

An Electro-Thermal State Matrix Framework for Interpretable PMSM Inverter Fault Diagnosis Using Chromatic Fingerprints

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Abstract: Fault detection in PMSM inverters is usually done through measurement or hand-crafted features of electrical and thermal parameters. Although such methods can perform with excellent accuracy in classification tasks, they provide limited insight into the physics of fault development. This paper presents a methodology for diagnosing faults in inverters through an interpretable fault diagnosis technique using Physical State Vector (PSV), Electro-Thermal State Matrix (ETSM), and Chromatic Fingerprints.

The suggested approach consists of first converting the raw data measured in PMSM into physical representations of the electrical, thermal, and electro-thermal features. Then, the data is represented in an ETSM, where electrical behavior, thermal conditions, and electro-thermal interrelations are distinctly distinguished. The ETSM is converted to a chromatic fingerprint, which is a graphical representation of the system state. To test the diagnostic potential of the proposed representation, the statistical color features obtained from the fingerprints are classified via a Random Forest model.

Validation of the experimental work was carried out by using publicly available data related to the fault diagnosis of the PMSM inverter, which included 10,892 samples from nine different operating conditions. Because each class is one continuous 10 Hz recording, a blocked temporal cross-validation is used as the primary protocol, and repeated stratified cross-validation is reported for comparison. The chromatic fingerprint reached $89.4 \pm 6.6\%$ accuracy and $84.9 \pm 8.9\%$ Macro-F1 in blocked cross-validation ($95.5 \pm 0.5\%$ and 93.6% in random folds), against $98.1 \pm 3.0\%$ for the raw sensors. Feature importance, grouped permutation importance, SHAP, and layer-ablation analyses showed that thermal descriptors were the main source of discriminative information in this dataset ($73.9 \pm 0.9\%$ of impurity importance), whereas removing the electro-thermal layer did not reduce accuracy, so no complementary information was demonstrated for it. Chromatic fingerprint distances correlated with class confusion (Spearman $\rho = -0.83$).

The presented results show a trade-off between diagnostic effectiveness and physical interpretability of the developed representation. In contrast to sensor-based methods, the proposed framework offers an electro-thermal representation, which is capable of providing both fault diagnosis and visualization of the PMSM fault states, within the limits of a single dataset.

Key-Words: PMSM fault diagnosis, Electro-Thermal State Matrix, Physical State Vector, Chromatic Fingerprint, Explainable Artificial Intelligence, Condition Monitoring, Random Forest

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1 Introduction

The Permanent Magnet Synchronous Motor (PMSM) is one of the most popular electrical machines that have been used in modern industrial systems owing to its high efficiency, high torque density, high dynamic performance, and high performance drive system capability. For this reason, the PMSM drive system has been increasingly used in many areas such as electric vehicles, industrial automation, robotics, aerospace systems, and renewable energy. The rising dependence on PMSM drive systems in mission-critical and safety-critical situations has led to a growing demand for condition monitoring and fault detection systems. [1]

In spite of the above-mentioned benefits, however, there are still some faults such as electrical faults, thermal faults, and inverter faults that can affect the drive system performance and cause its degradation.

The inverter faults are one of the most critical types of faults since the inverter is the main connecting point of the power source and the motor. Such inverter faults as open-circuit faults, short-circuit faults, switching faults, and thermal faults can change the properties of the drive system, which implies that it is necessary to take into account both electrical and thermal characteristics when diagnosing the fault. [2]

PMSM fault diagnosis techniques using conventional approaches may be divided into three major categories: signal processing-based, feature extraction-based, and machine learning-based techniques. Signal processing approaches typically involve the use of time domain, frequency domain, and time-frequency features that can be derived from current measurements, voltage, vibration, and temperature of the PMSM system to detect and identify faults. In recent times, machine learning and deep learning techniques have proven to have

superior diagnostic capabilities due to their ability to learn discriminative patterns from raw measurements or features. [3]

Though high classification performance is achieved in numerous studies, current methods can be considered black box classifiers since little understanding of the physical mechanisms governing the fault progression process is provided. In addition, most works consider electrical and thermal variables either separately or as elements of one feature vector without taking into account their relationship and the influence of electrical stress on the thermal behavior. Therefore, the obtained representations have poor physical interpretation and offer no information about the process of evolution of different fault classes in terms of various physical aspects. [4]

There has been increasing attention towards converting sensor readings into image-based forms such that the resulting patterns can be used for computer vision and pattern recognition tasks. Several coding methods have been developed for this purpose, including spectrogram representation, recurrence plot, Gramian Angular Fields, Markov Transition Fields, and other image-based representations which can represent one-dimensional data as patterns which can be easily discriminated through visual inspection. These methods have shown promising classification results in a variety of applications pertaining to condition monitoring and fault diagnostics. However, in most cases, these images have been generated based on some transformation of the signals and the purpose behind generating these images is mainly focused on classification. The physical meaning of these patterns cannot always be interpreted. [5], [6]

Driven by the above issues, this paper suggests a representation paradigm based on the combination of descriptor engineering, electro-thermal state modeling, and chromatic visualization into a single diagnostic workflow. Contrary to conventional direct image creation from raw measurement data, our approach involves first creating the meaningful descriptors based on physics-driven modeling and then structuring the extracted descriptors into an Electro-Thermal State Matrix (ETSM). Finally, the ETSM is converted into a Chromatic Fingerprint. As a result, our fingerprints represent the current state of the PMSM rather than individual sensor signals. [7]

These contributions of this research can be highlighted as follows:

- A physical state vector (PSV) representation is developed to map raw PMSM data into physically interpretable electrical, thermal, and electro-thermal attributes, with dimensionally consistent descriptor definitions and normalization fitted on training data only.
- An electro-thermal state matrix (ETSM) is developed to arrange these attributes into a

structured multi-layered representation that captures electrical, thermal, and interactions between them.

- A chromatic fingerprint generation scheme is developed to map ETSM representations into visual representations.
- An extensive explainability analysis is carried out based on feature importance analysis, grouped permutation importance, SHAP analysis, layer and sensor ablation, confusion analysis, and fingerprint distance analysis for studying the physical meaning of the proposed representation.
- A leakage-aware evaluation is used, combining repeated stratified and blocked temporal cross-validation, because every class of the dataset is one continuous recording.
- The experimental results on a publicly available PMSM inverter fault dataset show that the proposed approach retains a large part of the information in the original signal measurements (89.4% against 98.1% accuracy in blocked cross-validation) in a physically structured representation, and they show the limits of that representation: the information is almost entirely thermal, and the electro-thermal layer shows no complementary benefit.

In contrast to traditional methods of image encoding where the raw signal is directly converted into an image form, the proposed scheme first creates a physical state representation and then derives chromatic fingerprints from the electro-thermal state space.

Lastly, the rest of the paper is organized as follows. Section 2 provides an overview of the most relevant literature for PMSM fault diagnosis, explainable artificial intelligence, and fault representations using images. Section 3 explains the investigated PMSM fault data set. Section 4 introduces the proposed PSV-ETSM framework and the process of chromatic fingerprint creation. The experiment setup is detailed in Section 5, whereas the results are shown in Section 6, and Section 7 discusses them. Lastly, conclusions are drawn in Section 8.

