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Thermal Behavior Clustering of High-Voltage Electrical Equipment Using K-Means and Fuzzy C-Means

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ABSTRACT

Thermal monitoring of high-voltage electrical equipment is an important aspect of maintaining the reliability and operational safety of electrical power systems. Conventional classification approaches generally require labeled data and are limited in representing transitional thermal conditions. Therefore, this study proposes an unsupervised learning approach using K-Means and Fuzzy C-Means (FCM) clustering methods to analyze thermal behavior patterns in high-voltage electrical equipment based on thermal image features. The proposed model utilizes two main features extracted from thermal images, namely the percentage of white regions (% white) and non-white regions (% non-white), where white regions represent high-temperature areas. A total of 12 thermal images were used in the clustering process. Experimental results showed that the K-Means algorithm converged after only 2 iterations, whereas FCM required 53 iterations to achieve convergence . Both methods successfully identified dominant thermal patterns corresponding to Normal, Warning, and Hazardous conditions. The most extreme thermal condition was observed in data sample 6, which had a white-region percentage of 83.2647% and was consistently classified as Hazardous by both K-Means and FCM . In addition, FCM demonstrated superior capability in representing transitional thermal conditions through membership values. Data sample 3, with a white-region percentage of 56.5476%, was classified as Hazardous by K-Means but categorized as Warning by FCM with a dominant membership value of 0.702543 . These results indicate that FCM provides more flexible thermal behavior representation compared with hard clustering approaches. Overall, the proposed clustering-based approach demonstrates significant potential for real-time thermal condition assessment and predictive maintenance applications in high-voltage electrical equipment.

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1. INTRODUCTION

High-voltage electrical equipment plays a critical role in maintaining the reliability, stability, and continuity of electric power systems. Equipment such as transformers, insulators, switchgear, conductors, and other substation components operates continuously under electrical, thermal, environmental, and mechanical stresses. Abnormal operating conditions in these components are often reflected by changes in their physical signatures, including vibration, temperature rise, insulation degradation, and electrical discharge behavior. Previous studies in condition monitoring have shown that early fault diagnosis can be achieved by extracting measurable features from equipment behavior and comparing them with normal and faulty operating patterns (Betta et al., 2002). Therefore, the development of intelligent monitoring approaches is essential to support predictive maintenance and reduce the risk of unexpected failures in power system equipment.

Among various condition monitoring techniques, infrared thermography has become one of the most practical and widely used methods for detecting abnormal thermal behavior. Infrared thermal imaging enables non-contact inspection, fast observation, and safer evaluation of energized equipment without interrupting system operation (Pastuszak et al., 2013). Thermal anomalies are important diagnostic indicators because many electrical faults, including loose connections, conductor corrosion, contact resistance, overloading, insulation weakness, and component degradation, may generate abnormal heat before progressing into severe failures [10]. In the context of high-voltage power equipment, thermal imaging has been used to detect hidden faults and overheating conditions, especially in substation environments where manual inspection can be time-consuming and highly dependent on operator interpretation (J. Liu et al., 2024).

Recent developments in artificial intelligence and computer vision have encouraged the use of automated thermal image analysis for power equipment inspection. Liu et al. proposed a thermal-imaging-based abnormal heating detection framework for high-voltage power equipment by integrating thermal and visual information to improve segmentation accuracy under complex field conditions (J. Liu et al., 2024). Similarly, thermal defect detection of electrical components has been studied using image-based and learning-based approaches, showing that thermal patterns can provide meaningful diagnostic information for electrical maintenance applications (C. Liu et al., 2024). These studies confirm that thermal images are not only visual inspection tools, but also valuable data sources for intelligent condition assessment.

However, many existing approaches for thermal condition assessment rely on supervised learning, where the model requires labeled samples to distinguish between normal and abnormal conditions. Supervised methods such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Artificial Neural Network (ANN), and deep learning models have shown strong performance in several electrical engineering applications (Prenata, n.d.-b), (Prenata & Ridho'i, 2026), (Prenata, n.d.-a), (Prenata, 2023b), (Prenata, 2023a). For example, previous studies have applied SVM and KNN for classification and prediction tasks in power system reliability analysis (Prenata, n.d.-a), (Prenata, 2023b), while KNN has also been implemented for temperature classification in high-voltage electrical equipment (Prenata, 2023a). In another related study, metaheuristic and gradient-based training strategies were applied to predict transformer oil breakdown voltage under copper and iron contamination, demonstrating the relevance of AI-based methods in transformer condition assessment (Prenata, n.d.-b). Nevertheless, supervised learning approaches depend strongly on the availability and quality of labeled data, which may become a major limitation in thermal monitoring applications because hazardous thermal conditions are relatively rare, difficult to reproduce, and often require expert validation.

