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Wavelet Transform and Support Vector Machine Jointly Identify the Characteristics of Electricity Theft in Photovoltaic Systems of Dedicated Transformer Users

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Abstract. In order to solve the problem that the existing methods of electricity theft detection in dedicated user photovoltaic systems are difficult to capture subtle anomalies in non-stationary electricity consumption data, this paper introduces a method combining wavelet transform and support vector machine (WT-SVM). The Daubechies wavelet basis function is used to perform multi-scale decomposition of photovoltaic electricity consumption data, extract time-frequency features, and capture transient anomalies in electricity theft behavior. The extracted features are input into the SVM classification model, and the model is trained through the RBF kernel function. Grid search and cross-validation are used to optimize hyperparameters to improve the generalization ability of the model. The results show that under the same photovoltaic power theft detection dataset and test environment, the WT-SVM in this paper extracts time-frequency features through multi-scale wavelet decomposition and combines RBF (Radial Basis Function) and SVM classification, achieving an F1 score of 94.5%, a low latency of 35ms and a noise resistance of 91.2%, and outperforms the comparison model (Time-Freq Transformer: 62.4MB; MobileNetst: 5.7MB) with a lightweight of 2.1MB. The method in this paper has a good recognition effect on electricity theft behaviors such as current bypass, inverter tampering, and data injection, verifies the effectiveness of the fusion of wavelet time-frequency analysis and machine learning, and provides a high-precision and high-practicality solution for electricity theft detection in photovoltaic systems.

Key words. Photovoltaic system, Wavelet transform, Support vector machine, Time-frequency features, Electricity theft detection

1. Introduction

Against the backdrop of energy structural transformation and rapid development of renewable energy, the proportion of photovoltaic power generation systems in the power grid continues to increase, and the corresponding problem of electricity theft is also increasing. The electricity theft behavior of photovoltaic systems of dedicated transformer users [1-3] is highly concealed and uses new technical means, which poses a challenge to the safe and stable operation of the power grid and the economic benefits of power companies. The current electricity theft detection system based on traditional methods is difficult to accurately identify the carefully disguised abnormal electricity consumption patterns when faced with the intermittent and fluctuating electricity consumption characteristics unique to photovoltaic power generation [4]. In particular, under complex working conditions with rapid changes in light intensity and frequent load switching, the performance of existing detection methods can be significantly reduced, resulting in a large number of missed reports and false alarms. The current situation of insufficient detection capability has affected the actual effect of anti-electricity theft work and restricted the healthy development of the photovoltaic power generation industry [5,6]. It is necessary to develop new detection technologies with stronger adaptability and higher accuracy.

This paper introduces an innovative photovoltaic system electricity theft detection method. By organically combining the multi-scale analysis capability of WT with the classification advantage of SVM, a new research paradigm of physical feature extraction + machine learning classification is constructed. The proposed method uses Daubechies wavelet basis function for multi-level signal decomposition to capture transient abnormal characteristics in electricity consumption data. A feature space mapping strategy based on kernel techniques is designed to improve nonlinear classification capabilities. A parameter optimization mechanism is introduced to ensure the generalization performance of the model. By systematically integrating time-frequency analysis, feature engineering, and machine learning techniques, the proposed method improves the ability to identify electricity theft in complex electricity consumption scenarios while maintaining the lightweight of the algorithm, providing new technical ideas and solutions for the safe monitoring of photovoltaic systems.

2. Related Works

In recent years, scholars have conducted a lot of research in the field of electricity theft detection, mainly forming three major technical routes. The first category is the detection method based on deep learning [7,8]. Among them, Transformer is good at capturing long-distance dependencies in time series data, but its feature extraction ability is limited when processing non-stationary signals. GNN has advantages in processing topologically complex power grid data, but its computational complexity is high, resulting in poor real-time performance.Pamir et al. proposed the SSA-GCAE-CSLSTM (Salp Swarm Algorithm-Gate Convolutional Autoencoder-Cost-Sensitive Learning and Long Short-Term Memory) hybrid model [9]. The combination of gated recurrent units and convolutional autoencoders is used to optimize electricity theft detection. However, the model has too many parameters, making it difficult to deploy on edge devices and sensitive to noise. The second category is machine learning methods based on feature engineering [10,11]. Kawoosa A I et al. proposed the XGBoost (eXtreme Gradient Boosting) model based on extreme gradient boosting [12], which uses consumers' electricity usage patterns for analysis and is used for electricity theft detection. This method has difficulty capturing transient anomalies in non-stationary signals and has limited generalization capabilities for new electricity theft methods. The third category is the emerging graph neural network method [13,14]. Gao A's team improved the detection capability of group electricity theft by constructing a semi-supervised learning architecture consisting of a visualized Gramian angular field encoding and a contrastive learning architecture with small sample learning function [15]. This method requires complete user power topology information, which has the problem of difficulty in data acquisition in practical applications. The existing algorithms generally have insufficient recognition rates for concealed electricity theft behaviors such as inverter parameter tampering [16], and there are obvious seasonal performance fluctuations. A number of comparative experiments have found that the detection performance of current advanced detection models can be significantly reduced when dealing with the DC-side electricity theft behavior unique to photovoltaic systems [17]. This is mainly due to the fact that the DC-side signal characteristics are more hidden and easily disturbed by photovoltaic output fluctuations.

Wavelet-based fault detection methods have shown significant application potential in photovoltaic systems. An innovative fractional wavelet method has been proposed for detecting defects in photovoltaic systems, such as microcracks, wiring faults, and hot spots [18]. This method uses the multi-resolution characteristics of fractional Haar wavelets to improve the detection sensitivity of low-amplitude defects, providing a new perspective for improving the reliability of photovoltaic devices. Another study used empirical wavelet transform combined with hybrid convolutional recurrent neural network to identify and locate fault types in hybrid renewable energy systems [19]. The signal frequency components are decomposed and features are extracted by wavelet transform, and then classified using the optimized hybrid convolutional recurrent neural network to achieve high-precision identification of different fault types. These studies show that wavelet transform and its improved forms have broad application prospects in photovoltaic system fault detection and are outstanding in improving detection accuracy and sensitivity.

In order to achieve a breakthrough in technology, the integration of signal processing and machine learning has become a research hotspot. Janthong S used electrical profiles combined with random forests [20] to deeply analyze the behavior of each type of power customer, enhance and improve efficiency. Nian Z O U proposed an automatic encoder theft detection method for non-high-loss lines based on hourly periodic features combined with LSTM (Long Short-Term Memory) [21]. Liao L used the wavelet packet decomposition method to decompose the original battery voltage signal [22], and obtained high-quality low-frequency and high-frequency signal components to enhance the prediction effect of the model. By optimizing the filter bank design of WT [23], the feature extraction efficiency can be improved and the time-frequency resolution can be maintained. These studies provide important references for building an efficient and real-time electricity theft detection system. This paper designs a multi-resolution analysis framework based on Daubechies wavelet [24], develops a feature compression algorithm for support vector [25], and introduces edge computing architecture into this field for the first time.

3. Joint Recognition Method of WT and SVM

A. Wavelet Decomposition of Photovoltaic System Power Consumption Data

The electricity consumption data of photovoltaic systems has non-stationary and nonlinear characteristics. Traditional time domain or frequency domain analysis methods are difficult to effectively capture transient anomalies in electricity theft. This paper uses the Mallat fast WT algorithm [26] to perform multi-scale decomposition on electricity consumption data and extract time and frequency domain features. The mathematical definition of WT is formula (1):

$$\mathrm{W}\left(a,b\right)=\frac{1}{\sqrt{a}}\int_{-\infty}^{\infty}x\left(t\right)\psi^{*}\left(\frac{t-d}{a}\right)\mathrm{d}t \tag{1}$$

$x\left(t\right)$ is the original signal, and ψ is the wavelet function. Table 1 is a comparison table of wavelet basis functions.

Table 1. Comparison table of wavelet basis functions.

