Multi-Algorithm Collaborative Temperature Sensing In Wireless Power Systems: A Data-Driven Early Fault Detection Method

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The operation of wireless power systems (WPS) requires temperature monitoring because accurate temperature measurements help to detect overheating which serves as a fault warning. This research introduces an early fault detection system that uses multiple temperature sensing algorithms to analyze data for equipment failures. The Internet of Things (IoT) network gathers thermal measurements from various sensor units which undergo pre-processing through Savitzky-Golay filtering for noise reduction and principal component analysis for feature extraction. The Efficient Decision-tuned Least Squares Support Vector Machine (EDLSSVM) conducts fault detection while the Decision Tree (DT) model produces understandable rules to analyze threshold-crossing patterns. The two models combine their outputs through a consensus process which decreases false positive results and enhances overall system trustworthiness. The hybrid system combines nonlinear modeling with understandable rules to boost classification results which creates a dependable system that detects system faults and performs predictive maintenance in current WPS systems. The proposed consensus mechanism uses adaptive weights based on model confidence and decision consistency, which distinguishes it from traditional ensemble methods. The system automatically resolves conflicts by treating all models as equal. The research used both simulated data and real-time data to conduct their tests under different environmental conditions which included both STC and CEC testing scenarios. The multi-algorithm approach outperforms single-model methods, achieving 0.982 accuracy, 0.96 precision, 0.98 recall, and 0.97 F1-score. The results show that IoT monitoring systems combined with collaborative machine learning enable efficient real-time fault detection and predictive maintenance capabilities for modern WPS systems.

Keywords: Wireless power systems (WPS), temperature sensing, early fault detection, Internet of Things (IoT), Efficient Decision-tuned Least Squares Support Vector Machines (EDLSSVM).

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1. Introduction

WPS provide dependable and secure wireless energy transmission capabilities which enable multiple applications including electric vehicle charging and mobile device charging and additional use cases [1]. Excessive heat management represents a key operational hurdle because this condition serves as an initial warning sign for equipment faults which will eventually cause component failures [2]. The detection of faults at an early stage plays a vital role in enabling maintenance activities to be executed before problems arise [3]. The IoT and sensor networks experience rapid growth because they function as monitoring systems which gather and process grid data to achieve efficient power distribution in electrical systems [4]. WPS monitoring is a challenge because, once each subsystem requires high-speed real-time temperature measurements. Energy ecosystems consist of complex electronic systems that rely on interconnectivity and collect large amounts of data from multiple sources [5]. Wireless sensor networks (WSNs) are composed of low-power nodes communicating over wireless networks, enabling distributed data collection and processing [6]. The development of IoT technology allows WSNs to provide accurate data collection in real time, while WPS enables wireless energy transfer through inductive coupling and magnetic resonance and RF technologies [7]. Inductive coupling provides efficient power transmission for short distances while magnetic resonance technology enables flexible operation for mid-range power distribution. IoT networks use these systems to power their devices while transmitting data through multiple nodes which enables them to perform automatic monitoring and control functions. The system provides wireless charging capabilities for devices including smartphones and laptops [8]. Charging pads embedded in roadways and parking spaces allow electric vehicles to charge while in motion without cables. Similarly, WPS powers medical devices like pacemakers without external connections [9]. WPS enables consumers and industrial users to receive energy through its flexible delivery system which needs to detect operational faults when conditions change and body temperature patterns shift [10].

The objective is to find early-stage faults through real-time thermal fault detection with the use of various distributed temperature sensors and sophisticated ML methods, such as EDLSSVM. The contribution of the research is listed as follows.

- A collaborative multi-algorithm approach for early failure detection in WPS is focused on IoT-based temperature sensors alongside ML models such as EDLSSVM to provide improved diagnostic precision and robustness to the system by detecting incipient faults using thermal data in real-time.

- To utilize WPS-temperature-fault-data datasets, employing advanced pre-processing techniques like Savitzky-Golay filters to clean noisy data. Feature extraction employed PCA.

- Experimental results demonstrate that the multi-algorithm collaborative model significantly outperforms traditional single-algorithm approaches in terms of accuracy.

System overview: Section 2 provides an outline of the related work, Section 3 discusses techniques, Section 4 summarizes findings, Section 5 offers a discussion, and Section 6 concludes the research.

