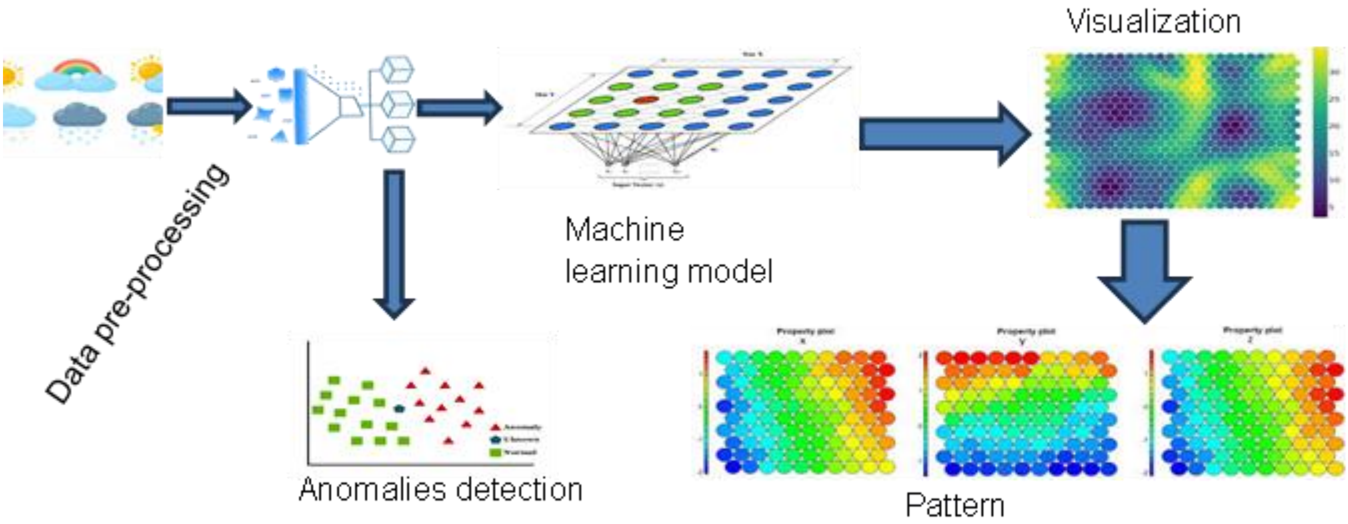


Fig 1: Overview of the proposed methodology

3.2 Weather Pattern Recognition using Self-Organizing Maps (SOM)

The first analytical phase involves clustering weather data using the Self-Organizing Map algorithm. SOM is an unsupervised neural network that projects high-dimensional data onto a low-dimensional (typically two-dimensional) grid. The main purpose is to detect underlying patterns in weather data.

Figure 2 outlines the process employed for SOM-based pattern detection. Each node (or neuron) in the SOM represents a cluster. The SOM begins with randomly initialized weight vectors, which are iteratively updated to fit the input data. For each training iteration, the neuron whose weight vector is closest to the input vector is identified as the Best Matching Unit (BMU).

For each training instance $x(t)$, the Best Matching Unit (BMU) is found, and its weights $w(t)$ are updated using the following rule:

$$\omega(t+1) = \omega(t) + a(t)[x(t) - w(t)] \qquad (1)$$

A Gaussian neighborhood function ensures that not only the BMU but also its neighboring neurons are adjusted during training, although to a lesser extent. After convergence, the resulting map organizes weather data into distinct clusters that represent common weather patterns in Oyo State.