Wavelet basis	Support length	Regularity	Symmetry	Vanishing moments	Application scenarios
Daubechies	8	High	Approx symmetric	4	Non-stationary signal analysis, feature extraction
Symlets	8	Medium	Symmetric	4	Signal denoising, speech processing
Coiflets	12	High	Approx symmetric	4	Signal compression, feature extraction
Biorthogonal	10	Medium	Asymmetric	3	Image compression, signal denoising
Haar	2	Low	Symmetric	1	Fast signal decomposition, edge detection
Meyer	∞	High	Symmetric	∞	High-precision signal analysis, theoretical research
Morlet	∞	High	Symmetric	∞	Time-frequency analysis, seismic signal processing

Table 1 compares the characteristics of commonly used wavelet basis functions, including support length, regularity, symmetry, and vanishing moment number. This paper selects the Daubechies wavelet basis function as the wavelet basis, which has compact support and high regularity and can achieve a good localization balance between the time domain and the frequency domain. The Daubechies wavelet basis function has excellent feature extraction capabilities in signal processing and is suitable for processing complex fluctuations in photovoltaic system power consumption data [27]. Discrete WT decomposition formula (2):

$$y[n]=\sum_{k} c_{j,k}\phi_{j,k}[n]+\sum_{j=1}^{J}\sum_{k} d_{j,k}\psi_{j,k}[n] \quad (2)$$

$y[n]$ is a discrete signal, $c_{j,k}$ and $d_{j,k}$ are the approximate coefficient and detail coefficient at scale j, respectively. $\phi_{j,k}[n]$ is the scale function, and J is the number of decomposition levels. In the data preprocessing stage, the original electricity consumption data is normalized to eliminate dimensional differences and ensure that the data is analyzed at the same scale. After normalization, the electricity consumption data is processed in segments, and the length of each segment is an integer power of 2 to meet the input requirements of WT. Segment processing can improve computational efficiency and better capture local features.

Multi-level wavelet decomposition is performed on each segment of data to obtain wavelet coefficients of different scales. Wavelet decomposition includes two parts: approximate coefficients and detail coefficients [28]. The approximate coefficient reflects the low-frequency components of the signal, mainly including the basic trend and stable characteristics of the power consumption data. The detail coefficient captures the high-frequency components of the signal and can effectively identify transient anomalies and mutation characteristics. Through multi-level decomposition, the characteristics of the power consumption data are analyzed layer by layer from coarse to fine, providing multi-level time-frequency information for the detection of power theft. Figure 1 is a diagram of the wavelet decomposition filter bank structure.

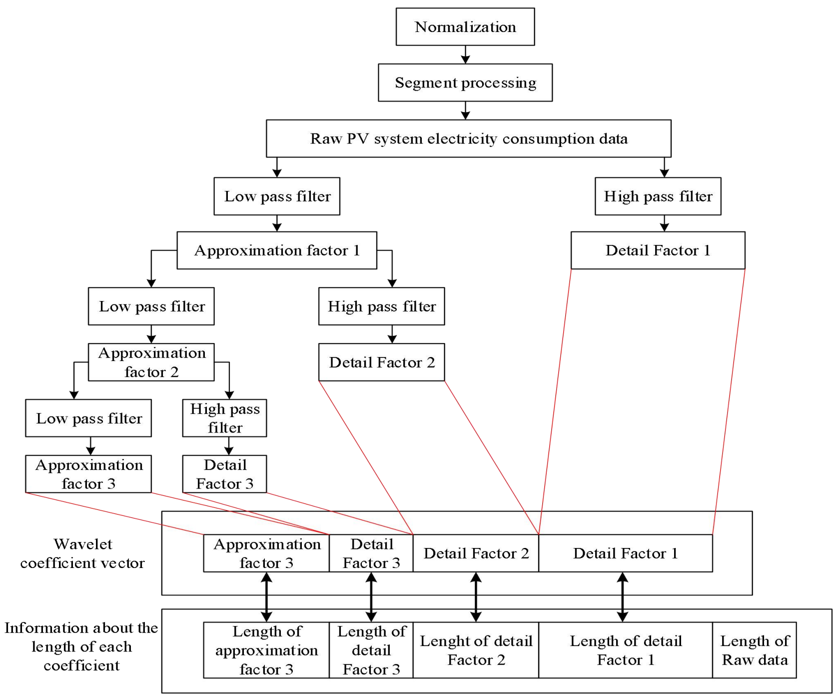

Figure 1. Wavelet decomposition filter bank structure.

Figure 1 shows the wavelet decomposition structure of the photovoltaic system power consumption data of the dedicated transformer user [29]. The original photovoltaic system power consumption data is normalized and segmented to eliminate dimensional differences and meet the input requirements of the WT. The data is decomposed at multiple levels through low-pass filters and high-pass filters to obtain approximate coefficients and detail coefficients at different scales. These coefficients are combined into wavelet coefficient vectors, and the length information of each coefficient and the original data is recorded at the same time. Through the wavelet decomposition filter, the time-frequency characteristics of the photovoltaic system electricity consumption data can be effectively extracted, providing a key foundation for the subsequent feature extraction and classification model training of electricity theft behavior.

In the process of wavelet decomposition, the Mallat fast algorithm is used to achieve efficient calculation. The filter bank implementation formula of the Mallat algorithm is formula (3):

$$\begin{cases} c_{j+1}[k] = \sum_n h[n-2k] a_j[n] \\ d_{j+1}[k] = \sum_n g[n-2k] a_j[n] \end{cases} \quad (3)$$

$c_{j+1}[k]$ is the approximate coefficient of the $j+1$ th layer, $h[n]$ is a low-pass filter, and $g[n]$ is a high-pass filter. The algorithm implements WT through a filter bank, avoiding direct integral calculations and reducing computational complexity. The input signal is low-pass and high-pass filtered to obtain approximate coefficients and detail coefficients, respectively. The approximate coefficients are downsampled and the above process is repeated to achieve multi-level decomposition. Through multi-level decomposition, the time-frequency characteristics of the signal are extracted layer by layer to capture subtle anomalies in electricity theft.

By analyzing the energy distribution and frequency components of the wavelet coefficients, potential abnormal signals are preliminarily identified. The energy distribution reflects the energy concentration of the signal in different frequency bands. Electricity theft can cause the energy in certain frequency bands to increase or decrease. Energy distribution calculation formula (4):

$$E_i = \sum_{j=1}^{N} \left| d_{i,j} \right|^2 \quad (4)$$

E_i is the energy value at the i -th scale. The frequency component is obtained by analyzing the spectral characteristics of the detail coefficients, which can identify abnormal frequency components. Through multi-scale decomposition and feature analysis, the abnormal features in the power consumption data are fully captured, providing a high-quality data foundation for subsequent feature extraction and classification. Fast Fourier transform formula (5):

$$X[k] = \sum_{n=0}^{N-1} x[n] \mathrm{e}^{-i2\pi gn/N} \quad (5)$$

$X[k]$ is the frequency domain signal, $x[n]$ is the time domain signal, and g is the frequency domain index. The results of wavelet decomposition provide key input for subsequent feature extraction and classification model training. Through multi-scale analysis, normal electricity use and electricity theft can be effectively distinguished, especially when the electricity theft behavior manifests as transient anomalies or local mutations. The multi-resolution characteristics of WT enable it to adapt to the complexity and diversity of photovoltaic system electricity consumption data, providing reliable technical support for electricity theft detection. Wavelet entropy calculation formula (6):

$$H_i = -\sum_{j=1}^{N} p_{i,j} \log\left(p_{i,j}\right) \quad (6)$$

$p_{i,j}$ is the probability distribution of the j th detail coefficient at the i -th scale. In practical applications, the computational efficiency and accuracy of wavelet decomposition directly affect the real-time and accuracy of electricity theft detection. This paper ensures the efficiency and stability of wavelet decomposition by selecting appropriate wavelet basis functions and optimization algorithms. Segmentation processing and normalization operations improve the efficiency and reliability of data processing, laying a solid foundation for subsequent steps.

B. Feature Extraction of Electricity Theft Behavior

Extracting key features from wavelet decomposition results is the core of electricity theft detection. This paper selects energy distribution, frequency component and wavelet entropy as feature indicators to characterize the characteristics of electricity consumption data from three dimensions: energy, frequency and complexity, in order to capture abnormal patterns in electricity theft. Figure 2 is a conceptual diagram of electricity theft feature extraction.