2. Related work

Recent studies have focused on improving fault detection in IoT-based wireless sensor networks (WSNs). The SVM energy-efficient system achieved 99% accuracy together with low false alarms but the system encountered problems with scalability [11]. The second method allowed sensor nodes to conduct autonomous fault detection without using data from their surrounding environment [12]. The RS-PPSO method combined machine learning and evolutionary computing to optimize BPNN weights, which resulted in both better prediction performance and faster training times [13]. The studies show progress towards accurate fault detection but three problems remain which include difficulties with scalability and real-time system operation.

Power systems now receive enhanced attention for their temperature monitoring processes and fault detection capabilities. The research developed a real-time monitoring system which combined modular hardware with blockchain technology to enable remote measurement and automatic alerts for overheating risks [14]. The research introduced a two-level CNN-based method for district heating systems which detects and identifies faults across multiple subsystems through thermal dynamics and renewable energy data analysis [15]. IoT-based fault diagnosis solutions enhance safety through their ability to identify operational problems and support immediate corrective measures [16]. The PAC application monitoring system uses real-time machine learning to track pressure and temperature and current and voltage data while Random Forest produced the most accurate results among all tested models [17].

Deep learning and optimization methods are used by advanced cyber-physical systems (CPS) methods to enhance their fault detection capabilities. The use of Recursive DL models with RGD increases prediction accuracy while temporal convolutions enable fault detection and root cause analysis according to [18]. The CURNet system boosts detection performance through its accuracy and recall capabilities which researchers tested at a 6.95 MW facility to achieve better maintenance results according to [19]. The distributed chaotic bat algorithm (DCBA) utilizes swarm intelligence and tent chaotic map technology to enhance its multi-sensor defect detection capabilities through improved search efficiency and prevention of local optimum solutions according to [20].

2.1. Research gap

Existing fault detection methods using ML and evolutionary techniques face three main problems which include difficulties with scalability and excessive false alarms and insufficient performance in real-time situations. The proposed EDLSSVM addresses these by combining LSSVM with decision-tuning and an efficient decision tree system which produces improved accuracy and decreased false alarms together with better scalability and real-time system adaptability.

3. Materials and methods

The research methodology uses a dataset of WPS-temperature-fault-data, implementing preprocessing methods including Savitzky-Golay filters and PCA in the feature extraction process. The EDLSSVM method is used for fault detection, classifying normal and abnormal states based on nonlinear temperature profiles. Fig. 1 describes the overall proposed methodology.