2 Related Work

2.1 PMSM Fault Diagnosis

The fault diagnosis of Permanent Magnet Synchronous Motor (PMSM) has been an area of considerable research interest owing to the increasing application of PMSM drives in industries, transportation, and renewable energy fields. Conventional diagnostic techniques mainly depend on the electrical, thermal, vibration, and magnetic parameters to diagnose fault conditions in the operation of the motor and the inverter. The traditional signal processing techniques make use of statistical measures, spectral analysis, wavelet

transforms, and model-based approaches to diagnose faults in varying operational conditions. [8]

As machine learning is developing rapidly, there has been a shift towards data-driven fault diagnosis techniques for PMSMs. There have been many research works that achieved high diagnostic accuracy by means of supervised learning algorithms like SVM, RF, kNN, XGBoost, and ANN. Recently, deep learning methods like CNN, LSTM network, and Transformer network have proven to be effective for automatic feature extraction and fault diagnosis. [9], [10]

Despite the high degree of success in terms of classification performance that is seen in many data-driven techniques, these techniques are mainly focused on improving the predictive accuracy rather than offering any physical insight into the mechanics of faults.

2.2 Image-Based Fault Representations

Image-based fault diagnosis has become an appealing research area owing to the great success that computer vision algorithms have achieved in pattern recognition problems. These algorithms involve mapping the one-dimensional sensor signal into a two-dimensional space before classifying the data. The main image encoding schemes are spectrogram, scalogram, recurrence plot, Gramian Angular Field (GAF), Markov Transition Field (MTF), and various time-frequency representations. [11], [6]

The transformation of sensor data to images helps in solving diagnostic problems via image analysis and deep learning methodologies. A number of studies have indicated superior fault classification results when employing CNNs trained on images obtained from vibration, current, acoustic, and temperature data. [12]

However, most of the current methods for creating images have been formulated to enhance the capacity for classification of the system rather than physical interpretability. In such situations, it becomes hard to relate the patterns in the images produced to the operational conditions of the system being monitored. As a result, the physical interpretation of the produced visual information becomes a challenge.

2.3 Interpretable and Physics-Aware Fault Diagnosis

To overcome the issues related to transparency when adopting only data-based solutions, recent interest has been paid to developing explainable and physics-informed fault diagnostics. They try to combine physical knowledge, engineering intuition, and machine learning methods with the aim of enhancing both accuracy and interpretation of the proposed models. In general, such models are more applicable to industrial problems where understanding of the root cause of a problem is crucial

along with its identification. [13], [14]

Some works on using physical descriptors, model-driven features, and XAI algorithms for rotating machines and power electronics systems have already been published. Nevertheless, although the transparency is increased due to their use, very few works have addressed the issue of physically structured visualization which takes into account the electrical, thermal, and electro-thermal aspects simultaneously. [15]

Unlike previous work, the current work presents a physically organized Electro-Thermal State Matrix (ETSM), which classifies electrical, thermal, and electro-thermal features into their respective physical layers before creating a visual representation of the fault. Chromatic fingerprints generated from the physical states space are not directly obtained from sensors' measurements but are obtained from a physically meaningful state space.

2.4 Relationship to earlier chromatic-monitoring work

Chromatic (colour-space) monitoring was introduced by the author for power-system protection: first for transmission-line fault diagnosis [16], and later for transformer inrush/fault discrimination [17] and HVDC fault classification in the Lab colour space [18]. In those works colour mapping was applied to electrical signal quantities. The present paper reuses only the general idea of representing system states as colour patterns. It differs in that (i) descriptors are first built as a physical state vector and arranged in an ETSM with separate electrical, thermal and electro-thermal layers before any colour mapping, (ii) it addresses PMSM inverter faults with combined electrical and thermal data, and (iii) it evaluates interpretability through importance, SHAP, ablation and distance analyses. No text or figures are reused from [16]–[18].

3 Dataset Description

For conducting the experiment, the publicly available PMSM inverter fault diagnosis dataset [2] is used. This dataset comprises 10,892 observations collected from an inverter-based Permanent Magnet Synchronous Motor (PMSM). There are nine operating classes included in the dataset, among which one is the normal operating condition, and others are inverter fault operating conditions. The data are recorded at 10 Hz, and each class is one continuous recording, so the dataset contains nine recordings in total and neighbouring samples are strongly correlated.

The data set comprises both electrical and thermal parameters from the PMSM drive system. The electrical data set includes the parameters of the phase currents I_a and I_b , the DC-link voltage V_{DC} ,

the DC-link current I_{DC} , and the diagnostic voltage signal V_D . In addition, there are three temperature sensors T_1 , T_2 , and T_3 for monitoring the thermal performance of the inverter system. Raw ADC values were converted to physical units with the conversion formulas distributed with the dataset (current $0.074 \cdot (\text{ADC} - 512)$ A; temperature from the NTC Steinhart–Hart equation, in $^{\circ}\text{C}$). The variables are listed in Table 1, and the number of samples per class is given in Table 2.

In order to assist in the fault diagnosis process, the data set provides nine operational conditions that are labeled with F0-F8. The data set contains normal operational, open-circuit fault, short-circuit fault, and thermal fault conditions. Due to the existence of both electrical and thermal parameters in the data set, the data set can be used for electro-thermal fault representation studies.

Table 1. Measured variables of the PMSM inverter dataset

Variable	Type	Meaning	Unit
I_a, I_b	Electrical	Phase currents	A
V_{DC}	Electrical	DC-link voltage	V
I_{DC}	Electrical	DC-link current	A
V_D	Electrical	Diagnostic voltage signal	V
T_1, T_2, T_3	Thermal	Inverter temperature sensors	$^{\circ}\text{C}$

Table 2. Number of samples per class

Class	n	%
F0	4,295	39.4
F1	692	6.4
F2	1,122	10.3
F3	407	3.7
F4	341	3.1
F5	412	3.8
F6	854	7.8
F7	1,735	15.9
F8	1,034	9.5

4 Methodology

4.1 Physical State Vector Construction

In order to develop the suggested framework, one must initially map the raw measurements made for the PMSM into a compact physical form known as the Physical State Vector (PSV). Rather than using the actual sensor measurements themselves, the suggested framework identifies a collection of

physical attributes which describe the electrical, thermal, and electro-thermal behavior of the PMSM system driven by an inverter. Let

$$x(t) = [I_a, I_b, V_{DC}, I_{DC}, T_1, T_2, T_3, V_D] \quad (1)$$

denote the raw measurement vector at time $[t]$, where $[I_a]$ and $[I_b]$ represent phase currents, $[V_{DC}]$ and $[I_{DC}]$ denote the DC-link voltage and current, $[T_1, T_2, T_3]$ are temperature measurements, and $[V_D]$ is the diagnostic voltage signal. From these measurements, a set of electrical and thermal descriptors is derived to characterize the system state in terms of current imbalance, power transfer, temperature distribution, and thermal stability.