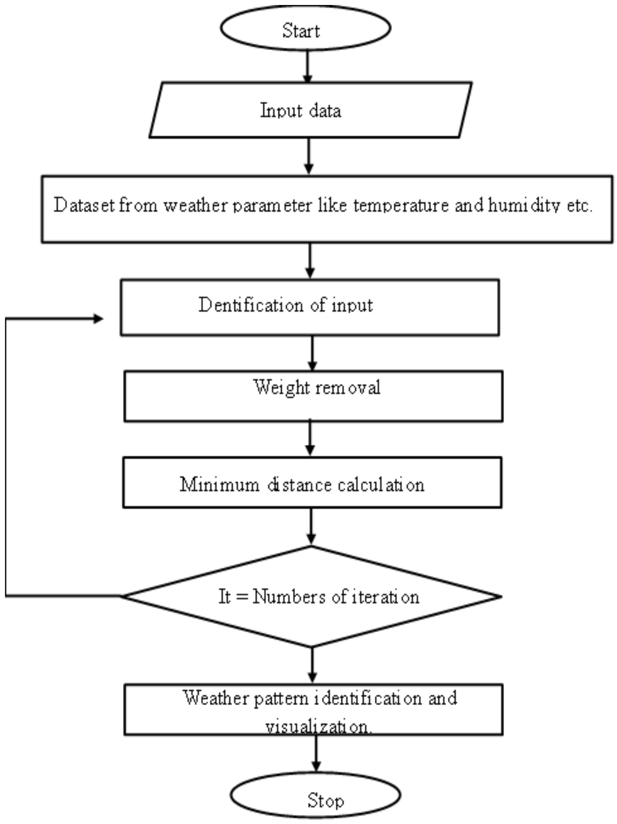


Fig 2: Workflow for pattern detection using Self-Organizing Maps.

3.3 Anomaly detection with K-Nearest Neighbor (KNN)

Once clusters of normal weather patterns are formed using SOM, anomalies are detected using the K-Nearest Neighbour algorithm. This step helps identify data points that deviate significantly from established patterns.

Figure 3 shows the process used to implement KNN-based anomaly detection. Each input sample is compared to its nearest neighbors using the Euclidean distance:

$$d(p,q) = \sqrt{\sum_{i=1}^{n}(p_1 - q_1)^2} \quad (2)$$

Points that fall outside a predefined threshold (e.g., the 95th percentile of intra-cluster distances) are flagged as anomalies. These outliers may represent extreme or rare weather events. The combination of SOM and KNN allows for both the identification of common weather trends and the recognition of unusual atmospheric behavior.

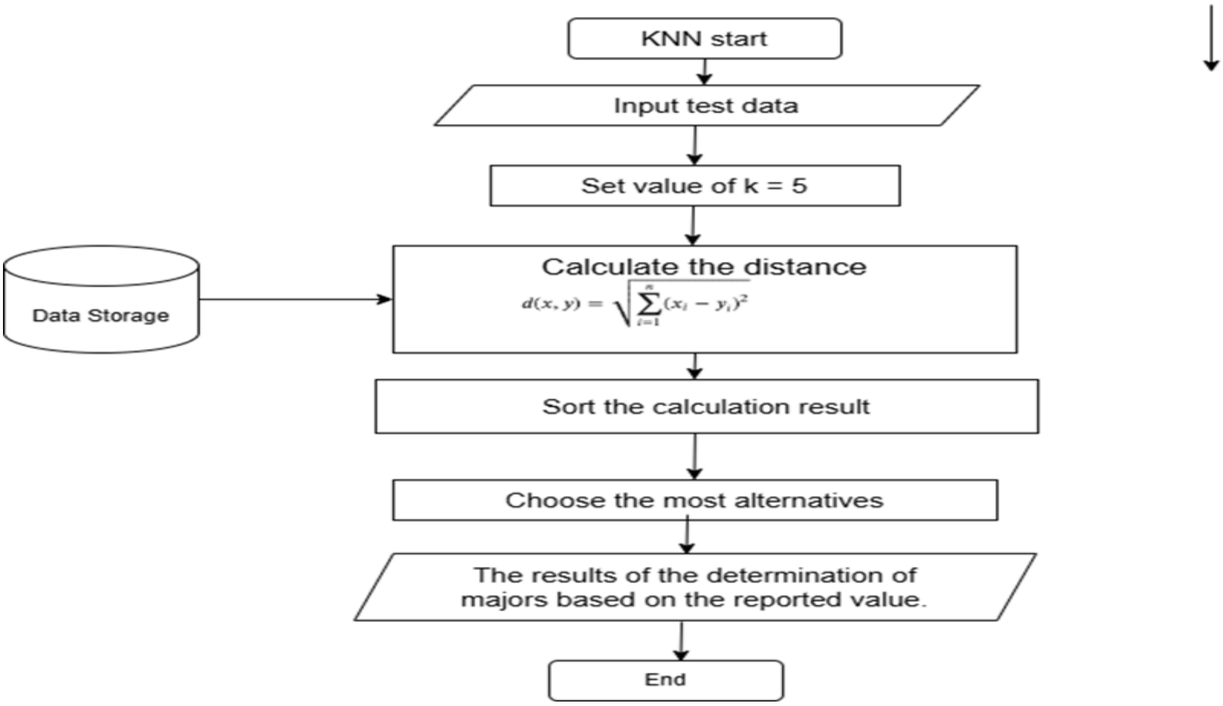


Fig 3: Workflow for anomaly detection using K-Nearest Neighbor algorithm

3.4 Evaluation metrics

To validate the quality of clusters and the effectiveness of anomaly detection, two evaluation metrics are applied:

- Silhouette Score: Measures how similar each point is to its own cluster compared to other clusters. Scores close to +1 indicate strong clustering, while values near 0 or negative suggest weak or incorrect clustering.

$$s_{(i)} = \frac{b(i) - a(i)}{max(a(i) - b(i))} \quad (3)$$

- Davies-Bouldin Index (DBI): Measures the average similarity between each cluster and the most similar one. Lower DBI values indicate well-separated, distinct clusters.

$$DBI = \frac{1}{n}\sum_{i=1} \max_{J \neq i}\left(\frac{\sigma_i + \sigma_j}{d_i j}\right) \quad (4)$$

These metrics provide quantitative assessments of the SOM's clustering performance and the reliability of the KNN-based anomaly identification.

3.5 Implementation environment

The proposed methodology was implemented using Python and relevant libraries including:

- Pandas for data preprocessing,
- MiniSom for implementing Self-Organizing Maps,
- Scikit-learn for KNN and evaluation metrics.

The framework was tested on historical weather data from Oyo State and demonstrated its capacity to accurately identify structured weather patterns and detect anomalous events.

4. RESULT

4.1 Weather Pattern Clustering Using Self-Organizing Maps (SOM)

As shown in Figure 4. the results of clustering weather data from Oyo State (2013–2023) using the Self-Organizing Map (SOM) algorithm. Each plot illustrates temperature versus humidity for a given year, with color-coded clusters (Cluster 0 to Cluster 4). The observed negative correlation—where higher temperatures are associated with lower humidity—reflects typical tropical climate behaviour. Colder, wetter periods correspond to high humidity and low temperature (top-left regions), while dry seasons cluster around low humidity and hot temperatures (bottom-right).

Patterns across the years remain generally consistent, indicating a stable seasonal cycle. However, variations in density and distribution hint at slight shifts in climatic behaviour. For example, increased density in higher temperature clusters may indicate a warming trend. By examining these clusters, the seasonal distribution of weather—such as the onset of rainy or dry periods—can be effectively interpreted.