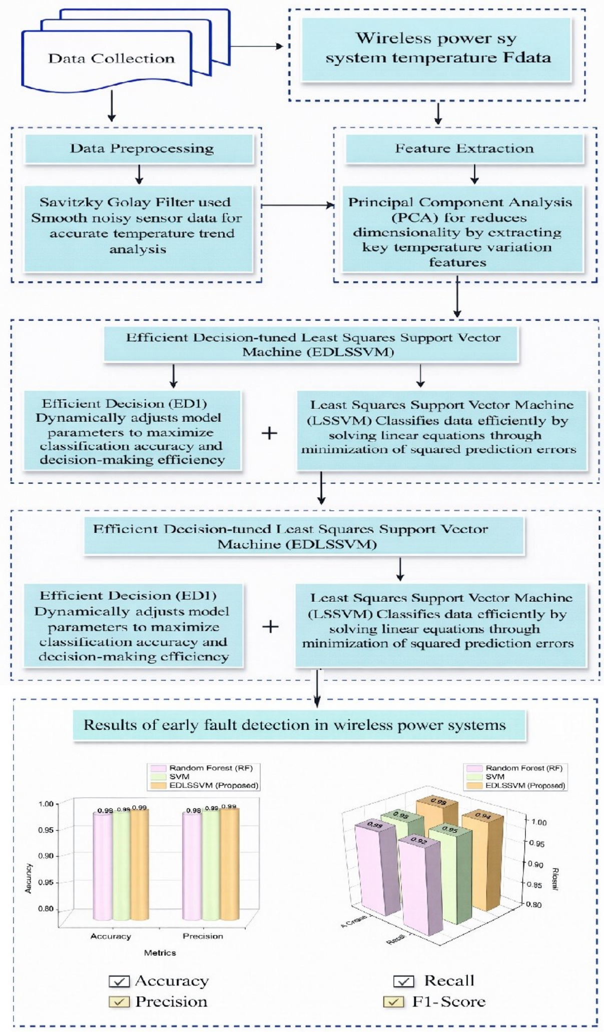


Fig. 1. Overall methodology flow

3.1. Dataset

WPS temperature fault data utilized in the Kaggle data. The dataset contains real-time temperature data from a number of distributed IoT sensors that were deployed within a WPS. IoT sensors generate synchronized temperature information together with a designated gateway, allowing for real-time monitoring and error-detection of WPS. The IoT monitoring network uses low-power wireless protocols to support real-time monitoring with latency tolerance. The gateways coordinate data packets which contain timestamp and sensor ID and temperature information to achieve dependable transmission with minimal data loss. Temperature thresholds were used to assign labels, which were applied uniformly across all sensors to create dependable training data and accurate fault detection results. The dataset includes IoT temperature data which contains three elements: sensor IDs, operating modes, and fault types. The data was labeled through thresholding methods and divided into two parts for conducting unbiased assessments.

Source: https://www.kaggle.com/datasets/programmer3/ wireless-power-system-temperature-fault-data/code

3.2. Pre-processing using Savitzky-Golay filtering

The WPS thermal monitoring system requires temperature data preprocessing to eliminate noise while maintaining critical patterns needed for accurate measurement. The Savitzky-Golay filter uses polynomial smoothing to maintain temperature patterns and operational disturbances because it functions differently from moving average filters (Equations 1-3).

$$O = e_0 + e_1 \left(w - w_\lambda\right) + e_2 \left(w - w_\lambda\right)^2 + \cdots + e_l \left(w - w_\lambda\right)^l \tag{1}$$

$$\varepsilon_M = \sum_{j=-N}^{N} \left(O - w_\lambda\right)^2 = \sum_{j=-N}^{N} \left(\sum_{l=0}^{M} e_l \left(T_j\right)^l - w_\lambda \right)^2 \tag{2}$$

$$\frac{\partial \varepsilon_M}{\partial e_j} = \sum_{j=-N}^{N} 2(T)^j \left(\sum_{l=0}^{M} e_l (T)^l - w\left[w_\lambda\right] \right) = 0 \tag{3}$$

Since it maintains temperature data smoothness without altering significant thermal trends. The Savitzky-Golay filter (order 3, window 11) reached optimal performance through empirical tuning, which achieved noise reduction while maintaining original signal characteristics through its symmetric extension method that protected against boundary distortion. Unlike moving average filters that distort temperature profiles and hide fault signatures, the Savitzky-Golay filter uses polynomial smoothing to fit the data, which preserves the original temperature signature and perturbations in the thermal signal associated with faults, as described in Equations (4-5).

$$\sum_{l=0}^{M}\left(\sum_{j=-N}^{N}(T)^{j+l}\right)e_l=\sum_{j=-N}^{M}(T)^j\left[w_\lambda\right] \tag{4}$$

$$e_{\lambda-n}=\sum_{n=-N}^{N}g_n w_{\lambda-n}=\sum_{n=\lambda-N}^{\lambda+N}g_{\lambda-n}w_\lambda \tag{5}$$

O is the Smoothed polynomial function, $e_0, e_1, e_2, \ldots e_l$ is described as the Polynomial coefficients, w : Independent variable, w_λ is the reference baseline value, ε_M is the error function, T_j is the temperature data point, M is the Maximum polynomial degree, N is described as the data points count, $\frac{\partial \varepsilon_M}{\partial e_j}$ is the error derivative, g_n is described data point coefficient, w_λ is the reference temperature, λ is the specific index, e_l is the polynomial term coefficient.

The Savitzky-Golay filter parameters (polynomial order and window length) were empirically selected to balance noise reduction and signal preservation. The method used symmetric extension to stop edge distortion while it protected essential thermal fault patterns and reduced noise.

3.3. Feature Extraction Using PCA

PCA was used to extract the key features from data by reducing dimensionality, maintaining meaningful variance, and eliminating redundancy, leading to more effective and accurate modelling for predictions concerning the environmental design. The temperature data underwent normalization through min-max scaling which was applied before the PCA analysis. The system used linear interpolation to fill in missing data while it detected outliers through zscore analysis and used closest valid values to substitute them.

$$\sum w=\lambda w \tag{6}$$

Equation (6) is the input data's covariance matrix, w is the principal component, and λ is the corresponding eigenvalue indicating the variance captured by w. The data underwent normalization before PCA analysis which selected component-based variance retention. The selected components optimized performance through dimensionality reduction. By retaining the given threshold of 95% under such a translational initiative, the initial components have been able to meet factors and give up a certain amount of variation. This way, important information is retained, but in a less complicated way.