For describing the state of electrical condition of the system, the following four descriptors have been created. The current difference descriptor $[I_{DIFF}]$, which describes the difference between the phase currents, the current ratio descriptor $[I_{RATIO}]$ for indicating the relative relationship of the phase currents, the DC power descriptor $[P_{DC}]$ for representing electrical energy transfer, and the current magnitude descriptor $[I_{MAG}]$. They are defined as

$$I_{DIFF} = |I_a - I_b| \quad (2)$$

$$I_{RATIO} = \frac{|I_a|}{|I_a| + |I_b| + \varepsilon_I} \quad (3)$$

$$P_{DC} = |V_{DC} I_{DC}| \quad (4)$$

$$I_{MAG} = \sqrt{I_a^2 + I_b^2} \quad (5)$$

with $[\varepsilon_I]$ being a small constant (10^{-6}) that is used to avoid division by zero when both currents vanish. The ratio is bounded, $I_{RATIO} \in [0, 1)$, because phase currents are bipolar and a direct ratio I_a/I_b is unstable near zero crossings, which a small constant cannot prevent. This can be seen to be an electrical compact model that can capture changes related to faulty inverters such as unbalanced current and power flow.

4.2 Thermal and Electro-Thermal Descriptor Construction

In order to represent the thermal state of the PMSM system, four thermal parameters can be obtained based on the three available temperature data. Specifically, the average temperature $[T_{AVG}]$ is used to denote the global thermal loading state, and the temperature range $[T_{RANGE}]$ denotes the extent of thermal non-uniformity in the inverter. In addition, the temperature standard deviation $[T_{STD}]$ is used to describe the thermal dispersion state, while the thermal uniformity index $[T_{UNI}]$ is the normalized temperature. They are defined by

$$T_{AVG} = \frac{T_1 + T_2 + T_3}{3} \quad (6)$$

$$T_{\text{RANGE}} = \max(T_1, T_2, T_3) - \min(T_1, T_2, T_3) \quad (7)$$

$$T_{\text{STD}} = \sqrt{\frac{1}{3} \sum_{i=1}^3 (T_i - T_{\text{AVG}})^2} \quad (8)$$

$$T_{\text{UNI}} = \frac{1}{1 + T_{\text{RANGE}}/T_{\text{AVG,K}}} \quad (9)$$

T_{STD} is the population standard deviation, because the three sensors are the complete sensor set. In Eq. (9) temperatures are in kelvin ($T_K = T_{\text{°C}} + 273.15$), so the ratio is dimensionless and $T_{\text{UNI}} \in (0, 1]$. For three sensors T_{RANGE} , T_{STD} and T_{UNI} are closely related (Section 6.4). The suggested thermal indicators are intended to reflect not only the overall thermal state of the system but also its spatial thermal distribution that can be influenced by any inverter faults like open circuit, short circuit, and over-temperature.

Every base descriptor x_k is mapped to $[0,1]$ before the interaction descriptors are formed:

$$\tilde{x}_k = \text{clip}\left(\frac{x_k - m_k}{\max(M_k - m_k, \varepsilon_n)}, 0, 1\right) \quad (10)$$

where m_k and M_k are the minimum and maximum of x_k estimated on the training data only (inside each cross-validation fold), ε_n guards against a zero range, and $\text{clip}(\cdot)$ restricts test values outside the training range. This removes any train/test leakage from the normalization.

Together with electrical and thermal indicators, an additional electro-thermal indicator is suggested to provide a description of the interplay between electrical operation and thermal behavior. The reason for introducing this new indicator lies in the fact that inverter faults almost never occur only in electrical or thermal values but are connected with the interplay between electro-thermal processes. Therefore, four descriptors reflecting interaction are defined. The first one takes into account power flow and average temperature, the second one reflects the connection between current imbalance and thermal dispersion, the third one describes the effect of the interplay between electrical loading and temperature dispersion, and the fourth one is a bounded residual showing how hot the system is relative to its electrical load. They are computed on the normalized, dimensionless descriptors, so that quantities with different units are never multiplied, and are described by

$$\text{ET1} = \tilde{P}_{\text{DC}} \tilde{T}_{\text{AVG}} \quad (11)$$

$$\text{ET2} = \tilde{I}_{\text{DIFF}} \tilde{T}_{\text{RANGE}} \quad (12)$$

$$\text{ET3} = \tilde{P}_{\text{DC}} \tilde{T}_{\text{RANGE}} \quad (13)$$

$$\text{ET4} = (\tilde{T}_{\text{AVG}} - \tilde{P}_{\text{DC}} + 1) / 2 \quad (14)$$

The electro-thermal descriptors have no SI units and are heuristic interaction indices, hypotheses about coupling and not measured physical quantities; their value is tested in Section 6.4. The ratio $|P_{\text{DC}}|/(I_{\text{MAG}} + \varepsilon)$ named “Electrical Energy Density” in an earlier version has units of volts and contains no thermal term, so it was removed from the ETSM and is examined only in the ablation. The electro-thermal descriptors can be considered a concise way to represent coupling mechanisms that take place between the electrical load and thermal behavior, to the extent that the ablation supports it.

4.3 Electro-Thermal State Matrix (ETSM)

While the suggested Physical State Vector offers a concise and physically interpretable description of the PMSM operating states, the extracted features are maintained as an unstructured collection of descriptors. In order to preserve the physical associations between the groups of descriptors and allow for a subsequent encoding process using color space, the Electro-Thermal State Matrix (ETSM) is presented.

The suggested matrix is built based on the three-layer structure reflecting the three main physical domains that are involved in the fault behavior of the inverter. The first layer corresponds to the electrical state of the system, while the second one reflects its thermal state. The third layer reflects the interactions between the two aforementioned physical domains. Thus, the ETSM is represented by

$$\text{ETSM} = \begin{bmatrix} \tilde{I}_{\text{DIFF}} & \tilde{I}_{\text{RATIO}} & \tilde{P}_{\text{DC}} & \tilde{I}_{\text{MAG}} \\ \tilde{T}_{\text{AVG}} & \tilde{T}_{\text{RANGE}} & \tilde{T}_{\text{STD}} & \tilde{T}_{\text{UNI}} \\ \text{ET1} & \text{ET2} & \text{ET3} & \text{ET4} \end{bmatrix} \quad (15)$$

Each row is indicative of a coherent physical state, while columns include the descriptors related to a common operational facet. In such a way, a compact $[3 \times 4]$ state representation that can preserve the hierarchy of the fault information is achieved. The matrix is dimensionless, and the ordering of columns within a row is a convention and not a physical one (Table 3).

The rationale for ETSM is two-fold. First of all, ETSM allows for a clear segregation of the effects of electrical, thermal, and electro-thermal processes on the representational process, making the representation more transparent. The second reason for using ETSM is connected to the matrix form, which makes it possible to use it as an intermediate representation for visualization, meaning that the translation of descriptors into a chromatic pattern is possible. In contrast to the feature vectors, ETSM preserves the information about the physical organization of descriptors, making the analysis both numerical and visual possible.

In addition to that, the structural nature of ETSM allows for comparing fault conditions based on their physical signature characteristics. This is shown in Section 6.8, where classes with similar fault characteristics create ETSMs with lower inter-class distance values compared to those created by classes with different fault behaviors. Thus, ETSM acts as a basic representation of the proposed model and is the main building block for the chromatic fingerprint generation as detailed in the next subsection.