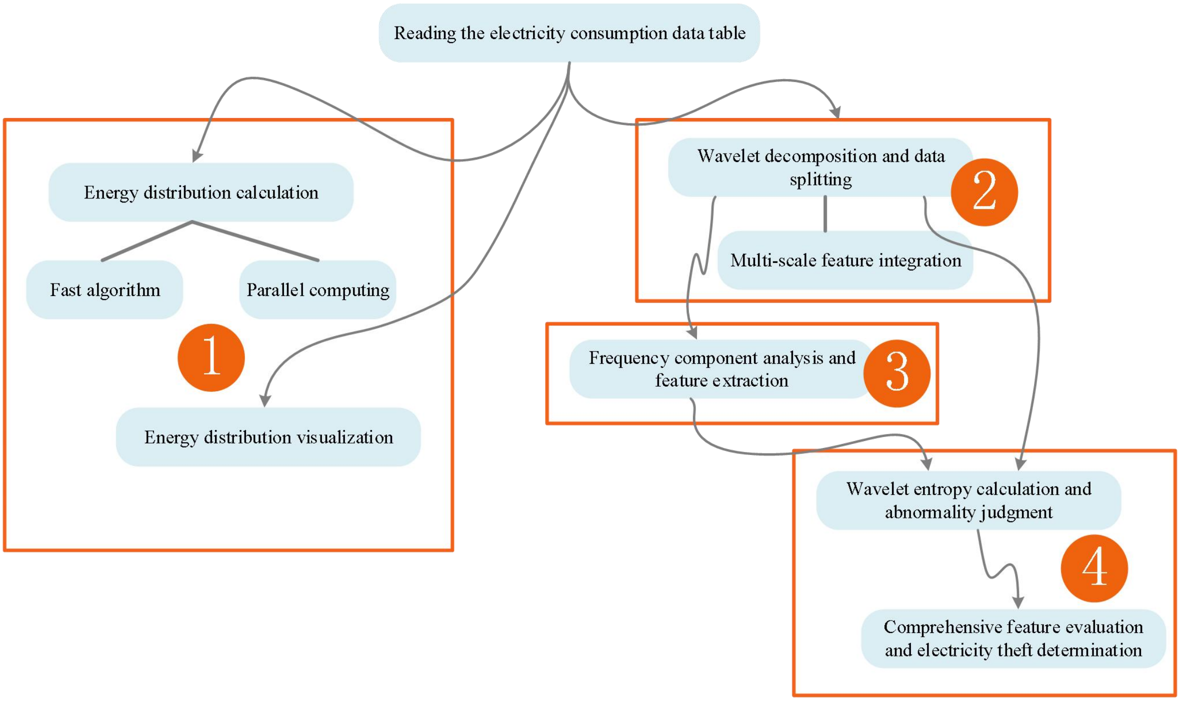

Figure 2. Concept diagram of electricity theft feature extraction.

Figure 2 shows the concept diagram of electricity theft feature extraction, which presents the whole process from raw electricity consumption data to the final determination of electricity theft in a clear process. Through rigorous calculation and analysis steps, multi-scale feature information is integrated to achieve accurate determination of electricity theft, providing support for the safe and stable operation of the power system. The energy distribution is obtained by calculating the sum of squares of wavelet coefficients at each scale, reflecting the energy concentration of the signal in different frequency bands. The energy concentration is as shown in formula (7):

$$C_i = \frac{\sum_{k\in\Omega} |F_i(k)|^2}{\sum_{k=1}^{N} |F_i(k)|^2} \quad (7)$$

Ω represents the range of a specific frequency band. Each section of electricity consumption data can be decomposed by wavelet to obtain the approximate coefficients and detail coefficients of each scale. The energy value of the detail coefficient of each scale is calculated. By calculating the energy value of each scale, the energy distribution characteristics of the signal in different frequency bands can be identified. Electricity theft usually causes the energy of certain frequency bands to increase or decrease. By analyzing the changes in energy distribution, abnormal signals can be preliminarily identified.

In actual operation, the calculation of energy distribution is not limited to a single scale, but through multi-scale analysis [30,31], the energy changes in each frequency band are integrated. The energy changes in the low-frequency band reflect the overall trend of the power load, and the energy changes in the high-frequency band may capture transient anomalies. Through comprehensive analysis of multi-scale energy distribution, the characteristics of electricity consumption data are comprehensively characterized, providing richer feature information for the detection of electricity theft. The weighted average formula (8) of multi-scale energy distribution is:

$$E_{weighted} = \sum_{i=1}^{L} \omega_i \cdot E_i \quad (8)$$

ω_i is the weight of the i-th scale. The identification of frequency components relies on analyzing the spectral characteristics of detail coefficients. Fast Fourier transform is performed on the detail coefficients of each scale to obtain the corresponding spectrum. The main frequency components are extracted and their amplitude characteristics are statistically analyzed. Electricity theft generates abnormal frequency components in a specific frequency band, and the analysis of spectral characteristics can capture these abnormal signals [32].

The frequency characteristics of a single frequency band are not sufficient to fully characterize the data features. Multi-scale analysis is used to synthesize the frequency changes in each frequency band. The frequency components in the low-frequency band reflect the periodic changes in the power load, and the frequency components in the high-frequency band can capture transient anomalies. The comprehensive analysis of multi-scale frequency components enhances the ability to characterize power consumption data and provides richer feature information for the detection of power theft.

Wavelet entropy is used to measure signal complexity and reflect the distribution of information at different scales. The probability distribution of detail coefficients at each scale is obtained during the calculation process. The wavelet entropy value of the corresponding scale is calculated. A higher wavelet entropy value indicates a higher signal complexity. Electricity theft can cause changes in signal complexity, and the change analysis of wavelet entropy helps to identify abnormal signals.

When calculating wavelet entropy, it cannot be limited to a single scale. Multi-scale analysis provides information on complexity changes in different frequency bands. The complexity changes in the low frequency band reveal the overall trend of the power load, and the complexity changes in the high frequency band capture transient anomalies. The comprehensive analysis of multi-scale wavelet entropy improves the ability to characterize the complexity of power consumption data and provides more feature information for the detection of power theft.

Features such as energy distribution, frequency components, and wavelet entropy together constitute feature vectors, which serve as the input of the SVM. The extraction process includes multiple steps. Each feature can be calculated from each segment of electricity consumption data, and statistics such as mean and variance can be calculated. All feature values can be normalized to eliminate dimensional differences and keep the feature dimensions consistent. The normalized features can be combined into a feature vector for classification model training and testing. The contribution evaluation formula (9) for feature screening is:

$$S_m = \frac{\text{Importance}\left(F_m\right)}{\sum_{m=1}^{M}\text{Importance}\left(F_m\right)} \quad (9)$$

$\text{Importance}\left(F_m\right)$ is the importance of the m th feature. The construction of feature vectors relies on multi-feature fusion. The combination of energy distribution and frequency components depicts the energy and frequency characteristics of electricity data. The introduction of wavelet entropy enhances the ability to capture changes in signal complexity. Multi-feature comprehensive analysis improves the ability to characterize the characteristics of electricity data and provides rich feature information for electricity theft detection.

Through comprehensive analysis of energy distribution, frequency components and wavelet entropy, the characteristics of electricity consumption data are fully characterized, and transient anomalies and complex patterns in electricity theft are captured. Energy distribution reflects the energy concentration of the signal, frequency components identify abnormal frequencies, and wavelet entropy measures the complexity of the signal. The combination of the three can effectively distinguish between normal electricity consumption and electricity theft. The feature extraction process is based on the wavelet decomposition results, making full use of the multi-resolution analysis capabilities of WT to adapt to the non-stationarity and complexity of photovoltaic system power consumption data.

In practical applications, in order to improve the efficiency of feature extraction, this paper uses a fast algorithm to calculate energy distribution and wavelet entropy, and accelerates frequency component analysis through parallel computing. Through experiments, the effectiveness of each feature is verified, the features that contribute most to the detection of electricity theft are selected, the dimension of the feature vector is reduced, and the training efficiency of the classification model is improved.

C. SVM Model Training

This paper uses SVM as the classification model and uses the RBF [33,34] kernel for nonlinear mapping. SVM is a classification algorithm based on statistical learning theory. It constructs the optimal classification hyperplane in high-dimensional space to achieve data classification. Its core idea is to improve the generalization ability of the model by maximizing the classification interval. Figure 3 is a schematic diagram of the SVM classification hyperplane.

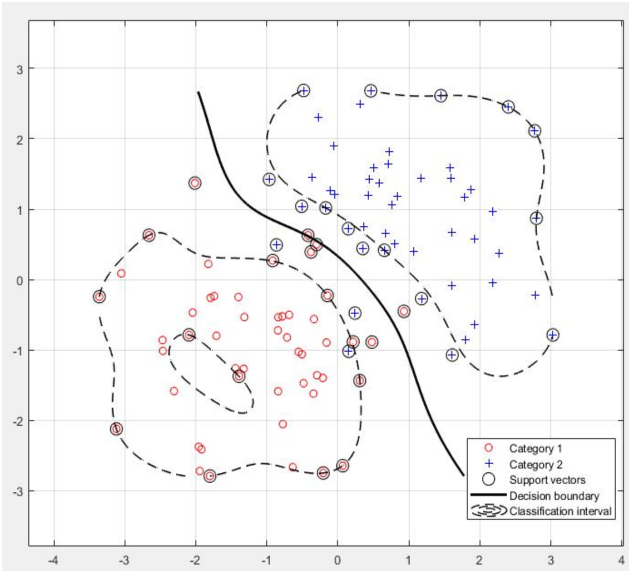

Figure 3. Schematic diagram of SVM classification hyperplane.