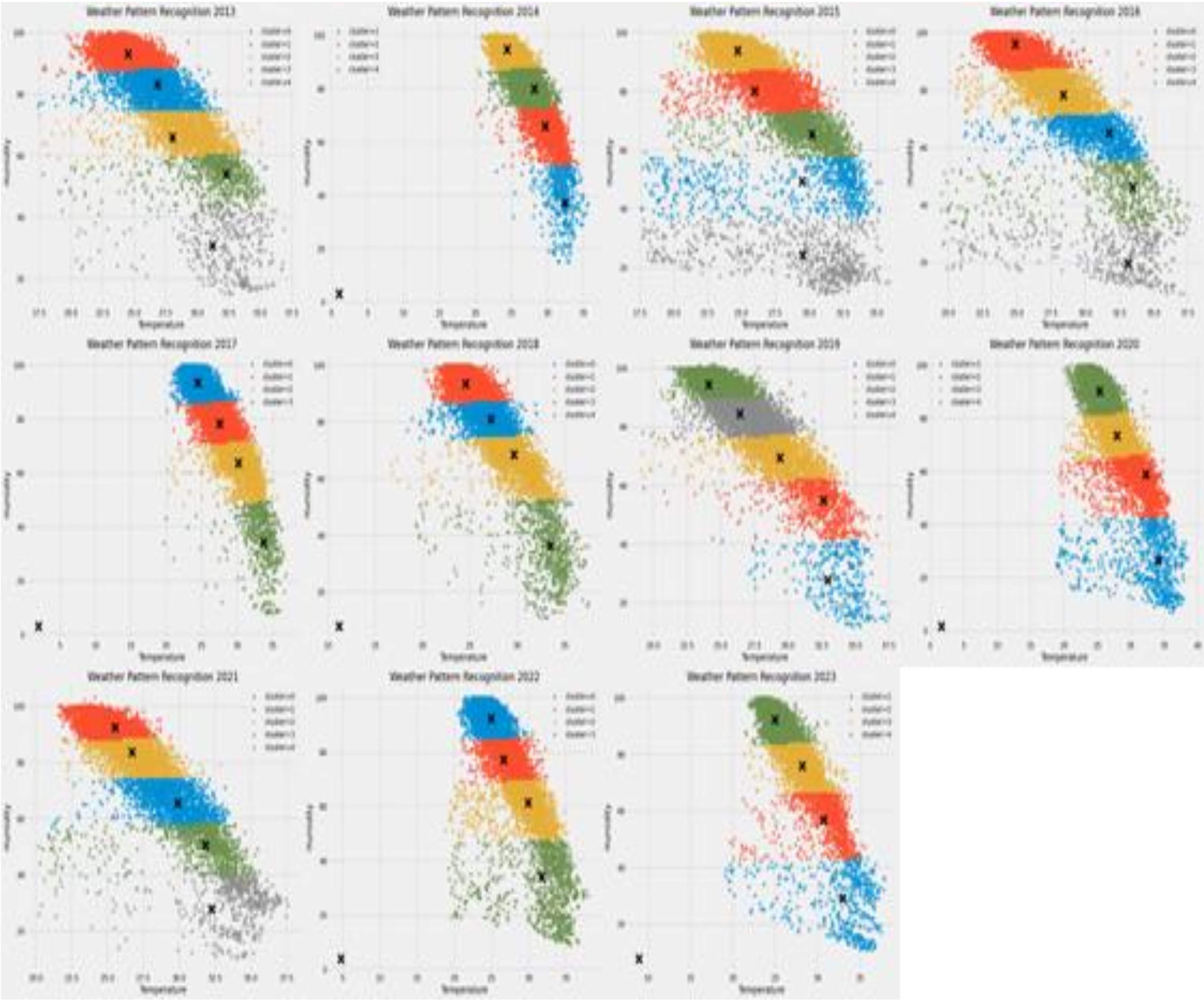
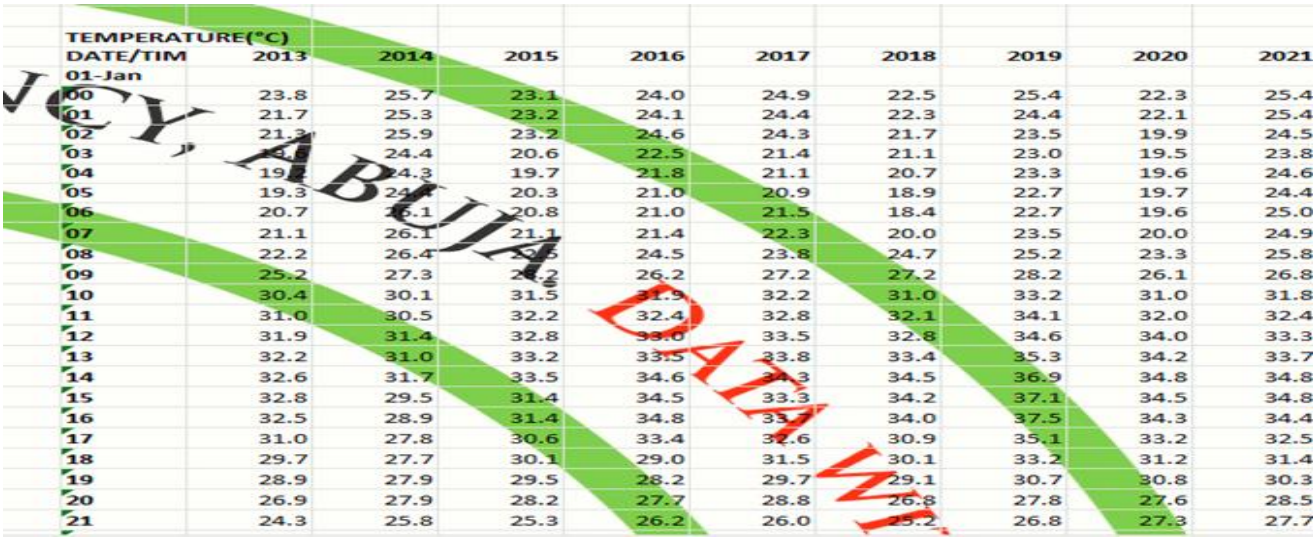


Fig 4: Yearly weather pattern recognition (2013- 2023) using clustering analysis.