Table 3. Descriptors of the revised ETSM

Layer	Descriptors	Physical meaning
Electrical	I_{DIFF} , I_{RATIO} , P_{DC} , I_{MAG}	Current imbalance, power transfer, current level
Thermal	T_{AVG} , T_{RANGE} , T_{STD} , T_{UNI}	Thermal level, spread and uniformity
Electro-thermal	ET1, ET2, ET3, ET4	Heuristic load-temperature interaction indices

4.4 Chromatic Fingerprint Generation

In order to create a visual representation of the physical state of electro-thermal system, the proposed method converts the ETSM into a chromatic fingerprint. Unlike other approaches, which encode raw values of the sensors into image pixels, the proposed method visualizes the physical state of the system represented by the ETSM.

The first row of ETSM is allocated for the red channel, which represents the electrical activity of the inverter. The second row of ETSM is allocated for the green channel, which defines the thermal condition of the system. The third row of ETSM is allocated for the blue channel, which represents the electro-thermal coupling interactions. Let

$$R = [\tilde{I}_{DIFF}, \tilde{I}_{RATIO}, \tilde{P}_{DC}, \tilde{I}_{MAG}] \quad (16)$$

$$G = [\tilde{T}_{AVG}, \tilde{T}_{RANGE}, \tilde{T}_{STD}, \tilde{T}_{UNI}] \quad (17)$$

$$B = [ET1, ET2, ET3, ET4] \quad (18)$$

denote the electrical, thermal, and electro-thermal descriptor groups, respectively. The descriptors are normalized into the range [0,1] by Eq. (10), with bounds estimated on the training data only.

4.5 Image Construction and Resizing Process

In turn, after normalization, the aforementioned three types of descriptors are placed within separate chromatic channels to generate the first version of an RGB representation of the ETSM. In particular,

the electrical descriptors correspond to the red channel, the thermal descriptors to the green one, and electro-thermal descriptors to the blue channel. Thus, a compact chromatic state representation is formed in which different color channels represent different features of the working conditions of the PMSM. Column j of the ETSM forms one pixel (R_j, G_j, B_j) of a 1×4 colour image; the descriptors that share a pixel are not physically related, so pixel colour is a visual convention.

Since there are only twelve descriptors in the original ETSM that are organized in the $[3 \times 4]$ pattern, the size of the representation in question is very small. For visualization and for compatibility with image-based models, the RGB matrix is resized via interpolation. Let

$$I_{RGB} = f(R, G, B) \quad (19)$$

denote the initial chromatic state representation derived from the ETSM. The final chromatic fingerprint is obtained through a resizing operation (bilinear interpolation)

$$CF = \text{Resize}(I_{RGB}, 64 \times 64) \quad (20)$$

where CF is the Chromatic Fingerprint image formed. Thus, the resizing method retains the relative spatial distribution of the descriptor groups while forming a visually understandable pattern that can be processed by standard image processing and machine learning methods. Resizing is not needed by the classifier of Section 4.6, which uses summary statistics, and Section 6.6 shows that it neither helps nor creates artificial patterns.

However, the obtained fingerprints do not depict single measurements from a particular sensor. Each fingerprint is rather an image of the general electro-thermal state of the PMSM system. Therefore, faults with the same electro-thermal state will have similar fingerprints, while those with completely different operating states will form different fingerprints.

4.6 Classification Framework

To test the efficacy of the developed representation, the created chromatic fingerprints are transformed into an ensemble of low dimensional image descriptors before classification. Instead of utilizing deep learning-based convolutional neural networks, the aim of this research is to examine if the suggested ETSM-based representation itself carries enough diagnostic information. Thus, the lightweight feature extraction process is used.

Each fingerprint is separately characterized by the statistical descriptors using the three color channels: red, green, and blue. The mean, standard deviation, minimum, and maximum values of each channel are calculated resulting in the twelve dimensional feature

vector.

$$F = \begin{bmatrix} R_{\text{mean}}, R_{\text{std}}, R_{\text{min}}, R_{\text{max}}, \\ G_{\text{mean}}, G_{\text{std}}, G_{\text{min}}, G_{\text{max}}, \\ B_{\text{mean}}, B_{\text{std}}, B_{\text{min}}, B_{\text{max}} \end{bmatrix} \quad (21)$$

that summarizes the chromatic distribution of the electro-thermal state.

The extracted feature vectors are then classified through the Random Forest classifier (100 trees, default scikit-learn settings, fixed random seed). Random Forest has been chosen due to its strength, efficiency, and feature importance for explainability evaluation. Repeated stratified cross-validation and blocked temporal cross-validation (Section 5.2) are employed to evaluate the classifier while maintaining the fault category distribution in the dataset. Performance evaluation has been performed with Accuracy and Macro-F1 metrics.

By utilizing PSV construction, ETSM representation, chromatic fingerprints extraction, and classification through machine learning approach, the proposed framework forms a full pipeline for interpretable PMSM inverter fault diagnosis by means of electro-thermal states.

5 Experimental Setup

5.1 Representations compared

The experimental setup that has been used for evaluation of the proposed Physical State Vector (PSV), Electro-Thermal State Matrix (ETSM), and Chromatic Fingerprint representation for PMSM inverter fault diagnosis is described in this section. For this purpose, the publicly available dataset for PMSM inverter fault diagnosis has been used, and it consists of 10,892 samples collected for various PMSM inverter fault diagnoses, including 4,295 samples of normal operation and 6,597 samples of various inverter faults divided into nine classes (F0–F8) of faults such as open-circuit faults, short-circuit faults, and thermal faults.

For the evaluation of the contribution of the proposed representation in different stages of the proposed framework, four different experimental setups have been considered. In the first experimental setup, the original sensor measurements (RAW) with the combination of the electrical and thermal variables have been utilized. The second experimental setup makes use of the PSV_{BASIC} representation with the derived electrical and thermal variables. The third experimental setup includes the PSV_{FULL} representation with the additional proposed electro-thermal variables. The fourth experimental setup has the proposed Chromatic Fingerprint representation obtained from the ETSM structure. Each of the PSV and fingerprint setups is evaluated

both with the descriptor definitions of the original submission and with the corrected definitions of Section 4; the corrected PSV_{FULL} is also called ETSM-12.

A Random Forest classifier was chosen for all classification tasks owing to its stability, computational efficiency, and compatibility with explainability analysis. Hyperparameter optimization was purposefully not performed to ensure fair comparison among the studied representations and to analyze the impact of the introduced representation building and chromatic coding steps.

5.2 Validation protocols

Two protocols are used instead of a single 80:20 stratified holdout. (i) **Random**: repeated stratified 5-fold cross-validation (5 repeats, 25 folds for the main comparison; 2 repeats for ablations). (ii) **Blocked**: each class recording is cut into 10 contiguous time blocks; fold k tests block k of every class, and 30 samples (3 s) on both sides of the test block are removed from the training data. Because every class is a single recording, random folds put neighbouring samples in both training and test sets: 96% of test samples in the random folds have a training sample 0.1 s away, against 0% in blocked folds. Blocked cross-validation is therefore the primary, leakage-controlled protocol; random folds are shown for comparison with the literature. All preprocessing is fitted inside the training part of each fold. Exact duplicates between training and test rows are rare (0.2%), and a label-permutation test gives 33.2% accuracy, at chance level (the majority-class rate is 39.4%).