Figure 3 is a schematic diagram of the SVM classification hyperplane, describing the classification of the SVM in two-dimensional space. By maximizing the classification interval, the SVM can improve the generalization ability of the model and classify new data more effectively. Before model training, the extracted feature vectors are normalized. The purpose of normalization is to eliminate the dimensional differences between features and ensure that each feature dimension has the same scale. Normalization formula (10):

$$x_{norm} = \frac{x-\mu}{\sigma} \quad (10)$$

μ is the mean of the eigenvalue, and σ is the standard deviation of the eigenvalue. Through standardization, it is possible to avoid some features having too much impact on the classification results due to their large dimensions. The SVM maps low-dimensional features to high-dimensional space through the kernel function to solve the nonlinear classification problem. This paper selects the RBF as the kernel function, as shown in formula (11):

$$K\left(x_i, x_j\right) = \exp\left(-\gamma \left\|x_i - x_j\right\|^2\right) \quad (11)$$

γ is a parameter of the kernel function, which controls the complexity of the high-dimensional space after mapping. The RBF kernel function can effectively process nonlinear data. By adjusting the parameter γ, the classification performance of the model can be flexibly controlled. The SVM is essentially a binary classification model. This paper adopts a one-to-one strategy to deal with multi-classification problems. The electricity theft behavior is divided into multiple categories such as normal electricity use, mild electricity theft, and severe electricity theft. A binary classification model is trained for every two categories. For k categories, a total of $\frac{k(k-1)}{2}$ binary classification models need to be trained. In the prediction stage, the final classification result is determined by a voting mechanism. The training process of the SVM is achieved by solving the optimization problem, formula (12):

$$I = \min_{Y,b,\xi} \frac{1}{2}\|Y\|^2 + A\sum_{i=1}^{n} \xi_i \quad (12)$$

Constraint formula (13):

$$y_i\left(Y \cdot x_i + q\right) \geq 1 - \xi_i, \quad \xi_i \geq 0 \quad (13)$$

Y is the normal vector of the classification hyperplane, q is the bias term, ξ_i represents the slack variable, and A represents the penalty coefficient, which is used to balance the classification interval and classification error. By solving this optimization problem, the optimal classification hyperplane can be found to ensure that the model can accurately distinguish different types of electricity consumption behaviors. During the model training process, grid search and cross-validation are used to optimize the hyperparameter penalty coefficient A and kernel function parameter γ of the SVM [35]. Grid search finds the optimal parameters by traversing all possible combinations within the preset parameter range. The objective function formula of grid search is (14):

$$\left(\widehat{A}, \widehat{\gamma}\right) = \arg\min_{C,\gamma} CVError\left(A, \gamma\right) \quad (14)$$

$\widehat{A}$ represents the optimal penalty parameter. Cross-validation divides the data set into a training set and a validation set to evaluate the classification performance of each set of parameters. The generalization ability of the model is improved through optimization to avoid overfitting problems. The error estimation formula of cross-validation (15) is:

$$CVError = \frac{1}{k}\sum_{i=1}^{k} \frac{1}{n_i}\sum_{j=1}^{n_i} \prod\left(y_{ij} \neq \hat{y}_{ij}\right) \quad (15)$$

k is the number of cross-validation folds, $\prod(\cdot)$ is the indicator function, and takes the value of 1 when the condition is met, otherwise it is 0. After the model training is completed, this paper uses accuracy, recall and F1 score as evaluation indicators to comprehensively evaluate the classification performance of the model. Accuracy reflects the correctness of the overall classification of the model, recall measures the model's ability to detect electricity theft, and F1 score combines precision and recall to evaluate the balanced performance of the model. In practical applications, in order to improve the efficiency of model training, the Sequential Minimal Optimization (SMO) algorithm is used to solve the optimization problem of the SVM. The SMO algorithm decomposes large-scale optimization problems into multiple small-scale sub-problems to improve computational efficiency. This paper also uses GPU (Graphics Processing Unit) parallel computing to accelerate the calculation process of the kernel function, further improving the speed of model training.

The training and optimization of the SVM model can be achieved through model parameter regulation. The high-dimensional processing capability and nonlinear classification characteristics of the SVM ensure that it can effectively handle the complexity and diversity of photovoltaic system power consumption data and improve the accuracy and generalization ability of power theft detection [36].

D. Model Parameter Optimization

In order to improve the generalization ability of the SVM model, this paper uses grid search and cross-validation to optimize the hyperparameters of the model. The performance of the SVM is highly dependent on the selection of hyperparameters, especially the penalty coefficient A and the RBF kernel function parameter γ. Through systematic parameter optimization, the classification performance of the model is improved and the overfitting problem is avoided.

Grid search is an exhaustive search method that finds the optimal hyperparameters by traversing all possible combinations within a preset parameter range. This paper selects the penalty coefficient A and the RBF kernel function parameter γ as the optimization target. The penalty coefficient A controls the model's tolerance to classification errors. A larger A value can reduce the classification error, but may lead to overfitting. A smaller A value can increase the classification interval, but may lead to underfitting. The RBF kernel function parameter γ controls the complexity of the kernel function. A larger γ value makes the kernel function more localized, and a smaller γ value makes the kernel function smoother.

The grid search range of the SVM penalty coefficient A and kernel function parameters was determined based on preliminary experiments and literature research [37,38]. In the implementation, the parameter ranges of A and γ can be defined first. Usually, the value range of A is $[10^{-3}, 10^{3}]$, and the value range of γ is $[10^{-3}, 10^{3}]$. The parameter space is divided into logarithmic scales to generate a parameter grid. For each set of parameter combinations, the SVM model is trained and its performance is evaluated. Table 2 is a sample table of parameter combinations of some penalty coefficients A and RBF kernel function parameters γ.

Table 2. Sample table of some parameter combinations.

Penalty coefficient A	RBF kernel function parameter γ value	Penalty coefficient A	RBF kernel function parameter γ value
0.001	0.001	0.1	0.1
0.001	0.002	0.1	0.2
0.001	0.003	0.1	0.3
0.001	0.004	1	1
0.001	0.005	1	2
0.001	0.006	1	3
0.001	0.007	10	10
0.001	0.008	10	20
0.001	0.009	10	30
0.001	0.01	100	100
0.01	0.001	100	200
0.01	0.002	100	300
0.01	0.003	1000	1000
0.01	0.004	1000	900
0.01	0.005	1000	800

Table 2 lists some parameter combinations within the set parameter range. These combinations cover values of different magnitudes from smaller to larger, and are used in subsequent cross-validation and other means. The performance of the model under each set of parameters can be evaluated, and the parameter configuration that enables the model to achieve the best performance in the photovoltaic system power theft detection task can be screened out.

Cross-validation is used to evaluate the performance of each parameter combination to ensure the stability and reliability of the model. This paper uses K-fold cross-validation (K=5) to divide the data set into a training set and a validation set. The data set is randomly divided into 5 subsets, and 4 of them are used as training sets each time, and the remaining 1 subset is used as a validation set. This can be repeated 5 times to ensure that each subset is used as a validation set once. Through cross-validation, the data set can be fully utilized and the performance fluctuation caused by different data divisions can be reduced.

In cross-validation, this paper selects the F1 score as the performance evaluation indicator. The F1 score is the harmonic mean of the precision and recall rate, which can comprehensively reflect the classification performance of the model. The F1 score calculation formula (16):

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (16)$$

The calculation formulas for precision and recall are (17):

$$\left\{ \begin{aligned} &\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \\ &\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \end{aligned} \right\} \quad (17)$$

TP is a true positive, FP is a false positive, and FN is a false negative. By maximizing the F1 score, it can find the optimal parameter combination that balances precision and recall. The paper uses a logarithmic scale to divide the parameter range of A and γ, generate all possible combinations of A and γ, and form a parameter grid. For each set of parameter combinations, the F1 score of the model is evaluated using k-fold cross validation, and the parameter combination that gives the highest F1 score on the validation set is selected as the hyperparameter of the final model.

Through grid search and cross validation, the parameter space is systematically explored to find the optimal hyperparameter combination. The exhaustive nature of grid search ensures that no potential excellent parameter combinations are missed, and the stability of cross validation ensures the reliability of the evaluation results. As an evaluation indicator, the F1 score can comprehensively reflect the classification performance of the model and avoid the limitations of a single indicator.