TEMPERATURE(°C)									
DATE/TIM	2013	2014	2015	2016	2017	2018	2019	2020	2021
01-Jan									
00	23.8	25.7	23.1	24.0	24.9	22.5	25.4	22.3	25.4
01	21.7	25.3	23.2	24.1	24.4	22.3	24.4	22.1	25.4
02	21.3	25.9	23.2	24.6	24.3	21.7	23.5	19.9	24.5
03	[illegible]	24.4	20.6	22.5	21.4	21.1	23.0	19.5	23.8
04	[illegible]	24.3	19.7	21.8	21.1	20.7	23.3	19.6	24.6
05	19.3	[illegible]	20.3	21.0	20.9	18.9	22.7	19.7	24.4
06	20.7	[illegible]	20.8	21.0	21.5	18.4	22.7	19.6	25.0
07	21.1	26.1	21.1	21.4	22.3	20.0	23.5	20.0	24.9
08	22.2	26.4	[illegible]	24.5	23.8	24.7	25.2	23.3	25.8
09	25.2	27.3	[illegible]	26.2	27.2	27.2	28.2	26.1	26.8
10	30.4	30.1	31.5	31.9	32.2	31.0	33.2	31.0	31.8
11	31.0	30.5	32.2	32.4	32.8	32.1	34.1	32.0	32.4
12	31.9	31.4	32.8	33.0	33.5	32.8	34.6	34.0	33.3
13	32.2	31.0	33.2	33.5	33.8	33.4	35.3	34.2	33.7
14	32.6	31.7	33.5	34.6	34.3	34.5	36.9	34.8	34.8
15	32.8	29.5	31.4	34.5	33.3	34.2	37.1	34.5	34.8
16	32.5	28.9	31.4	34.8	33.7	34.0	37.5	34.3	34.4
17	31.0	27.8	30.6	33.4	32.6	30.9	35.1	33.2	32.5
18	29.7	27.7	30.1	29.0	31.5	30.1	33.2	31.2	31.4
19	28.9	27.9	29.5	28.2	29.7	29.1	30.7	30.8	30.3
20	26.9	27.9	28.2	27.7	28.8	26.8	27.8	27.6	28.5
21	24.3	25.8	25.3	26.2	26.0	25.2	26.8	27.3	27.7