5.3 Metrics and statistics

Diagnostic accuracy was measured based on the Accuracy metric and Macro-F1 metric. The former represents general classification ability while the latter allows for evaluating all fault classes equally despite differences in the number of samples in them. Results are reported as mean $\pm$ SD over folds, with 95% confidence intervals using the Nadeau–Bengio correction for correlated resampled folds, and representations are compared with a corrected resampled paired t-test with Holm correction. Apart from that, Feature Importance analysis (impurity and grouped permutation importance), SHAP explainability analysis, Principal Component Analysis (PCA), layer, sensor and descriptor ablation, confusion matrices, descriptor correlation (Spearman, VIF), and fingerprint distance analysis (Mantel test) were utilized to examine interpretability and discriminative properties of the proposed representations. All tables and figures of Section 6 were generated by a single script (run_experiments.py), which is available from the author on request and runs all experiments on the public dataset.

6 Results

6.1 Classification performance

Raw sensors give the best result, $99.17 \pm 0.17\%$ in random and $98.08 \pm 3.01\%$ in blocked cross-validation (Table 4, Figure 1 (Appendix)). The revised ETSM-12 descriptors reach 96.64% and 92.26%, and the chromatic fingerprint 95.50% and 89.38%. The fingerprint step costs 1.1 points of accuracy in random and 2.9 in blocked cross-validation relative to the ETSM-12 descriptors, a significant drop in Macro-F1 (Holm-corrected $p = 0.009$ in blocked folds, $p < 0.001$ in random folds), probably because the four statistics per channel do not keep the identity of each descriptor. PSV_{FULL} is not more accurate than PSV_{BASIC} (Holm $p = 0.41$). Blocked folds have a standard deviation of 6–7 points, so performance depends on which part of each recording is held out. The submitted pipeline gives 95.42% and 89.48%, which reproduces the original result; the corrections to the descriptors and the leakage-free normalization do not change it (Section 6.6).

In summary, the representation keeps a large part of the diagnostic information, but under the leakage-controlled protocol the loss relative to the raw sensors is 8.7 points of accuracy for the fingerprint. The benefit of the representation is its structure and interpretability, and it is not a gain in accuracy.

Table 4. Accuracy (mean $\pm$ SD, %) and Macro-F1 (%) of the investigated representations Accuracy panel.

Representation	Random	Blocked
RAW	99.17 ± 0.17	98.08 ± 3.01
PSV _{BASIC} (submitted)	97.04 ± 0.31	92.64 ± 6.01
PSV _{FULL} (submitted)	96.70 ± 0.38	92.22 ± 5.94
Fingerprint (submitted spec.)	95.42 ± 0.47	89.48 ± 6.81
PSV _{BASIC} (revised)	96.81 ± 0.28	92.74 ± 5.96
ETSM-12 = PSV _{FULL} (revised)	96.64 ± 0.32	92.26 ± 6.12
Chromatic Fingerprint (revised)	95.50 ± 0.48	89.38 ± 6.60

Table 4. Accuracy (mean $\pm$ SD, %) and Macro-F1 (%) of the investigated representations Macro-F1 panel.

Representation	Random	Blocked
RAW	98.94	97.88
PSV _{BASIC} (submitted)	95.87	90.04
PSV _{FULL} (submitted)	95.38	89.55
Fingerprint (submitted spec.)	93.39	85.03
PSV _{BASIC} (revised)	95.52	90.17
ETSM-12 = PSV _{FULL} (revised)	95.31	89.61
Chromatic Fingerprint (revised)	93.62	84.87

6.2 Feature-space analysis

Figure 2 (Appendix) shows two-dimensional PCA projections of the standardised raw sensors and of the revised ETSM-12 descriptors. The first two components explain 41.8% of the variance of the raw data and 74.9% of the ETSM-12 descriptors. The silhouette score with respect to the class labels is -0.03 for the raw data and 0.02 for ETSM-12 in the full feature space (-0.19 and -0.01 in the projection). Both are close to zero, so the ETSM-12 space is only modestly more compact, and neither separates the classes well in an unsupervised linear projection; separation is achieved by the supervised classifier.

6.3 Descriptor importance

Figure 3 (Appendix) shows impurity importance of the twelve revised descriptors for a Random Forest trained on the ETSM-12 descriptors (mean $\pm$ SD over 25 models in random folds and 10 models in blocked folds). This model differs from the fingerprint classifier, so Figure 3 (Appendix), Figure 4 (Appendix) and Figure 7 (Appendix) describe the information content of the ETSM and not the internal mechanics of the fingerprint classifier. In blocked folds T_{AVG} ($21.0 \pm 1.2\%$), T_{UNI} ($19.3 \pm 0.9\%$), T_{RANGE} ($17.3 \pm 0.7\%$) and T_{STD} ($16.3 \pm 0.8\%$) dominate, followed by ET4 (9.0%); the electrical descriptors are each below 3%. Grouped permutation importance gives a different ranking inside the thermal layer: permuting T_{AVG} lowers Macro-F1 by 26.3 ± 5.3 points and T_{STD} by 15.1 ± 5.7 , but T_{RANGE} by only 2.0 ± 2.2 , because these descriptors are almost interchangeable.

6.4 Layer contribution, ablation and redundancy

Table 5 summarizes the layer contributions. Impurity shares are $73.3 \pm 0.9\%$ (thermal), $18.7 \pm 0.9\%$ (electro-thermal) and $8.1 \pm 0.2\%$ (electrical) in random folds, and $73.9 \pm 0.9\%$, $18.3 \pm 1.1\%$ and $7.8 \pm 0.6\%$ in blocked folds; they sum to 100% (the 99.9% reported earlier was rounding, and the 77.5/13.9/8.5% values are superseded by the revised descriptors). Layer ablation gives: thermal only 95.87 / 91.86% (random / blocked), electrical only 54.46 / 54.67%, electro-thermal only 92.44 / 87.38%, E+T 96.80 / 92.74%, T+X 95.89 / 91.34%, E+X 92.72 / 88.61%, and all layers 96.64 / 92.26% (Figure 4 (Appendix)). The electro-thermal layer adds nothing measurable: E+T without it is as accurate as all three layers, and permuting the layer lowers Macro-F1 by only 2.5 points. Its 18% impurity share is not evidence of independent information, because its descriptors are functions of temperature; ET4 is an exact linear combination of $\tilde{T}_{AVG}$ and $\tilde{P}_{DC}$ (VIF is infinite), and ET1–ET3 contain $\tilde{T}_{AVG}$ or $\tilde{T}_{RANGE}$.

Within the thermal layer, T_{RANGE} , T_{STD} and T_{UNI} are almost perfectly rank-correlated ($|\rho| \geq 0.998$; Figure 5 (Appendix)), with VIF values of 308–7,792. Dropping T_{UNI} and T_{RANGE} together lowers blocked accuracy from 92.26% to 90.97%. Dropping T_{STD} lowers it to 89.96% and T_{AVG} to 90.78%, whereas dropping any other single descriptor changes it by at most 0.3 points. The thermal layer therefore holds about two independent descriptors (T_{AVG} and a spread measure), and importance is shared among the correlated ones. The earlier statement that ET1 was the most important electro-thermal descriptor is not supported: ET4 ranks highest in impurity, and individual electro-thermal descriptors have permutation drops below 1 point.

Table 5. Layer contribution (impurity share and grouped permutation) and layer ablation (accuracy, %) Importance measures.