3.4. Fault Detection using Efficient Decision-tuned Least Squares Support Vector Machine (EDLSSVM)

The hybrid EDLSSVM-Decision Tree method improves fault detection in WPS. EDLSSVM improves its probabilistic classification ability through decision-tuning while the DT system presents understandable rules. Together, they accurately classify normal and abnormal data, reduce false positives, and enable reliable real-time detection of early faults.

- The system creates understandable monitoring rules by its data classification system which uses essential features to classify different data types, as demonstrated in Equation (7). The DT creates temperature monitoring rules which use threshold comparisons to evaluate incoming data against established limits. The system sends an immediate alert when temperature levels exceed their critical limit which helps operators quickly identify WPS problems.

$$E\left(H\left(d_{n_j}(w)\right)=\sum_{j=1}^{i=o}d_{n_l}^{i}(w)\right. \tag{7}$$

$E\left(H\left(d_{n_j}(w)\right)\right)$ is the energy at the j th decision node. $d_{n_l}^{i}(w)$ are membership values for the j th level decision point at the node. The system detects faults in real time by using a consensus mechanism which combines DT and LSSVM outputs to establish agreement and resolve conflicts through confidence weighting. It is possible to determine the energy of the data level nodes on levels using the equation provided for the fault detection described in Equation (8).

$$FH(H)=\sum_{n=J}^{n=l}\frac{E\left(H\left(d_{n_j}(w)\right)\right)}{\sum_{n=1}^{n=l}\left(EH\left(d_n(w)\right)\right.}\log_2\frac{E\left(H\left(d_{n_j}(w)\right)\right)}{\sum_{n=1}^{n=l}\left(EH\left(d_n(w)\right)\right.} \tag{8}$$

$FH(H)$ is the total energy at the H -th decision level, $E\left(H\left(d_{n_j}(w)\right)\right)$ is the energy at the j -th data node, and $E\left(H\left(d_{n_j}(w)\right)\right)$ is the total energy across all decision nodes at level m. The following is the fault detection segment of feature trees and the characteristic node-specific computation Equation (9).

$$FH\left(\frac{H_j}{B}\right)=-\sum_{n=1}^{l}\frac{E\left(B_j\left(d_n(w)\right)\cap E\left(d_n(w)\right)\right)}{\sum_{n=1}^{l}E\left(B_j\left(d_n(w)\right)\right)}\cdot FH\left(H\cap B_j\right) \tag{9}$$

$FH\left(\frac{H_j}{B}\right)$ is the flexible segmentation of a feature tree based on the B_j the feature. $\left(B_j\left(d_n(w)\right)\right.$ described the energy B_j of the feature node. $FH\left(H\cap B_j\right)$ intersection shows how features together with their combined effects detection faults. The equation shows this relationship through its data in Equation (10).

$$\text{Egain}\left(B_j,H\right)=FH(H)-FH\left(\frac{H}{B_j}\right)\tag{10}$$

Egain $\left(B_j,H\right)$ is the gain feature, $FH(H)$ is the total energy at the H - the decision level, $FH\left(\frac{H}{B_j}\right)$ is the described energy at the decision level when excluding the B_j feature.

The hybrid WPS method uses LSSVM to forecast thermal fault patterns based on IoT sensor data which enables smart fault detection together with precise prediction and effective task scheduling to minimize both maintenance periods and system downtime. The thermal data classification process uses LSSVM through its least-squares method to identify critical faults which leads to improved system reliability and better system toughness in Equation (11).

$$e(w)=x^s\varnothing(w)+a\tag{11}$$

The best fits training data $\left\{\left(w_j,z_j\right)\right\}_{j=1}^{m}$, where $w_j\epsilon Q^m, z_j\epsilon\{-1,1\}$ and $\varnothing(w)$ is a nonlinear mapping to a feature space with great dimensions. Primal optimization predicts faults from WPS thermal data and enables real-time intelligent responses using equality constraints (12-13).

$$\min_{x,a,\xi} I(\omega,\xi)=\frac{1}{2}\|x\|^2+\frac{D}{2}\sum_{j=1}^{m},\xi_j^2\tag{12}$$

$$Z_j\left(x^s\varnothing\left(w_j\right)+C\right)=1-\xi_j,\quad j=1,..m\tag{13}$$