This limitation opens an opportunity for unsupervised learning methods, particularly clustering-based approaches, to analyze thermal behavior without requiring predefined class labels. K-Means is one of the most widely used clustering algorithms due to its simplicity, computational efficiency, and ability to group data based on feature similarity (Macqueen, n.d.). In thermal image analysis, K-Means can be used to separate operating patterns based on extracted features such as hotspot intensity, white-region percentage, or non-white thermal distribution. However, K-Means applies a hard clustering mechanism, in which each data point is assigned exclusively to one cluster. This characteristic may be less suitable for thermal behavior analysis when the transition between normal and hazardous conditions is gradual rather than strictly separated.

Fuzzy C-Means (FCM) offers a more flexible alternative because it allows each data sample to have membership values in more than one cluster (Bezdek, 1981). This soft clustering mechanism is particularly relevant for thermal condition assessment because thermal degradation often occurs progressively. A thermal sample may not be completely normal or completely hazardous; instead, it may show a transitional behavior between the two states. Previous research on FCM-based image segmentation also supports the usefulness of fuzzy clustering for representing uncertainty and gradual boundaries in image-based analysis (Miao et al., 2020). Therefore, FCM has strong potential for modeling thermal behavior patterns in high-voltage electrical equipment, especially when the dataset is limited and the boundary between operating categories is not sharply defined.

The application of K-Means and FCM has also been explored in transformer-related studies. Prenata et al. applied K-Means and FCM to analyze dielectric behavior clustering in transformer oil contaminated with copper and iron particles, showing that clustering methods can reveal intrinsic patterns in electrical insulation data without relying entirely on supervised labels (Prenata et al., 2026). In broader transformer diagnostics, intelligent and fuzzy-based methods have also been used to address nonlinear and uncertain degradation behavior, such as transformer fault diagnosis based on dissolved gas analysis (Abdelwahab et al., 2025). These findings strengthen the argument that clustering approaches are suitable for electrical condition monitoring problems involving uncertainty, limited samples, and gradual degradation processes.

Based on the above discussion, a research gap can be identified. Previous thermal monitoring studies have mainly focused on supervised classification, object detection, or deep learning-based abnormal heating detection (J. Liu et al., 2024), (C. Liu et al., 2024), (Olivatti et al., 2018), (Prenata, 2023a). Meanwhile, clustering-based analysis of thermal behavior using simple extracted features from high-voltage electrical equipment remains relatively limited. In particular, there is still a need to compare hard clustering and soft clustering approaches for distinguishing thermal behavior patterns from thermal image features. This comparison is important because K-Means may provide a simple and direct grouping result, while FCM may offer additional interpretability through membership degrees that represent transitional thermal behavior.

Therefore, this study proposes Thermal Behavior Clustering of High-Voltage Electrical Equipment Using K-Means and Fuzzy C-Means. The thermal images are processed by extracting two main features, namely the percentage of white regions and the percentage of non-white regions. These features are then used as inputs for K-Means and FCM clustering to identify intrinsic thermal behavior patterns in the observed equipment. The main contribution of this study is the implementation and comparison of hard and soft clustering mechanisms for thermal behavior analysis. K-Means is used to provide direct cluster assignment, while FCM is used to evaluate the degree of membership of each sample to normal and hazardous thermal clusters. Through this approach, the study is expected to provide a simple, interpretable, and label-independent alternative for early thermal condition assessment in high-voltage electrical equipment.

2. METHOD

This study employed two unsupervised learning methods, namely K-Means and Fuzzy C-Means (FCM), to perform thermal condition clustering of high-voltage electrical equipment based on thermal images. The input data consisted of BMP-format thermal images obtained from transformer monitoring and other high-voltage electrical equipment. Each thermal image was processed using image processing techniques to extract two primary features, namely the percentage of white regions (% white) and the percentage of non-white regions (% non-white). The percentage of white regions was used as a representation of high-temperature areas in the thermal object.

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The first stage involved thermal image feature extraction. The developed program read 24-bit BMP images and calculated the number of white and non-white pixels. Pixels were categorized as white when their RGB values satisfied the conditions red > 200, green > 200, and blue > 200. Subsequently, all extracted features were normalized using the Min-Max normalization method to transform the data into a range between 0 and 1 before clustering was performed.