Layer	Impurity share (blocked)	Perm. F1 drop (blocked, pts)
Electrical	$7.8 \pm 0.6\%$	17.5 ± 2.4
Thermal	$73.9 \pm 0.9\%$	76.2 ± 7.6
Electro-thermal	$18.3 \pm 1.1\%$	2.5 ± 1.7
All layers	100%	—

Table 5. Layer contribution (impurity share and grouped permutation) and layer ablation (accuracy, %) Layer ablation.

Layer	Only this layer (random / blocked)	Without this layer (random / blocked)
Electrical	54.5 / 54.7	95.9 / 91.3
Thermal	95.9 / 91.9	92.7 / 88.6
Electro-thermal	92.4 / 87.4	96.8 / 92.7
All layers	96.6 / 92.3	—

6.5 Sensor ablation and dataset dependence

Table 6 shows that without the temperature sensors the raw-sensor model reaches only 55%, close to the 39.4% majority-class rate, while temperature alone gives 98.7% and 97.6%. In this dataset the discriminative information is therefore almost entirely thermal. The class statistics show a very small within-class temperature spread (standard deviation of T_{AVG} is 0.0–0.4 °C in F0–F5), while class means of F0–F5 differ by tenths of a degree (12.2–13.0 °C) and the thermal-fault classes F6–F8 have means of 16.8–18.8 °C. Because each class is one recording, the classifier may partly recognise the recording and not the fault. This cannot be excluded with the available data.

Table 6. Raw-sensor ablation, accuracy (%) in random /blocked cross-validation

Sensors used	Random	Blocked
All 8	99.16	98.08
Temperature only (T1–T3)	98.65	97.59
Without T1–T3	55.10	55.15
Currents only (I_a , I_b , I_{DC})	54.45	54.57
Without V_D	99.18	98.19
T1 only /T2 only /T3 only	85.7 /83.6 / 66.3	82.2 /79.2 / 58.5

6.6 Sensitivity, normalization and resizing controls

Table 7 and Table 8 show that the corrections to Eqs. (3), (9) and (10) are needed for correctness but have almost no effect on accuracy: ε changes it by at most 0.11 points (random) and 0.23 (blocked), and fitting normalization on the whole dataset, as in the submission, gives 95.38% against 95.46%. Normalization variants change the fingerprint accuracy by up to 1.4 points (random) and 1.8 points (blocked). Resizing makes no practical difference, and shuffling the columns does not change the

result, because the classifier uses order-invariant statistics. The 64×64 image therefore adds nothing for classification and is kept only for visualisation. The ETSM-12 descriptors used directly are 1.1–2.9 points more accurate than the fingerprint statistics.

Table 7. Sensitivity of accuracy (%), random / blocked

Variant	Random	Blocked
$\varepsilon_I = 10^{-9} / 10^{-6} / 10^{-3} / 10^{-1}$ (revised I_{RATIO} , ETSM-12)	96.60 / 96.64 / 96.61 / 96.53	92.18 / 92.26 / 92.19 / 92.03
Submitted $I_a/(I_b+\varepsilon)$, ε from 10^{-9} to 10^{-1} (PSV _{FULL})	96.64–96.69	92.11–92.22
Fingerprint, train-fit min–max	95.46	89.38
Fingerprint, robust 1–99 percentile	95.25	89.01
Fingerprint, z-score squashed to [0,1]	94.67	88.48
Fingerprint, no scaling	96.06	90.29
Fingerprint, global min–max (leaky, as submitted)	95.38	89.46

Table 8. Resizing controls for the fingerprint, accuracy (%), random /blocked

Variant	Random	Blocked
No resize (4 values per row)	95.48	89.55
Nearest neighbour	95.48	89.55
Bilinear	95.46	89.38
Bicubic	95.36	89.34
Bilinear, columns shuffled	95.27	89.35
ETSM-12 flattened (no image statistics)	96.64	92.26

6.7 Confusion matrix

Figure 6 (Appendix) shows the row-normalised confusion matrix of the fingerprint Random Forest in blocked folds (pooled out-of-fold predictions; rows are true classes, each row sums to 1, so the diagonal is the recall). Recall in blocked folds is 0.99 (F0), 0.83 (F1), 0.84 (F2), 0.74 (F3), 0.92 (F4), 0.98 (F5), 0.81 (F6), 0.90 (F7) and 0.68 (F8); in random folds it is 0.99, 0.85, 0.84, 0.86, 0.93, 0.97, 0.96, 0.98 and 0.98. The largest confusions are $F8 \leftrightarrow F6$ (0.23 and 0.19) and $F3 \rightarrow F2$ (0.17), and $F1 \rightarrow F2$ (0.09) also appears. Errors concentrate in the thermal-fault classes F6–F8 and in F1–F3, and the normal class is recognised almost perfectly.

6.8 Chromatic fingerprint analysis

Figure 7 (Appendix) shows the class-mean fingerprints (each of four pixels enlarged for display) and Figure 8 (Appendix) the distance matrices. For each class c , the mean fingerprint μ_c is the average over its samples, and $d_{ij} = \|\mu_i - \mu_j\|_2$ over the $64 \times 64 \times 3$ image. Because this ignores within-class spread, $\tilde{d}_{ij} = d_{ij}/(s_i + s_j)$ is also shown, with s_c the mean distance of samples to μ_c . The closest pairs are F0–F2 (4.1), F1–F3 (4.4), F1–F5 (5.3) and F7–F8 (5.4); F6 is farthest from F1–F5 (40–44), and F0–F6 is 38.3. The Spearman correlation between d_{ij} and the symmetrised confusion rate is $\rho = -0.827$ (Mantel permutation $p < 0.001$) for the Euclidean distance and -0.845 for $\tilde{d}_{ij}$ in random folds (-0.814 and -0.838 in blocked folds): classes that are far apart in fingerprint space are confused less. An earlier statement that F6 and F7 are close is not supported (F6–F7 is 16.2, F6–F8 14.0). Because the fingerprint is computed from the same descriptors, this correlation shows that the fingerprint reflects class similarity in descriptor space and not an independent physical validation.

6.9 SHAP analysis

SHAP values were computed with TreeExplainer for the Random Forest trained on the twelve ETSM descriptors, using 400 held-out samples of the first blocked fold. Figure 9 (Appendix) shows the mean absolute SHAP value of each descriptor stacked by class; bar length shows magnitude only, and segments show which classes the descriptor helps to recognise. T_{AVG} ranks first (summed mean $|\text{SHAP}|$ 0.59), followed by T_{UNI} (0.29), T_{STD} (0.26), T_{RANGE} (0.25) and ET4 (0.24); I_{MAG} is the largest electrical descriptor (0.08). Direction (positive values push the prediction toward a class) is available in the beeswarm plots in the supplementary results. The ranking agrees with the impurity and permutation results, subject to the correlated-descriptor cautions of Section 6.4.

6.10 Second classifiers

With HistGradientBoosting the ranking is the same: RAW 99.29 / 97.63%, ETSM-12 97.23 / 93.67% and fingerprint 96.06 / 91.21% (random / blocked). With logistic regression it is RAW 93.99 / 92.78%, ETSM-12 91.25 / 89.71% and fingerprint 88.59 / 87.04%. The conclusions are therefore not specific to Random Forest.