Here, $D>O$ regulates the trade-off between maximizing the margin and reducing the training error as a regularization parameter. Introducing Lagrange multipliers α_j the Lagrangian is given in Equation (14). It helps to identify early signs of faults, such as overheating or abnormal thermal gradients, by examining sensor data related to thermal faults and system performance.

$$\begin{aligned}K(x,b,\propto,\xi)&=\frac{1}{2}\|X\|^2+\frac{D}{2}\sum_{j=1}^{m}\xi_j^2\\&\quad-\sum_{j=1}^{m}\propto_j\left[z_j\left(x^s\varnothing\left(w_j\right)+C\right)-1+\xi_j\right]\end{aligned}\tag{14}$$

The conditions for optimality lead to solving the following linear system as described in Equation (7). Where $\Omega_{ji}=L\left(w_j,w_i\right)=\varnothing\left(w_j\right)^S\varnothing\left(w_j\right)$ is the kernel matrix. The decision-tuning process uses an iterative approach to optimize model parameters until classification error is minimized. The system reaches its end point when loss values become constant and the system uses updated regularization and kernel parameters to model nonlinear thermal patterns. It adjusts to real-time environmental changes and detects faults in early stages, which are appropriate for predictive maintenance activity. The researchers used grid search to find the best LSSVM parameters which minimized cross-validation error while selecting a model that showed consistent performance across all test folds. It also increases the resilience and reliability of WPS in terms of efficient operation and minimizing downtime. The LSSVM equation variables are defined in Table 1.

The RBF kernel bandwidth (σ) needed testing from 0.1 to 1.0 until finding its optimal value which achieved a balance between model complexity and generalization performance. The optimal σ was selected through cross-validation to minimize classification error. The RBF kernel captured nonlinear thermal patterns which improved early fault detection accuracy.

The hybrid proposed method has developed an EDLSSVM feature to enhance fault detection in unlimited WPS. The outputs of DT and LSSVM are fused through a consensus mechanism that stresses agreement, resolves conflicts, and assigns confidence weights to each. The framework distinguishes transient variations from true faults through the application of DT and LSSVM while the consensus mechanism decreases false positive rates by targeting consistent deviations. The ensemble method produces the weighted sum of the outputs of DT and LSSVM, followed by the application of a threshold for deciding fault classification. The EDLSSVM model utilized 5-fold cross-validation to validate its performance through a comprehensive testing process. The dataset was shuffled before each fold, and a fixed random seed was used to maintain reproducibility. The Decision Tree and LSSVM models were trained separately for each fold, and their results were merged through the use of consensus voting. The evaluation metrics (accuracy, precision, recall, F1-score) were averaged across all folds. The process underwent multiple iterations to establish stable results which maintained consistent performance throughout testing. The system uses EDLSSVM and DT to deliver both probabilistic classification results and readable rule outputs which improve its ability to identify faults and conduct maintenance operations in real time as shown in algorithm 1.

Table 1. Variables and their explanation

Variable	Meaning
w	Weight vector in the high-dimensional feature space
$e(w)$	Final decision function
X	Coefficient vector
x^S	Feature vector
α	Constraint weight
$\phi(w)$	Nonlinear feature mapping from high-dimensional space to input space
Z_j	Target label for the j th sample ($\in \{-1,1\}\backslash in\backslash\{-1,1\backslash\}$)
w_j	Input sample
m	Total number of training samples
ξ_j	Squared-error (slack) variable for the jth constraint
$\lVert X\rVert^2$	Squared Euclidean norm of the weight vector (measures model complexity)
D	Regularization parameter (trade-off between margin size and squared error)
α_j	Lagrange multiplier associated with the jth constraint
C	Bias term (offset of the decision function)
Ω_{ji}	Kernel matrix entry, $\Omega_{ji} = L\left(w_j, w_i\right) = \varnothing\left(w_j\right)^S \varnothing\left(w_j\right)$
$L\left(w_j, w_i\right)$	Kernel function, here RBF: exp $\left(-\frac{\lVert w_j - w_j\rVert^2}{\sigma^2}\right.$
σ	Kernel bandwidth parameter in the RBF kernel
$f(w)$	Decision function: $e(w) = \sum_{j=1}^{m} \propto_j L\left(w_j, w_i\right) + c$
$\begin{bmatrix} a \\ \alpha \end{bmatrix}$	Vector of unknowns (bias term and language multipliers) to be solved
$\begin{bmatrix} 0 \\ z \end{bmatrix}$	Right-hand side vector in the linear system representing training labels
$\begin{bmatrix} 0 & 1^s \\ 1 & \Omega + \frac{1}{D} J \end{bmatrix}$	Augmented matrix in combining constraints and kernel for solving the system