In practical applications, in order to improve the efficiency of parameter optimization, parallel computing is used to accelerate the grid search and cross-validation process. By allocating parameter combinations to multiple computing nodes, the computing time is reduced. In addition, an early stopping strategy is adopted. During the cross-validation process, if the performance of a parameter group is significantly lower than the current optimal value, the evaluation of the group of parameters is terminated in advance to improve computing efficiency.

This paper implements parameter optimization of the SVM model. The combination of grid search and cross-validation systematically finds the optimal hyperparameter combination and improves the generalization ability and classification performance of the model. The optimization process provides a reliable model foundation for electricity theft detection.

E. Computational Efficiency Optimization

In the signal processing stage, the improved Mallat fast WT algorithm is used to reconstruct the calculation process. The filter bank structure is reconstructed by introducing multi-phase decomposition technology, and the traditional convolution operation is decomposed into multiple parallel sub-filter operations. The calculation sequence based on cache optimization is designed, and register prefetching and loop unrolling technology are used to improve data locality. Implement a multi-scale parallel decomposition strategy, allowing computational tasks at different decomposition levels to be executed synchronously. The filter bank reconstruction formula (18) for polyphase decomposition is:

$$H\left(z\right)=\sum\nolimits_{k=0}^{M-1}z^{-k}E_k\left(Z^M\right) \quad (18)$$

$E_k\left(Z^M\right)$ is the multiphase component and M is the decomposition factor. In the feature calculation phase, the calculation process of energy distribution, frequency component and wavelet entropy is reconstructed. The energy distribution calculation is optimized using SIMD (Single Instruction Multiple Data) instruction set to achieve vectorized parallel computing. Frequency component analysis is optimized by FFT (Fast Fourier Transform) algorithm, and mixed radix algorithm is used to improve computational efficiency. Wavelet entropy calculation introduces approximate calculation and table lookup method to reduce the overhead of complex logarithmic operations.

A three-level parallel acceleration architecture is designed. In data-level parallelism, the input signal is divided into fixed-size data blocks, and each CUDA thread block (Compute Unified Device Architecture Threads) processes a specific data block. Shared memory is used to optimize data access mode and reduce global memory access latency. In task-level parallelism, a multi-stream processing pipeline is built to achieve asynchronous overlap of kernel function calculation and data transmission, and the correctness of calculation is ensured through event synchronization mechanism. In model-level parallelism, the core matrix calculation of the SVM is decomposed into multiple parallel sub-matrix operations, and a warp-level reduction algorithm is used to accelerate the result aggregation. The warp-level optimization formula (19) of the parallel reduction algorithm is:

$$\begin{aligned}&\forall tid\in\left[0,31\right],s\left[tid\right]\oplus=s\left[tid+16\right]\\&s\left[tid\right]\oplus=s\left[tid+8\right]\\&\cdots\\&s\left[tid\right]\oplus=s\left[tid+1\right]\end{aligned} \quad (19)$$

$\oplus$ represents the reduction operator. A three-level processing pipeline architecture is constructed. The first-level pipeline is responsible for data preprocessing, including data standardization and segmentation processing. Double buffering technology is used to achieve parallel computing and data transmission. The second-level pipeline performs feature extraction in parallel and dynamically allocates computing resources through the task scheduler. The third-level pipeline implements classification decisions and optimizes the prediction process of the SVM. Data exchange is achieved between pipelines at all levels through a ring buffer, and lock-free programming is used to ensure thread safety.

A zero-copy memory access mechanism is implemented to eliminate unnecessary data transfer between the host and the device. A unified memory architecture is used to simplify the programming model, and data access is optimized through prefetching strategies. Intelligent cache strategies can be designed to dynamically adjust cache size and replacement algorithms based on computing characteristics. Memory alignment optimization is performed on frequently accessed data structures to improve cache hit rate.

Dynamic resource allocation algorithms based on load prediction can monitor the real-time computing load of the system and use work stealing algorithms to balance the task allocation of each computing unit. An elastic computing resource pool can be designed to dynamically adjust the GPU stream processor configuration according to task requirements. A fine-grained power management strategy can be implemented to optimize energy efficiency through dynamic voltage and frequency adjustment. The power consumption model formula (20) for dynamic voltage and frequency adjustment is:

$$P = C_{eff} \cdot V^2 \cdot f + I_{leak} \cdot V \quad (20)$$

C_{eff} is the effective capacitance, V is the operating voltage, f is the clock frequency, and I_{leak} is the leakage current. This paper designs a hybrid task scheduling strategy, which uses static scheduling for computationally intensive tasks and dynamic scheduling for data-related tasks. It implements a task priority queue to ensure that critical path tasks are executed first. A task dependency analyzer can be developed to automatically identify parallelization opportunities. Task slicing technology is used to decompose large tasks into subtasks that can be executed in parallel. Table 3 is the parameters involved in this paper.

Table 3. Parameter list.

Parameters meet	Parameter function	Parameters meet	Parameter function
ψ	Wavelet Function	a	Scale parameter
b	Translation parameter	c	Approximation coefficient
d	Detail coefficient	g	Frequency domain index
Ω	Specific frequency range	ω	Weights of multi-scale energy distribution
μ	The mean of the eigenvalues	σ	Standard deviation of eigenvalues
γ	Kernel function parameters	q	Bias term for classification hyperplane
ξ	Slack variables	A	Penalty coefficient

In the process of studying the joint identification of electricity theft characteristics of photovoltaic systems of dedicated transformer users by WT and SVM [39], a variety of key parameters are involved. Table 3 clearly shows the various parameters and their functions, and quickly and intuitively grasps the parameter system involved in the study. This lays the foundation for the subsequent understanding of the analysis and processing of electricity consumption data by WT and the construction and training of SVM models.

The computational efficiency optimization scheme proposed in this paper builds a complete parallel computing system through the collaborative design of algorithm reconstruction and hardware acceleration. At the algorithm level, multi-phase decomposition and SIMD optimization are used to parallelize the computing process. At the hardware level, a three-level parallel acceleration scheme is designed based on the CUDA architecture. The real-time performance of the system is ensured through pipeline design and dynamic resource scheduling, and the hardware utilization is maximized by combining memory access optimization and intelligent task scheduling. The systematic optimization method provides an effective technical solution for real-time processing of power big data.

4. Experimental Results

A. Wavelet Decomposition Process

The experimental data in this paper are derived from the operation monitoring records of the actual photovoltaic system, covering normal power consumption behavior and various power theft behaviors such as current bypass, inverter tampering, and data injection. The test scenario parameters are designed according to the IEEE 2030.5 standard and refer to the actual power grid monitoring data. Various noise conditions and data loss conditions are simulated in the experiment to ensure the robustness of the results. All comparison models are run under the same test environment, and the verification results are evaluated by cross-validation and independent test sets.

The decomposition level of wavelet decomposition directly affects the computational cost and the refinement of feature extraction. A higher decomposition level can capture more detailed features, but it will increase the computational complexity. This paper experimentally found that when the decomposition level is 5, the model achieves a good balance between computational efficiency and feature extraction capabilities. Further increasing the decomposition level will lead to a significant increase in computational cost, while the improvement in model performance is limited.In the operation of photovoltaic systems, accurate analysis of electricity consumption data is crucial. Electricity consumption data reflects the operating status of the system and hides clues to abnormal situations such as electricity theft. As a powerful signal processing tool, wavelet decomposition can effectively analyze non-stationary electricity consumption data at multiple scales. Figure 4 clearly shows the application effect of wavelet decomposition in the analysis of photovoltaic system electricity consumption data.