6.11 Check with the converted file distributed with the dataset

The comparison of Table 4 was repeated on processed_data/converted_dataset.csv exactly as distributed with the dataset, whose temperature columns are negative values in °C (the file seems to apply a different conversion from the one

used in the main analysis, and Eq. (9) is applied after adding 273.15). The results are in Table 9. They are within 0.4 points of Table 4 for every representation, and the conclusions do not change: the fingerprint is significantly less accurate than the ETSM-12 descriptors in Macro-F1 in blocked folds (Holm-corrected $p = 0.015$) and in random folds ($p < 0.001$), and PSV_{FULL} is not more accurate than PSV_{BASIC} .

Table 9. Accuracy (mean $\pm$ SD, %) and Macro-F1 (%) on the distributed converted_dataset.csv
Accuracy panel.

Representation	Random	Blocked
RAW	99.17 $\pm$ 0.16	98.08 $\pm$ 3.01
PSV_{BASIC} (submitted)	97.04 $\pm$ 0.32	92.58 $\pm$ 5.87
PSV_{FULL} (submitted)	96.70 $\pm$ 0.39	92.47 $\pm$ 6.15
Fingerprint (submitted spec.)	95.67 $\pm$ 0.45	89.83 $\pm$ 6.44
PSV_{BASIC} (revised)	96.83 $\pm$ 0.32	92.63 $\pm$ 6.09
ETSM-12 = PSV_{FULL} (revised)	96.58 $\pm$ 0.39	92.31 $\pm$ 6.10
Chromatic Fingerprint (revised)	95.42 $\pm$ 0.42	89.62 $\pm$ 6.46

Table 9. Accuracy (mean $\pm$ SD, %) and Macro-F1 (%) on the distributed converted_dataset.csv
Macro-F1 panel.

Representation	Random	Blocked
RAW	98.94	97.87
PSV_{BASIC} (submitted)	95.84	89.96
PSV_{FULL} (submitted)	95.31	89.76
Fingerprint (submitted spec.)	93.85	85.74
PSV_{BASIC} (revised)	95.53	89.93
ETSM-12 = PSV_{FULL} (revised)	95.18	89.48
Chromatic Fingerprint (revised)	93.48	85.41

7 Discussion

Raw sensors give the highest accuracy, and the ETSM and fingerprint representations lose accuracy: 6 points for the ETSM-12 descriptors and 8.7 points

for the fingerprint in blocked cross-validation (2.5 and 3.7 points in random folds). This loss is the price paid for a compact, physically structured representation; it is larger than the 2–4 points that random cross-validation suggests, and it is more variable (SD 6–7 points). The fingerprint representation should therefore be regarded as an interpretable summary of the system state and not as an accuracy-improving transformation.

The analyses agree that thermal descriptors carry most of the discriminative information in this dataset: 73.9 $\pm$ 0.9% of impurity importance, the largest permutation drop, and a model with temperature alone almost as accurate as the raw sensors. They do not show that thermal behaviour governs fault progression: the dataset consists of steady-state class labels, importance measures are associative, and the dominance may partly reflect how the dataset was built. Each class is a single recording with very small within-class temperature spread and class means that differ by tenths of a degree, so the classifier may partly recognise the recording and not the fault. Validation on data with several recordings per class is needed.

The electro-thermal layer did not demonstrate complementary information. Removing it does not reduce accuracy, its descriptors are functions of temperature, and ET4 is a linear combination of two other descriptors. The layer remains a way to organise and visualise load–temperature interactions, and whether better-designed interaction descriptors add information is an open question.

The fingerprint distances correlate with confusion ($\rho = -0.83$), which supports using the fingerprint to compare fault states; since both are derived from the same descriptors, this is a consistency check and not independent validation. The 64×64 resizing does not affect classification and the classifier uses order-invariant statistics, so the spatial layout of the image carries no information in the present pipeline. A classifier that uses the spatial structure (for example a CNN on the ETSM) is future work.

The lightweight feature extraction and the Random Forest were chosen deliberately to test the representation. The second classifiers (Section 6.10) show the same ordering, so the conclusions are not specific to Random Forest.

7.1 Limitations

- A single public dataset and drive platform was used; no cross-dataset validation was done.
- Each class is a single recording, so recording identity and fault class are confounded. Blocked cross-validation removes temporal leakage but cannot remove this confounding.
- Only steady-state class labels are available; fault progression and degradation were not studied, and no claims about them are made.

- Importance measures are associative and affected by correlated descriptors; they do not establish causality.
- The electro-thermal descriptors are heuristic and were chosen with this dataset at hand.
- Hyperparameters were not tuned, and deep models were not evaluated.

7.2 Practical implications

The representation lets an engineer inspect a fault condition by electrical, thermal and electro-thermal descriptors, and compare fault classes through fingerprint distances. In this dataset, temperature sensing was the most informative source; whether this holds for other platforms and fault types needs validation, and it should not be taken as a general recommendation for monitoring.

8 Conclusions

This paper presented a PSV–ETSM–Chromatic Fingerprint representation for PMSM inverter fault diagnosis, with corrected and dimensionally consistent descriptors and a leakage-aware evaluation. On a public dataset the fingerprint reached $89.4 \pm 6.6\%$ accuracy and $84.9 \pm 8.9\%$ Macro-F1 in blocked cross-validation ($95.5 \pm 0.5\%$ and 93.6% in random folds), against $98.1 \pm 3.0\%$ for raw sensors. Thermal descriptors carried most of the discriminative information ($73.9 \pm 0.9\%$ of impurity importance), while the electro-thermal layer did not show complementary information. The fingerprint distance correlated with class confusion ($\rho = -0.83$), and the 64×64 resizing had no effect on classification. The results support the representation as a physically structured summary of the system state, at a cost in accuracy, and they are limited by the single dataset in which each class is one recording. Future work includes validation on multi-recording and multi-platform data, redesigned electro-thermal descriptors, models that use the spatial structure of the ETSM, and dynamic modelling of fault development.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the author(s) utilized artificial intelligence (AI) technologies solely for the purpose of linguistic refinement and grammatical correction. Following the application of these tools, the author(s) comprehensively reviewed, verified, and edited the resulting text. The author(s) maintain full accountability and responsibility for the accuracy, integrity, and final content of the publication.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Ziyad Almajali conceived the method, implemented the software, carried out the experiments and the analysis, and wrote the manuscript.

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Conflicts of Interest

The author has no conflicts of interest to declare that are relevant to the content of this article.

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APPENDIX

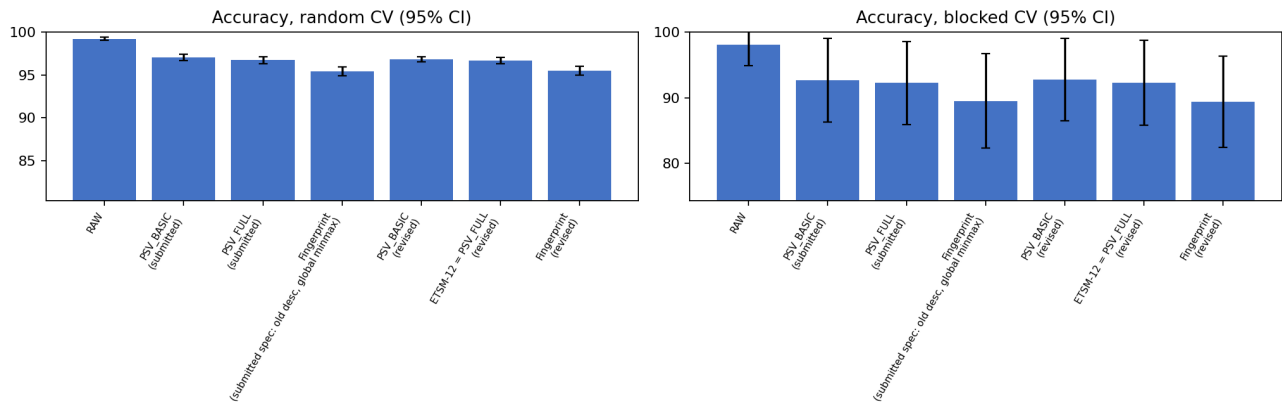


Fig. 1. Accuracy (95% CI) of the investigated representations under random and blocked cross-validation.