2.1. K-Means Clustering Method

The K-Means clustering procedure used in this study is illustrated in Figure 1. The process began with thermal image input and feature extraction, followed by Min-Max normalization. Initial centroids were then generated as the starting reference points for the clustering process. The Euclidean distance between each data sample and the centroid was calculated to determine the nearest cluster membership. After all data samples were assigned to their closest clusters, the centroid values were updated based on the average values of all cluster members. This iterative process continued until no further changes occurred in the cluster membership, indicating that the K-Means algorithm had converged.

The K-Means method applied a hard clustering approach, meaning that each data sample could belong to only one cluster. In this study, three clusters were defined, namely Normal, Warning, and Hazardous. The interpretation of each cluster was determined based on the centroid value of the % white feature. Clusters with the lowest centroid values were categorized as Normal, intermediate centroid values as Warning, and the highest centroid values as Hazardous.

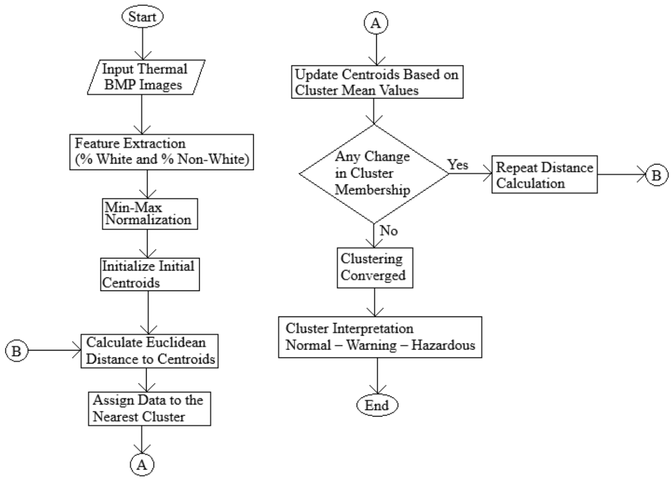


Figure 1. Flowchart of K-Means method

2.2. Fuzzy C-Means Clustering Method

The overall workflow of the Fuzzy C-Means clustering method is presented in Figure 2. Similar to K-Means, the FCM process began with thermal image input, feature extraction, and Min-Max normalization. However, unlike K-Means, FCM initialized a membership matrix randomly instead of assigning data directly to a single cluster.

The FCM algorithm then calculated fuzzy centroids based on the membership values of each data sample. Subsequently, the membership values for all data samples were iteratively updated according to their distances from all centroids. The iterative process continued until the maximum membership change became smaller than the predefined epsilon threshold, indicating convergence of the FCM algorithm.

Unlike K-Means, FCM implemented a soft clustering approach, allowing each data sample to possess membership values for multiple clusters simultaneously. Consequently, FCM was able to represent transitional thermal conditions more effectively than hard clustering methods. In this study, the final cluster interpretation was also categorized into Normal, Warning, and Hazardous conditions based on the centroid values of the % white feature.

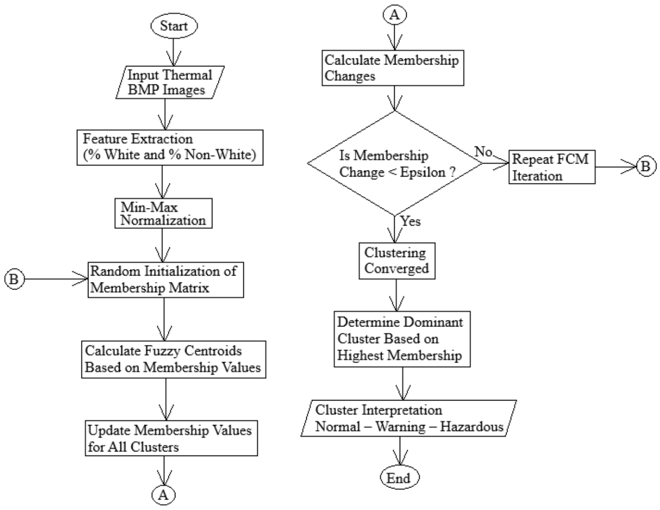
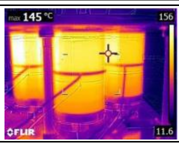


Figure 2. Flowchart of Fuzzy C-Means method

3. RESULT DAN ANALISIS

The experiments were conducted using 12 thermal images obtained from various thermal conditions of high-voltage electrical equipment. The thermal dataset consisted of safe conditions, transitional thermal conditions, and hotspot conditions with high thermal intensity. Each thermal image was processed using image processing techniques to obtain two primary features, namely the percentage of white regions (% white) and the percentage of non-white regions (% non-white). In this study, white regions represented high-temperature areas in the thermal image. Therefore, a higher percentage of white regions indicated a stronger overheating condition in the observed object.