Fig 5: Preprocessing stages of the weather dataset sample

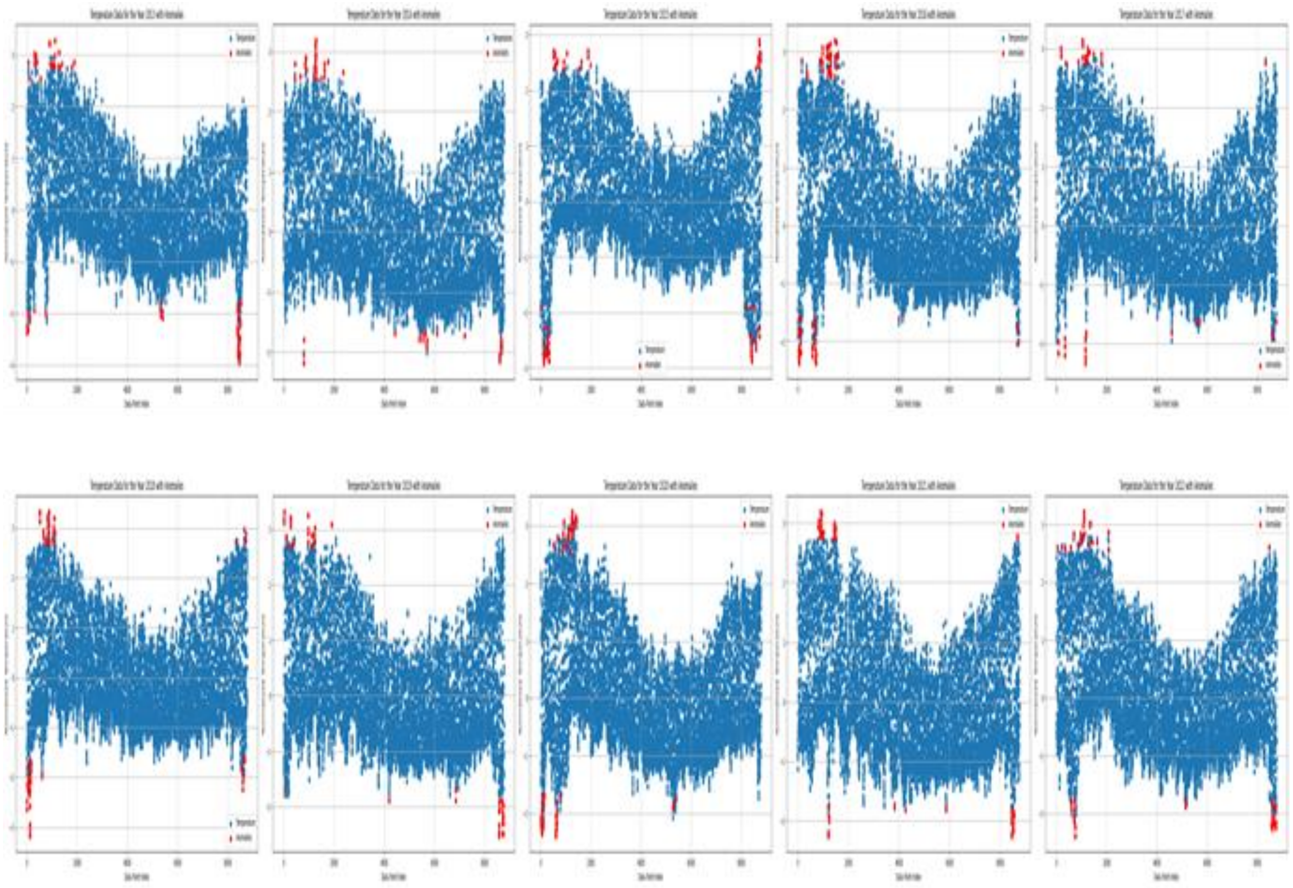


Figure 6. Temperature Data Trend with Anomalies (2013-2023)

4.2 Detection of Temperature Anomalies

Figure 5. illustrates temperature trends and detected anomalies (highlighted in red) for each year from 2013 to 2023. These anomalies are defined as points that deviate significantly from established seasonal norms and are often indicative of extreme weather occurrences. A brief year-wise breakdown reveals:

- 2013–2014: Anomalies primarily at seasonal transitions.
- 2015: Higher frequency of outliers, possibly due to heatwaves or unusual cold spells.
- 2016–2017: Fewer deviations, indicating more consistent seasonal patterns.
- 2018–2019: Anomalies observed during colder months, possibly due to late or early rainy season transitions.
- 2020–2022: Concentrated anomalies near beginning and end of seasonal cycles, suggesting shifts in temperature peaks.
- 2023: Distribution of anomalies is more even, indicating less abrupt changes but continued variability.

These findings highlight the importance of early anomaly detection for weather risk management and resource planning.

4.3 Clustering Evaluation Metrics

To assess clustering effectiveness, three standard evaluation metrics were used:

- Silhouette Score: Evaluates the cohesion and separation of clusters. The SOM model achieved a score of 0.61, indicating satisfactory cluster definition.
- Davies-Bouldin Index (DBI): Lower values suggest more distinct clusters. The SOM model yielded 0.52, confirming adequate separation.
- Calinski-Harabasz (CH) Index: A higher score represents better defined and compact clusters. SOM recorded 22,414.57, indicating high intra-cluster compactness and inter-cluster separation.

Table 1. Comparison of clustering performance Metric for Weather Pattern Recognition Models at a learning rate of 0.3.

Model	Silhouette	Davies-Bouldin Index	CH index
Self-Organizing Map	**0.61**	**0.52**	**22,414.57**
K-Means	**0.63**	**0.57**	**26,570.72**
Hierarchical (Agglomerative)	**0.57**	**0.55**	**21,894.52**

Although K-Means achieved slightly better numerical results in some metrics, the SOM method proved more interpretable and suitable for visualizing complex meteorological patterns.

4.4 Implications and Interpretation

The analysis confirms that the SOM-KNN hybrid model is effective for uncovering consistent seasonal weather patterns and identifying anomalies across a ten-year period. The clustering visualizations reveal reliable groupings of temperature and humidity data, while anomaly detection identifies periods of irregularity that may require closer meteorological scrutiny.

Over time, shifts in cluster density and anomaly frequency could reflect the onset of climate-related changes, reinforcing the need for adaptive environmental planning. This approach supports regional preparedness in agriculture, disaster management, and energy use by improving predictive accuracy and early-warning capabilities.