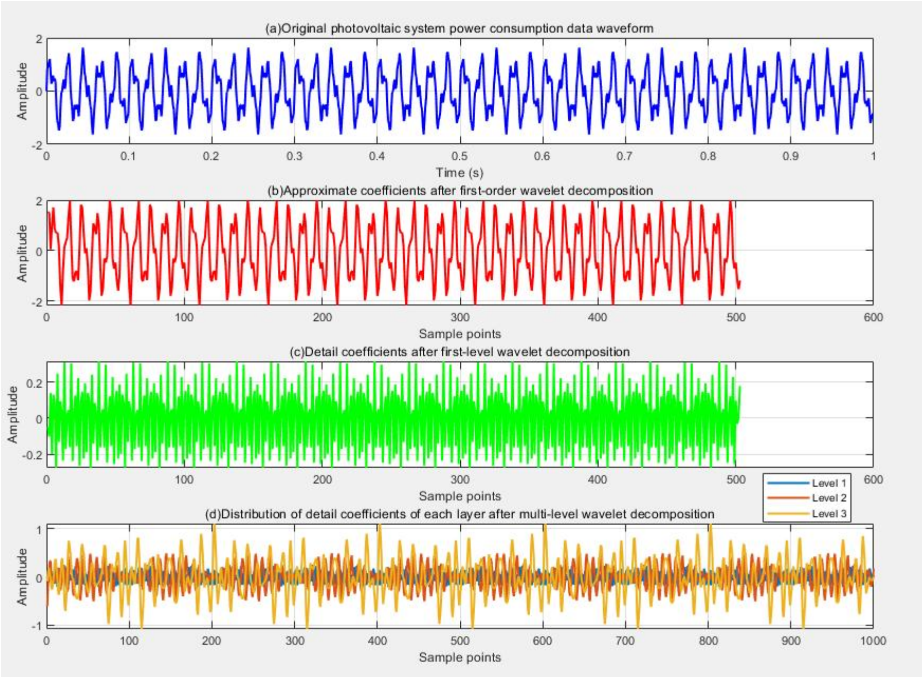

Figure 4. Schematic diagram of wavelet decomposition process. Figure 4 (a) Waveform of original photovoltaic system power consumption data; Figure 4 (b) Approximate coefficient diagram after first-level wavelet decomposition; Figure 4 (c) Detailed coefficient diagram after first-level wavelet decomposition; Figure 4 (d) Multi-level wavelet decomposition diagram.

When studying photovoltaic system power consumption data, wavelet decomposition is an important analytical tool that can analyze data at different scales and frequencies. Figure 4 intuitively shows the effect of wavelet decomposition in processing photovoltaic system power consumption data, including the original photovoltaic system power consumption data waveform and the coefficients after wavelet decomposition at different levels. The original waveform in Figure 4 (a) shows complex fluctuations, because the actual photovoltaic system power consumption is affected by multiple factors such as light intensity and equipment operating status, and has obvious non-stationary characteristics. In Figure 4 (b), after the first-level wavelet decomposition, the approximate coefficient reflects the overall trend and main components of the signal, showing a relatively smooth waveform, because the low-frequency part contains the basic change characteristics of the signal; the detail coefficient in Figure 4 (c) captures the rapid changes and transient characteristics in the signal, and its waveform is more high-frequency and complex.

Multi-level wavelet decomposition further refines the analysis of the signal. The distribution of detail coefficients at each layer shows the high-frequency components at different scales. As the number of decomposition layers increases, subtle changes and high-frequency fluctuations in the signal can be captured more finely, which is of great significance for discovering abnormal fluctuations in electricity consumption data and capturing transient changes caused by possible electricity theft.

Figure 4 intuitively demonstrates the multi-scale characteristics of wavelet decomposition, which helps people understand how wavelet decomposition decomposes complex photovoltaic system electricity consumption data into components of different frequencies and scales, laying the foundation for subsequent research on electricity consumption data feature extraction and anomaly detection based on wavelet analysis. By analyzing the decomposition results, an intuitive basis is provided for the in-depth analysis and processing of photovoltaic system power consumption data using wavelet decomposition technology, which helps to improve the ability to mine potential information in photovoltaic system power consumption data and improve the accuracy and effectiveness of power theft detection applications.

B. Joint Analysis of Multi-Scale Energy Distribution and Frequency Components

In the operation monitoring and management of photovoltaic systems, accurately grasping the characteristics of power consumption data is the key to achieving efficient energy utilization and effective anomaly detection. Electricity consumption data is a complex non-stationary feature, containing rich frequency components and energy distribution information. Wavelet decomposition, as a powerful multi-scale analysis tool, decomposes the original signal at different scales to reveal the detailed characteristics of the signal at each scale. This paper deeply explores the energy distribution law and frequency component characteristics of photovoltaic system power consumption data at multiple scales to mine potential information in the data and identify abnormal power consumption behavior. Figure 5 shows the results of the joint analysis of multi-scale energy distribution and frequency components.

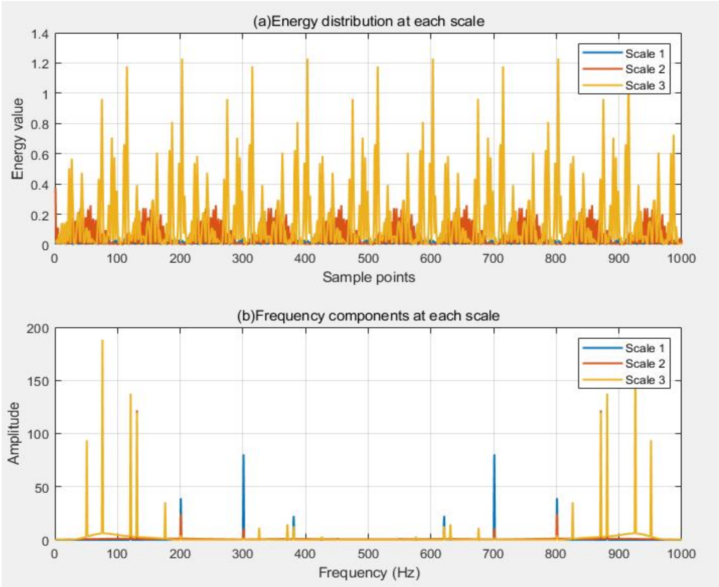

Figure 5. Multi-scale energy distribution and frequency component analysis diagram.Figure 5 (a) Multi-scale energy distribution diagram; Figure 5 (b) Multi-scale frequency component diagram.

Figure 5 shows the energy distribution of each scale and the frequency component of each scale. In the energy distribution diagram of each scale in Figure 5 (a), lines of different colors represent the energy distribution of scale 1, scale 2, and scale 3, respectively.The energy of each scale shows a relatively discrete and irregular distribution at the sample point. Because the power consumption data of the photovoltaic system itself is affected by many complex factors such as the change in the light intensity of the photovoltaic panels and the random start and stop of the power equipment, these factors lead to the non-uniform distribution of the energy of the signal at different scales.

It can be seen from the frequency component diagram in Figure 5 (b) that the frequency amplitudes at different scales also vary greatly. At scale 1, the frequency component has a higher amplitude at a specific frequency and a lower amplitude at other frequency ranges. The situation is similar for scales 2 and 3, but the specific frequency distribution and amplitude are different. Due to the multi-scale characteristics of wavelet decomposition, different scales can capture information in different frequency ranges in the signal. Therefore, the frequency component distribution at different scales can reflect the energy concentration and change characteristics of the signal in different frequency bands.

In terms of anomaly detection, by observing the changes in energy and frequency distribution at different scales, abnormal fluctuations in electricity consumption data can be more keenly detected. When the energy or specific frequency components at a certain scale change abnormally, it means that there are abnormal situations such as electricity theft in the system, which provides important clues for abnormal diagnosis and processing. For optimizing the operation and management of photovoltaic systems, this information helps to reasonably arrange the operation of electrical equipment, improve energy efficiency, and reduce operating costs. The joint analysis of multi-scale energy distribution and frequency components provides strong support for the research of this paper, making the analysis of photovoltaic system power consumption data more in-depth and comprehensive.

C. RBF Kernel Mapping Effect

In the study of machine learning and data analysis, the processing and conversion of data features is a key link to improve model performance. As an effective means of mapping data from low-dimensional space to high-dimensional space, RBF kernel mapping has unique advantages in processing nonlinear separable data. In order to intuitively present the actual effect of RBF kernel mapping and the change in data distribution, Figure 6 shows a schematic diagram of RBF kernel mapping.

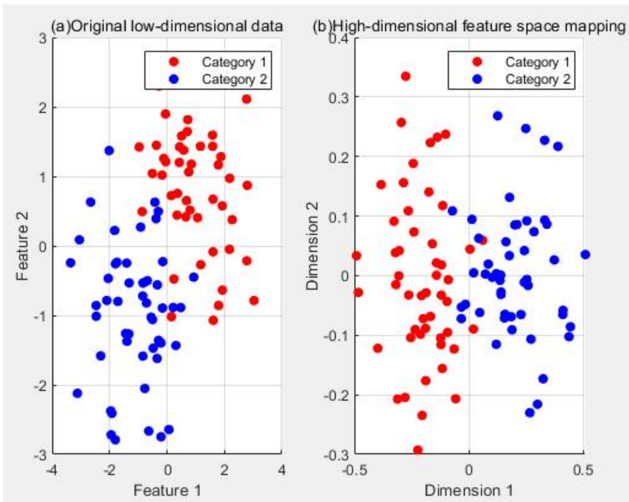

Figure 6. Schematic diagram of RBF kernel mapping. Figure 6 (a) Original low-dimensional data; Figure 6 (b) Mapping result of high-dimensional feature space.