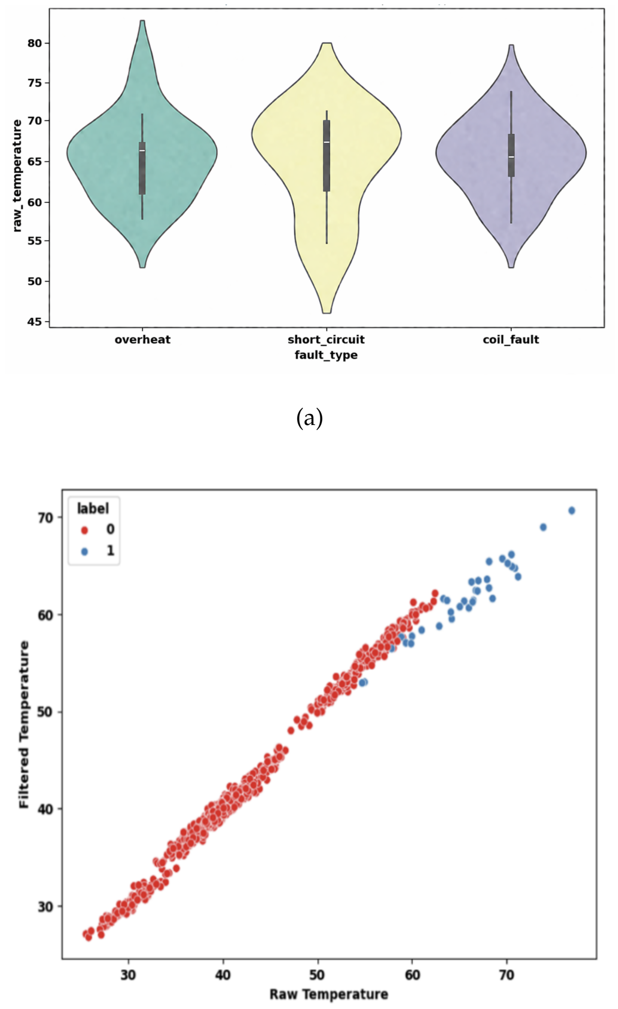
Algorithm 1. EDLSSVM

```
Initialize sensor data and model parameters
sensor_data = load_sensor_data()
decision $_{tree}$ = initialize $_{decision_{tree(}}$ )
lssvm_model = initialize_lssvm()
Preprocess the data (filter noise)
preprocessed_data = apply_savitzky_golay_filter(sensor_data)
Train the Decision Tree on the preprocessed data
    decision_tree.train(preprocessed_data)
Train the LSSVM model using historical thermal data
lssvm_model.train(preprocessed_data)
Make predictions for fault detection
dt_predictions = decision_tree.predict(preprocessed_data)
lssvm_predictions = lssvm_model.predict(preprocessed_data)
Combine results using decision-tuning (combine DT and LSSVM outputs)
    combined_predictions = combine_predictions(dt_predictions,lssvm_predictions
Identify faults (classify as normal or abnormal)
fault_status = classify_faults(combined_predictions)
Output the result
if fault_status == "Abnormal":
    trigger_maintenance_alert()
Else:
    continue monitoring ()
End
```

4. Result

The model operated with shuffled data sets based on a fixed seed to ensure a reproducible outcome and cross-validation to avoid any overfitting while maintaining model robustness. This section presents the model results, including parameter settings, evaluation metrics, and comparative analysis. The experiments used Python on a system which had an Intel® Core i9 processor and 8 GB RAM and Windows 11 operating system.

Fig. 2(a) shows the temperature distribution by fault type, highlighting distinct ranges for overheating, short circuit, and coil faults. Fig. 2(b) shows a comparison between filtered temperatures and raw temperatures which are shown according to fault labels. The filtered data improves separation between normal and fault states, aiding the identification of thermal anomalies.