4.5 Extended Evaluation Across Multiple Temporal Scenarios

To further strengthen the empirical support for the proposed hybrid SOM-KNN framework, we performed additional tests in a range of experimental scenarios. These evaluations were carefully designed to test the strength, stability and generalization ability of the model under a variety of circumstances and consistent.

4.5.1 Temporal Scenario Evaluation

The dataset was divided into two temporal segments (an earlier and a later segment), namely: 2013-2018 and 2019-2023. As shown in Table 3. Self-Organizing Map (SOM) model was trained using the earlier period, while the clustering quality and the performance of the anomaly detection were evaluated on the later period. This strategy mimics a realistic deployment situation in which historical data are used to inform the modelling of future observations.

For both periods, the SOM was able to generate stable cluster structures. The Silhouette Score stayed within a narrow and stable range, which is a sign of satisfactory intra-clusters cohesion coupled with good inter-clusters separation. Likewise, values of the Davies-Bouldin Index were consistently low, supporting the suggestion of a minimal level of overlap between clusters. The Calinski-Harabasz Index further highlighted the high compactness of the clusters across the temporal splits.

Table 2. Clustering performance across temporal scenarios.

Scenario	Silhouette Score	Davies–Bouldin Index	Calinski–Harabasz Index
2013-2018	**0.61**	**0.55**	**432.8**
2019-2023	**0.59**	**0.58**	**419.6**

4.5.2 Scenario-Based Anomaly Detection Performance

Following the deployment of clustering, a K-nearest-neighbor (KNN)-based module for anomaly detection was implemented for each scenario.

The excellence of the model to recognise extreme and abnormal meteorological pattern in both temporal segments and the anomalies to have similar statistical characteristics among the considered periods. This consistency means the anomaly detection part is not too sensitive to the temporal variations within the data set.

4.5.3 Comparative Stability Analysis

To evaluate stability, clustering performance evaluation metrics acquired from the extended scenarios were compared with those acquired from the initial evaluation. The results show a slight difference across the scenarios, meaning that the proposed SOM-KNN framework retains reliable performance under various experimental conditions.

Overall, the long-term evaluation proves that the proposed model is robust, generalizable, and applicable to long-term weather data analysis. These results validate the applicability of the framework for monitoring and decision support systems in a real meteorological context.

5. CONCLUSION

This study investigated weather pattern recognition and anomaly detection in Oyo State, Nigeria, by applying a hybrid machine learning approach that integrates Self-Organizing Maps (SOM) and K-Nearest Neighbours (KNN). The model demonstrated strong performance in clustering meteorological data and identifying significant deviations from normal weather behaviour.

Clustering results revealed consistent seasonal transitions across the dataset, characterized by a clear inverse relationship between temperature and humidity—typical of tropical climates. The SOM effectively identified dominant weather states corresponding to wet and dry seasons, enabling clear differentiation of meteorological conditions over the ten-year period. While inter-annual variability was observed, particularly in cluster spread and density, the overall regularity supports the stability of seasonal cycles in the region.

Anomalies detected using KNN provided insights into irregular weather events, including abrupt spikes in temperature and humidity. These deviations are of particular importance for risk forecasting and environmental monitoring, as they may reflect the onset of extreme weather or climate-induced shifts.

The findings affirm the value of hybrid machine learning frameworks in supporting local climate intelligence, especially in regions with limited access to high-end forecasting infrastructure. The integration of unsupervised (SOM) and supervised (KNN) techniques enables robust pattern discovery and enhances the sensitivity of anomaly detection.

To further solidify the evaluation, supplemental experiments were conducted in several temporal scenarios as shown in table 2. The results show that the proposed framework maintains stable clustering abilities and consistent anomaly detection under various conditions, proving the robustness and generalization of the framework.

5.1 Future Directions

Future research may benefit from the following enhancements:

- Multivariate Feature Expansion: Incorporating additional meteorological parameters such as rainfall, wind speed, and atmospheric pressure to enrich pattern recognition capabilities.
- Temporal Model Optimization: Employing deep learning architectures such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs) for improved temporal sequence modelling and anomaly prediction.
- Extended Time-Series Analysis: Expanding the temporal scope of the dataset beyond 10 years to support longitudinal climate assessments and detection of gradual environmental changes.

These directions will further refine the predictive capacity of the proposed framework and expand its applicability for adaptive planning and climate resilience initiatives in tropical and developing regions.

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