Table 1. Thermal Dataset for K-Means and FCM Clustering

Data	Thermal Image	% White	% Non-White	Initial Category
1		18.6	81.4	Safe (0)
2		34.3	65.7	Safe (0)
3		56.5	43.5	Hazardous (1)
4		2.8	97.2	Unknown
5		0	100	Safe (0)
6		80.3	19.8	Unknown

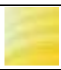
Data	Thermal Image	% White	% Non-White	Initial Category
7		1.13	98.87	Safe (0)
8		1.4	98.6	Safe (0)
9		1.63	98.37	Safe (0)
10		0.094	99.906	Safe (0)
11		0.09	99.91	Safe (0)
12		0.124	99.876	Safe (0)

Table 1 shows that most data samples had very low white-region percentages, generally below 2%. This indicates that the majority of thermal objects were operating under safe or normal conditions. However, several samples exhibited significantly higher white-region percentages, particularly data sample 3 with 56.5% and data sample 6 with 80.3%, indicating the presence of substantial thermal hotspots.

Data sample 6 exhibited the highest white-region percentage, visually demonstrating a strong dominance of high-temperature areas in the thermal image. In contrast, data samples 10 and 11 had the lowest white-region percentages, namely 0.094% and 0.09%, respectively, indicating highly stable thermal conditions.

In addition, two data samples were intentionally assigned an initial category of "Unknown," namely data samples 4 and 6. These data were included to evaluate the capability of unsupervised learning methods in identifying thermal patterns without predefined labels. This characteristic represents one of the main advantages of clustering approaches compared with supervised learning methods such as Single Perceptron, SVM, and KNN, which require labeled training data.

3.1. Thermal Distribution Based on White-Region Percentage

Based on the thermal feature distribution, most data samples were concentrated in regions with low white-region percentages. This finding indicates that normal thermal conditions dominated the experimental dataset. Nevertheless, data samples 3 and 6 were positioned relatively far from the remaining data due to their significantly higher white-region percentages.

This phenomenon demonstrates that the % white parameter is highly effective in representing thermal behavior in high-voltage electrical equipment. As thermal hotspots begin to appear in thermal images, the white-region area increases substantially and can therefore be used as a reliable basis for thermal condition clustering.

From a physical perspective, such conditions are associated with localized temperature increases on the surface of high-voltage equipment caused by several factors, including overload conditions, insulation degradation, loose electrical connections, and cooling system failures. Therefore, thermal pattern identification using clustering methods is highly important for supporting predictive maintenance and early fault detection.

3.2. K-Means and Fuzzy C-Means Clustering Results

The experimental results showed that the K-Means algorithm achieved convergence after only 2 iterations, whereas the Fuzzy C-Means (FCM) algorithm required 53 iterations to reach stable clustering conditions . This difference in the number of iterations indicates that K-Means has a simpler computational process compared with FCM.

In K-Means, each data sample is directly assigned to a single cluster based on the nearest Euclidean distance to the centroid. Consequently, convergence can be achieved rapidly. In contrast, FCM continuously updates the membership matrix for all data samples and clusters, resulting in a larger number of iterations.

However, the larger number of iterations in FCM produces richer clustering information compared with K-Means. This is because each data sample does not belong exclusively to one cluster, but instead possesses membership values for all clusters.

Table 2. Thermal Clustering Results Using K-Means and FCM

Data	% White	K-Means	FCM	Dominant Membership
1	18.5556	Normal	Normal	0.627091
2	36.5556	Warning	Warning	0.966010
3	56.5476	Hazardous	Warning	0.702543
4	2.87438	Normal	Normal	0.999030
5	0	Normal	Normal	0.997686
6	83.2647	Hazardous	Hazardous	0.998007
7	1.31187	Normal	Normal	0.999825
8	1.40157	Normal	Normal	0.999884
9	1.63177	Normal	Normal	0.999981
10	0.093985	Normal	Normal	0.997914
11	0.0886525	Normal	Normal	0.997901
12	0.127714	Normal	Normal	0.997993

Table 2 shows that most thermal data were consistently clustered by both methods. Data samples with low white-region percentages, such as samples 5, 10, 11, and 12, were consistently classified as Normal by both K-Means and FCM.