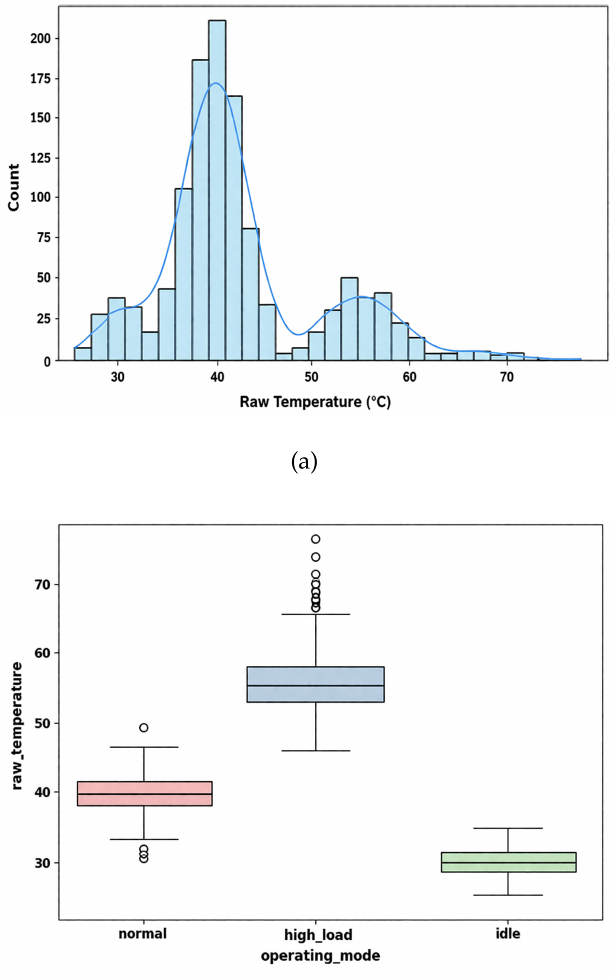


(a)

(b)

Fig. 2. (a) Temperature distribution by fault type
(b) Filtered vs raw temperature by fault label

Fig. 3(a) displays temperature data through its histogram and kernel density estimation which shows that most temperatures occur at lower levels. The boxplot in Fig. 3(b) displays temperature data for three operating modes which are normal high load and idle with high temperatures recorded during high load mode.



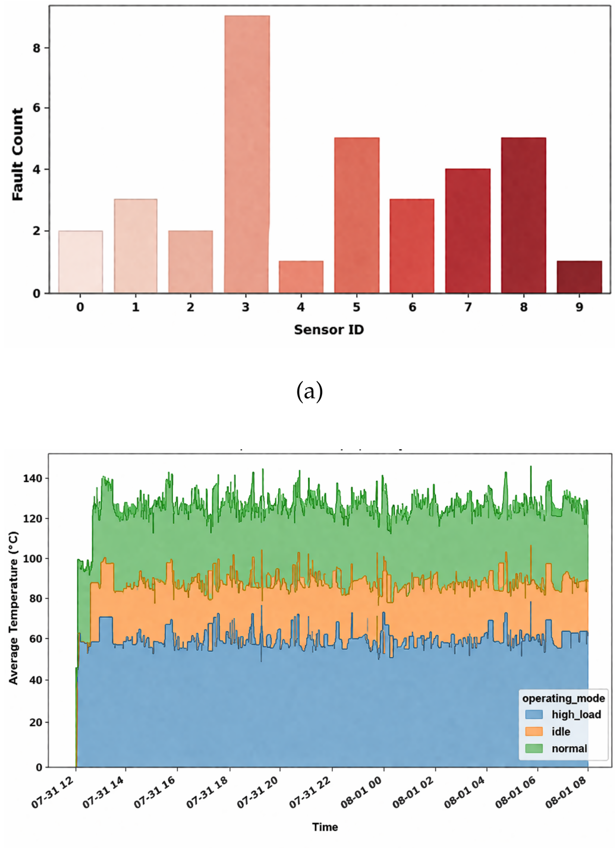
(a)

(b)

Fig. 3. (a) Distribution of raw temperature
(b) Raw temperature by operating mode

Fig. 4(a) shows faults detected per sensor, with Sensor 2 having the highest count, highlighting variations in sensor performance. Fig. 4(b) presents temperature trends by operating mode over time, showing average temperatures for normal, high load, and idle modes, with high load reaching the highest peaks. The figures show how faults spread and how temperatures change between various operational states.

The metrics used to evaluate the EDLSSVM method for WPS in early fault detection methods are F1-score, recall, accuracy, and precision. Training the hybrid model costs O (n^2), costing O (n)inference time in a six-hour run, with the model being supported near in real time. Other common techniques like Random Forest (RF) [21] and Support Vector Machine (SVM) [21] were contrasted



(a)

(b)

Fig. 4. (a) Number of faults detected per sensor (b) Temperature trends by operating mode

with EPS-LSSVM.