Figure 6 is divided into two parts. Figure 6 (a) shows the original low-dimensional data, where the red and blue data points represent different categories respectively. These data points are mixed with each other in low-dimensional space, with disorderly distribution and no obvious linear separable boundaries. This reflects that in low-dimensional space, it is difficult to directly classify data, and traditional linear classification methods are difficult to achieve ideal results.

Figure 6 (b) shows the visualization result of dimensionality reduction to two-dimensional space after RBF kernel mapping through multidimensional scaling technology. Compared with the figure 6 (a), the distribution of the two types of data points has changed significantly. Their distribution in space is more regular, and the distinction between them is significantly enhanced. This result is produced because the RBF kernel function can map the original low-dimensional data to a high-dimensional space through nonlinear transformation according to the distance relationship between data points. In the high-dimensional space, the originally tightly entangled data of different categories are redistributed, thereby revealing the potential linear structure between them. The RBF mapping process is equivalent to constructing a representation that is more suitable for data distribution in the high-dimensional feature space, so that different types of data can be more clearly distinguished in the space, thereby improving the classification effect.

From an algorithmic perspective, Figure 6 clearly shows how RBF kernel mapping enhances the separability of data, providing an intuitive effect verification for the classification algorithm based on RBF technology, which helps to study and understand the advantages and potential of the algorithm in processing nonlinear data. In practical applications, it provides a reference for solving similar nonlinear data classification problems. In the detection of electricity theft in photovoltaic systems, electricity consumption data presents complex nonlinear characteristics. By using RBF kernel mapping technology, data features can be better extracted and the accuracy of identifying electricity theft behavior can be improved. According to the RBF mapping diagram, it can also assist in the optimization of system parameters. By observing the distribution of data after mapping in high-dimensional space under different parameter settings, the parameters of the RBF kernel function can be adjusted to achieve the best data processing effect.

D. Wavelet Time-Frequency Analysis of Different Types of Electricity Theft

In the study of electricity theft detection in photovoltaic systems, it is crucial to accurately identify different types of electricity theft. As a powerful time-frequency analysis tool, WT can clearly show the characteristics of signals at different times and frequencies, which helps to distinguish between signals generated by normal electricity use and various electricity theft behaviors. In order to intuitively present the time-frequency characteristics of different electricity theft behavior signals after WT, Figure 7 shows the WT time-frequency analysis.

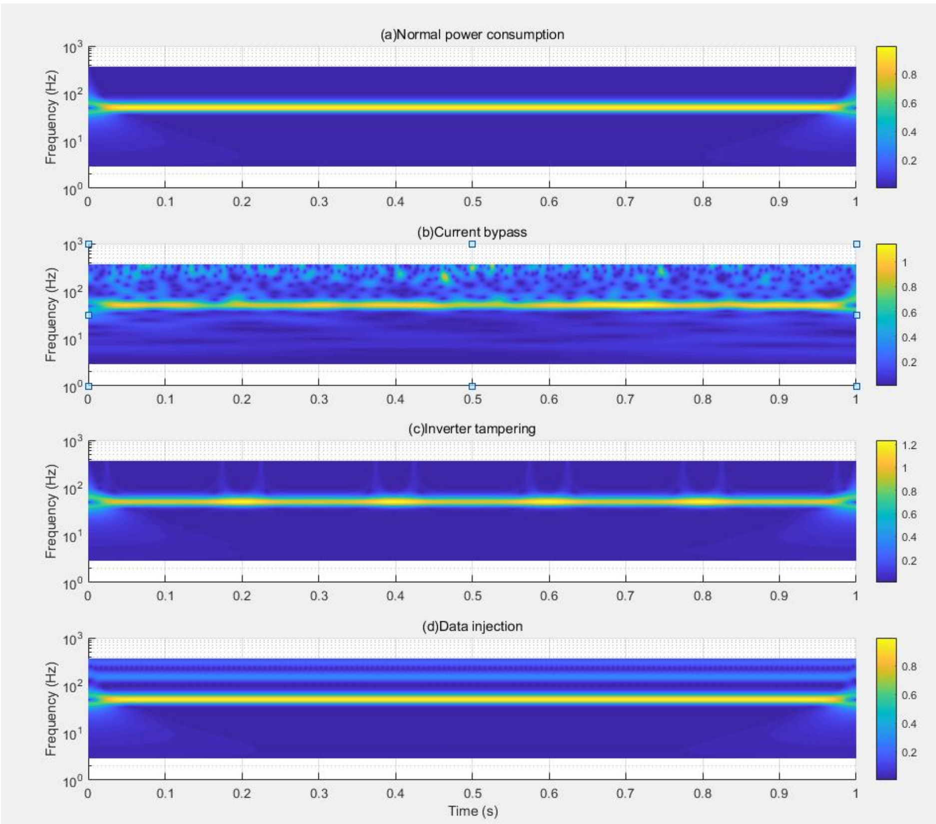

Figure 7. WT time-frequency analysis. Figure 7 (a) Normal power consumption time-frequency analysis; Figure 7 (b) Current bypass time-frequency analysis; Figure 7 (c) Inverter tampering time-frequency analysis; Figure 7 (d) Data injection time-frequency analysis.

In the field of power system monitoring and management, accurate identification of power theft is of great significance to ensure the stability and fairness of power supply. Traditional power consumption signal analysis methods are difficult to meet the needs when faced with complex and diverse power theft methods. As an advanced time-frequency analysis tool, WT can deeply analyze signals from different time and frequency scales, opening up new paths for power theft detection. Figure 7 shows the wavelet time-frequency analysis results of different types of electricity theft. The energy of normal power consumption signals is concentrated and stable, while electricity theft behaviors such as current bypass, inverter tampering, and data injection show obvious changes in frequency components. Current bypass theft introduces high-frequency transient signals, inverter tampering causes periodic interference, and data injection theft is manifested as multi-band energy concentration. These features provide important feature basis for building classification models.

As shown in Figure 7 (a), during normal power consumption, the energy is stably concentrated in a fixed frequency band, showing a stable highlight band. Under normal circumstances, the power grid equipment operates stably, the signal is mainly composed of a single fundamental wave, and there is less external interference. In the WT time-frequency diagram, the energy is concentrated and stable in the time dimension. The current bypass stealing behavior corresponds to Figure 7 (b). In addition to the main energy band, discrete highlights appear in the high-frequency area. Because current bypass stealing introduces high-frequency transient signals, it is simulated by superimposing high-frequency signals in specific time periods. These high-frequency signals cause the energy in the high-frequency area to be concentrated, breaking the stable state of the normal signal. Figure 7 (c) shows that the energy distribution of inverter tampering has obvious periodic characteristics in the main frequency area. Because the inverter tampering changes the power output characteristics, it introduces periodic interference by modulating the normal signal, and the corresponding characteristics are shown in the time-frequency diagram. Figure 7 (d) shows that the data injected into the power theft shows multi-frequency harmonic characteristics, and highlighted areas appear in multiple frequency bands. Since data injection theft is to inject harmonic signals into the system to interfere with metering, the signal frequency components become complex by superimposing harmonics of different frequencies, which is manifested as multi-band energy concentration in the time-frequency diagram.

WT time-frequency analysis has an important impact on the research of this paper. In the study of electricity theft detection algorithms, an intuitive signal feature reference is provided for the design and optimization of the algorithms. Researchers can extract feature quantities based on the unique features of different electricity theft behaviors on the time-frequency graph, build more effective classification models, and improve the accuracy and efficiency of electricity theft detection. In practical applications, these time-frequency analysis graphs can help power management personnel quickly and accurately determine whether there is electricity theft in the photovoltaic system and the type of electricity theft, and take appropriate measures to deal with it in a timely manner to ensure the normal operation of the photovoltaic system and the rational use of power resources.

E. Model Performance Analysis

In identifying the characteristics of electricity theft in photovoltaic systems of dedicated transformer users, it is very important to accurately and efficiently detect electricity theft and process complex power data. This involves the rational allocation of power resources and is related to the stable operation and economic benefits of the system. In the research in this field, a variety of models have been applied to related tasks. Comprehensively evaluating the performance of these models and the model in this paper has become a key link in optimizing the system and improving detection efficiency. In order to further explore the performance differences of different models in electricity theft detection and power data analysis, this paper systematically tests multiple models including WT-SVM, Time-Freq Transformer, MobileNets, GWNN (Graph Wavelet Neural Network), and HybridSNN (Hybrid Spiking Neural Network) by comprehensively considering multiple dimensions such as model accuracy, operating efficiency, storage requirements, and anti-interference ability. The data are shown in Table 4.

Table 4. Model performance data table.