3.3. Analysis of Hazardous Thermal Conditions

Data sample 6 exhibited the most extreme thermal condition, with a white-region percentage of 83.2647% and a non-white-region percentage of 16.7353% . Both clustering methods consistently classified this sample as Hazardous.

In the FCM method, data sample 6 obtained a membership value of 0.998007 for the Hazardous cluster, whereas the membership values for the other clusters were only 0.00158139 and 0.00041119 . This finding indicates that data sample 6 possesses highly distinctive thermal characteristics that are significantly different from those of the Normal cluster.

Visually, the thermal image of data sample 6 exhibited a very large dominance of white regions. This condition indicates a severe thermal hotspot with the potential to damage high-voltage electrical equipment if not addressed immediately.

In practical electrical power system applications, such conditions may indicate overheating caused by overloads, insulation degradation, or poor electrical connections. Therefore, the capability of clustering methods to automatically identify hotspots has significant potential for supporting AI-based monitoring systems and predictive maintenance strategies.

3.4. Analysis of Transitional Thermal Conditions

One of the most interesting findings in this study was observed in data sample 3. This sample had a white-region percentage of 56.5476% and a non-white-region percentage of 43.4524% . The K-Means method classified data sample 3 as Hazardous, whereas FCM classified it as Warning. In the FCM method, data sample

3 obtained a dominant membership value of 0.702543 for the Warning cluster and 0.245935 for the Hazardous cluster.

These results indicate that FCM is more capable of representing transitional thermal conditions compared with K-Means. K-Means applies a hard clustering approach in which data are forced into a single cluster. In contrast, FCM applies a soft clustering approach, allowing data to maintain relationships with multiple clusters simultaneously.

From a physical perspective, the thermal condition represented by data sample 3 indeed lies within the transition region between normal operation and overheating. The white region in the thermal image was already relatively large, although not as dominant as in data sample 6. Therefore, the FCM approach is more realistic for representing gradual overheating phenomena in high-voltage electrical equipment.

3.3. Comparative Analysis of K-Means and FCM

Overall, K-Means demonstrated advantages in computational speed and clustering simplicity. This can be observed from its ability to achieve convergence after only 2 iterations. Nevertheless, FCM provided more comprehensive information through membership values. This information is particularly important for thermal monitoring systems because overheating conditions in high-voltage electrical equipment generally occur gradually rather than instantaneously.

Therefore, FCM has greater potential for implementation in intelligent thermal monitoring systems because it is capable of representing the confidence level of thermal conditions. Meanwhile, K-Means is more suitable for rapid clustering applications with lower computational requirements.

The results of this study demonstrate that unsupervised learning approaches using K-Means and FCM can be effectively utilized for thermal behavior analysis in high-voltage electrical equipment without requiring initial data labels. Furthermore, this approach has strong potential for further development in real-time monitoring, predictive maintenance, and intelligent fault diagnosis applications in electrical power systems.

4. CONCLUSION

This study successfully implemented K-Means and Fuzzy C-Means (FCM) methods for thermal behavior clustering in high-voltage electrical equipment based on thermal image features. The proposed model utilized the percentage of white and non-white regions extracted from thermal images as the primary clustering features. Experimental results showed that K-Means achieved convergence after only 2 iterations, while FCM required 53 iterations to reach stable clustering conditions . The results also demonstrated that both methods were capable of identifying three thermal behavior categories, namely Normal, Warning, and Hazardous.

The highest thermal intensity was observed in data sample 6, which had a white-region percentage of 83.2647% and was consistently classified as Hazardous by both clustering methods . Meanwhile, data sample 3, with a white-region percentage of 56.5476%, produced different clustering interpretations. K-Means directly classified the data as Hazardous, whereas FCM classified it as Warning with a dominant membership value of 0.702543 . This finding indicates that FCM is more effective in representing gradual thermal transitions and intermediate overheating conditions through soft clustering mechanisms.

Overall, K-Means demonstrated advantages in clustering speed and computational simplicity, while FCM provided richer information through membership values that better represent gradual overheating phenomena. Therefore, FCM has stronger potential for implementation in intelligent thermal monitoring systems and predictive maintenance applications for high-voltage electrical equipment.

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