The performance metrics of the system include accuracy shows the total number of correct classifications and precision shows the percentage of correctly predicted faults that were not misidentified as false positives and recall shows the system's capacity to find actual faults while making the least number of errors and F1-score provides a balanced measurement between precision and recall that works best with datasets have unequal distribution of classes.

Table 2 and Fig. 5 present the comparative performance of the models. EDLSSVM achieves its highest accuracy rating of 98.2% through superior detection abilities which exceed Random Forest's 93%, CNN's 89% and SVM's 95% systems for identifying normal and faulty conditions. The system achieves accurate fault detection with 96% precision while using nonlinear modeling to handle complex thermal patterns which results in better classification performance.

Table 2 and Fig. 6 present recall and F1-score results. EDLSSVM achieves the highest recall (0.98), detecting nearly all true faults and minimizing missed detections.

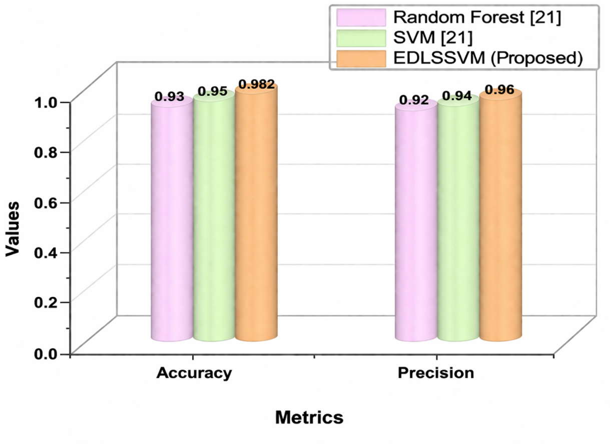


Fig. 5. Comparison of Accuracy and Precision

The F1-score of 0.97 shows the model's ability to correctly identify faults while maintaining precise output through its assessment of both precision and recall metrics.

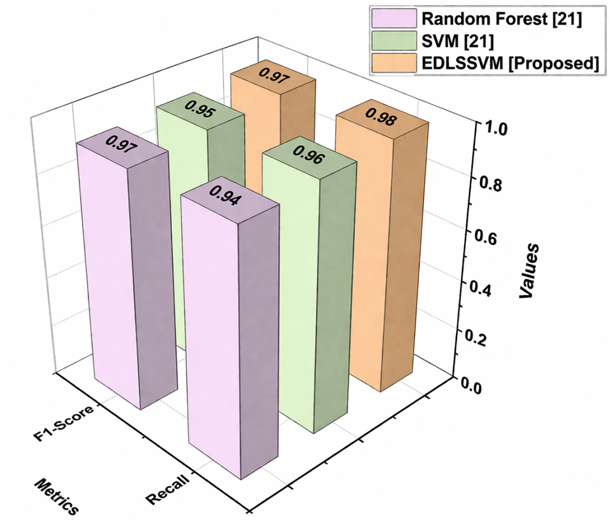


Fig. 6. Outcomes of Recall and F1-score

EDLSSVM improves fault detection capabilities compared to SVM and RF because it can handle noisy data, data imbalance and data that exhibits nonlinear characteristics, results in decreased false positive rates and increased recall rates and improved decision boundary assessment.

5. Conclusion

The study presents a data-driven method which detects early faults in WPS through multiple temperature sensing systems that include EDLSSVM. An IoT-based network collects real-time thermal data which uses Savitzky-Golay filtering and PCA for feature extraction during preprocessing. The hybrid model achieves better results than traditional

Table 2. Performance comparison of fault detection

Algorithm	Accuracy	Precision	Recall	F1-score
Random Forest [21]	0.93	0.92	0.94	0.93
CNN [22]	0.89	0.88	0.87	0.89
SVM [21]	0.95	0.94	0.96	0.95
EDLSSVM [Proposed]	0.982	0.96	0.98	0.97

methods because it produces 0.982 accuracy, 0.96 precision, 0.98 recall and 0.97 F1-score while decreasing false positive rates. The system requires correct sensor information but it struggles to handle extensive simultaneous operations in actual time. The research will develop better data fusion methods which will enhance the system's ability to automatically learn from new faults while they will support monitoring and predictive maintenance across extensive commercial spaces. Future work will test performance using different sensor configurations and various data conditions, while they work to decrease IoT latency which will enable quicker fault detection and continuous monitoring.

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