Model	F1-score (%)	Calculating delay (ms)	Parameter quantity(MB)	Noise immunity (%)
WT-SVM	94.5	35	2.1	91.2
Time-Freq Transformer	93.8	80	62.4	89.1
MobileNets	92.3	45	5.7	90.5
GWNN	90.6	150	38.9	84.2
HybridSNN	88.9	18	1.5	80.7

From the results in Table 4, the F1 score of WT-SVM reaches 94.5%, showing a high classification accuracy. This is due to its ability to effectively use kernel methods such as RBFs to mine nonlinear relationships in data when processing small-scale data with relatively clear features.When the hardware platform is Intel Core i7-10700K CPU (3.8GHz, 8 cores and 16 threads) and the GPU is NVIDIA GeForce RTX 3080 (10GB video memory), the calculation delay is only 35ms and the parameter volume is only 2.1MB. This is because the model structure of the SVM is relatively simple and does not require a lot of parameter training, which makes it perform well in terms of computing speed and storage requirements. The 91.2% noise resistance shows that it has good resistance to noise interference in the data.

The F1 score of Time-Freq Transformer is 93.8%, which is also a good performance. The Transformer model is good at capturing long-distance dependencies in time series data and can effectively extract features when processing complex power signals. Its computational delay is 80ms and its parameter size is as high as 62.4MB. The reason is that the Transformer model contains a large number of self-attention mechanisms and multi-layer neural network structures, which greatly increases the amount of computation and model size. The noise resistance is 89.1%, which means that its performance can be affected to a certain extent in the presence of noise.

MobileNetst's F1 score is 92.3%, with a computational delay of 45ms and a parameter size of 5.7MB. It combines the advantages of edge computing, processes data locally, reduces the delay caused by data transmission, and the model structure is designed to be lightweight, so the parameter scale is relatively small. The 90.5% noise resistance shows that it has a certain resistance to noise.

GWNN has an F1 score of 90.6%, a calculation delay of 150ms, and a parameter size of 38.9MB. This model is based on graph neural network and has certain advantages in processing power network data with complex topology. However, the computational complexity of graph neural network is high, resulting in long computational delay and more model parameters. The noise resistance is 84.2%, indicating that its performance degrades significantly in a noisy environment.

The F1 score of HybridSNN is 88.9%, the computational delay is only 18ms, and the parameter size is 1.5MB, which is the model with the shortest computational delay and the smallest parameter size among all models. This is due to the unique event-driven mechanism of the spiking neural network, which greatly improves the computing efficiency. However, its noise resistance is 80.7%, which is relatively low. This means that in scenes with more noise, its classification performance can be greatly affected.Although HybridSNN has advantages in latency, its low noise immunity limits its reliability in real-time applications. In contrast, WT-SVM achieves a better balance between latency and noise immunity and is more suitable for electricity theft detection under complex working conditions.

These results have many impacts on research. In terms of model selection, if high requirements are placed on computational efficiency and lightweight, and deployment is required on resource-constrained edge devices, WT-SVM and HybridSNN are better choices. In algorithm optimization, researchers can refer to the advantages and disadvantages of these models, improve the model structure or training methods in a targeted manner, and improve the comprehensive performance of the model on different indicators. For actual application scenarios such as photovoltaic system power theft detection, these data can help determine the most suitable model to achieve efficient and accurate detection and better cope with complex field environments and noise interference.

5. Experimental Discussion

This paper constructs a new hybrid architecture that integrates WT and SVM, which achieves breakthrough progress in photovoltaic system power theft detection through multi-level technology. At the theoretical level, the study combines wavelet multi-resolution analysis with statistical learning theory, and proposes a machine learning paradigm based on time-frequency domain feature enhancement, which solves the feature extraction bottleneck of traditional methods in processing non-stationary power signals and builds a bridge between physical models and data-driven methods. In terms of algorithm design, the model's ability to characterize complex power consumption patterns is improved by introducing an adaptive wavelet packet decomposition strategy and a dynamic kernel parameter optimization mechanism. A Daubechies wavelet basis function optimization scheme for photovoltaic power consumption characteristics is developed, a feature selection algorithm based on the energy-entropy joint criterion is designed, and incremental learning optimization of SVMs is realized. These innovations enable the model to demonstrate significant advantages in multiple performance dimensions, and show excellent noise resistance when dealing with complex working conditions such as sudden changes in illumination.

The WT-SVM method introduced in this paper shows significant advantages in photovoltaic system electricity theft detection by combining the time-frequency analysis capability of wavelet transform and the efficient classification characteristics of support vector machine. Compared with existing deep learning methods, this method avoids the deployment difficulties caused by large-scale parameters and shows stronger applicability in practical scenarios with limited resources. Compared with feature engineering methods, it effectively captures transient anomalies in non-stationary signals through multi-scale decomposition, improving its adaptability to complex power consumption scenarios. These characteristics enable WT-SVM to achieve a better balance between accuracy, efficiency and generalization ability, providing a more practical solution for photovoltaic system safety monitoring.

In actual industrial deployment, the WT-SVM framework proposed in this paper faces the following potential challenges and coping strategies: The photovoltaic system power consumption data contains sensitive information such as user power consumption patterns and equipment status, which may cause privacy leakage risks. For this reason, federated learning technology can be used to implement distributed model training, or differential privacy technology can be used to protect data. As the scale of photovoltaic systems expands, the model needs to process larger data sets and complex power consumption patterns. Data processing can be accelerated through distributed computing architecture, and localized reasoning can be implemented in combination with edge computing to improve scalability.

From the perspective of academic value, this study provides a new method framework for power big data analysis, promotes the cross-integration of signal processing and artificial intelligence, and the proposed lightweight architecture opens up new ways for the application of edge computing in power systems. However, the study also exposes some problems that need to be solved. In terms of model generalization, the adaptability of the current model to the new distributed photovoltaic grid-connected scenario still needs to be further verified. To meet this challenge, future research should focus on exploring the application of transfer learning and domain adaptation technology. The generalization ability of the model in new scenarios can be improved by fine-tuning the pre-trained model on the power grid data in different regions. Or introduce technologies such as adversarial generative networks to build a cross-domain feature alignment mechanism to enhance the robustness of the model to complex working conditions. At the algorithm level, the real-time dynamic update mechanism is not yet perfect. In the future, it can be combined with online learning technology to achieve dynamic optimization of model parameters. In engineering applications, deep integration with the existing SCADA system is still a problem to be solved, which requires the development of standardized interfaces to support seamless integration of models. By improving these limitations, the practical applicability and promotion value of the model can be further improved.

Looking ahead, photovoltaic electricity theft detection technology is an important development direction, and future research will further explore its applicability in independent photovoltaic systems and other distributed energy scenarios. The establishment of a multimodal fusion detection system can combine multi-source information such as power data, video surveillance, and IoT perception to build a comprehensive monitoring network; the application of deep learning technology can build a lifelong learning system with online update capabilities; the introduction of trusted artificial intelligence technology can ensure the interpretability of detection results and the transparency of decision-making; the integration of digital twin technology and edge intelligence can bring revolutionary changes to this field. The WT-SVM framework proposed in this paper provides key technical support for this evolution. With the advancement of the construction of new power systems, security monitoring technology based on artificial intelligence can play a more important role. The results of this study have laid a solid foundation for subsequent technological innovation and provided valuable reference for research in related fields.

6. Conclusions

This study introduces an innovative method combining wavelet transform and support vector machine, which is successfully applied to the detection of electricity theft in photovoltaic systems. The time-frequency characteristics of electricity consumption data are extracted by wavelet transform, and efficient nonlinear classification is achieved by support vector machine. The model performs well in detection accuracy, computational efficiency and noise resistance, providing a solution with both high accuracy and engineering practicality for the detection of electricity theft in photovoltaic systems. However, the generalization ability, real-time dynamic update mechanism and deep integration with SCADA system for new distributed photovoltaic grid-connected scenarios still need to be further explored and improved. Future research directions can focus on multimodal data fusion, adaptive learning algorithm optimization and the introduction of trusted artificial intelligence technology to improve the robustness and interpretability of the model. These improvements will help to cope with complex and changeable practical application scenarios and promote the intelligent upgrade of new power systems.

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Consent to Publish

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Author Contribution

Lvlong Hu: Edited and refined the manuscript with a focus on critical intellectual contributions.

Le Chang, Haihong Wang, Xinyu Peng: Participated in collecting, assessing, and interpreting the date. Made significant contributions to date interpretation and manuscript preparation.

Lvlong Hu, Zeju Xia: Provided substantial intellectual input during the drafting and revision of the manuscript.

Conflicts of Interest

The authors declare that they have no financial conflicts of interest.

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