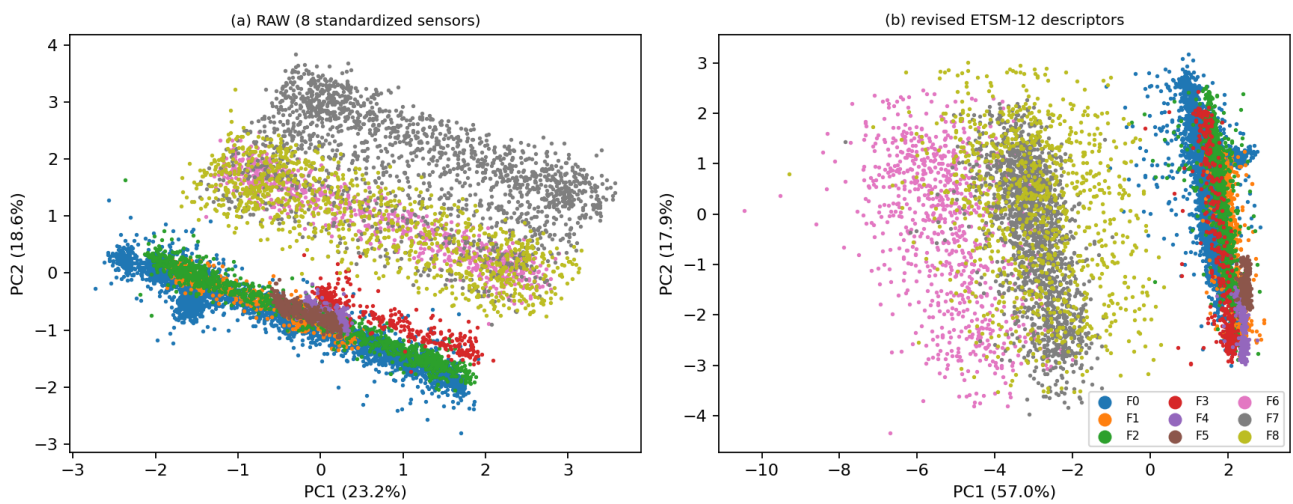


Fig. 2. PCA projections of (a) the standardised raw sensors and (b) the revised ETSM-12 descriptors.

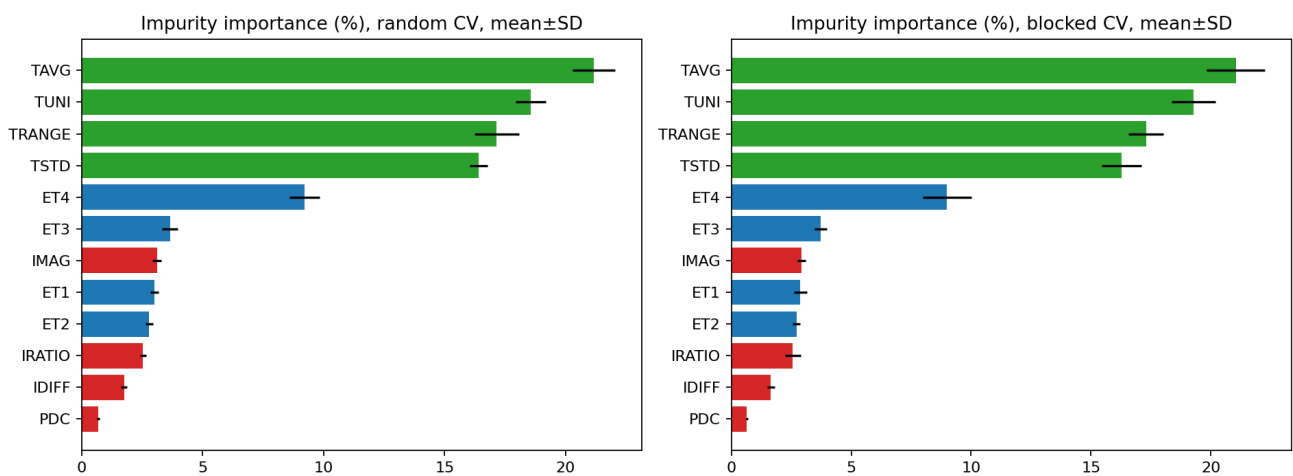


Fig. 3. Impurity importance of the ETSM descriptors (mean $\pm$ SD; red electrical, green thermal, blue electro-thermal).

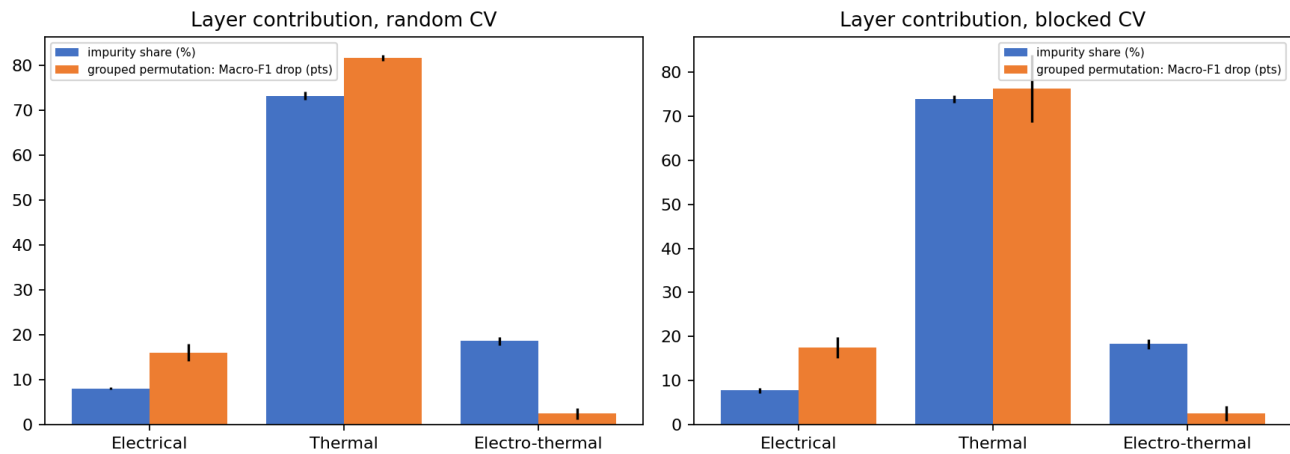


Fig. 4. Layer contribution by impurity share and grouped permutation (Macro-F1 drop).

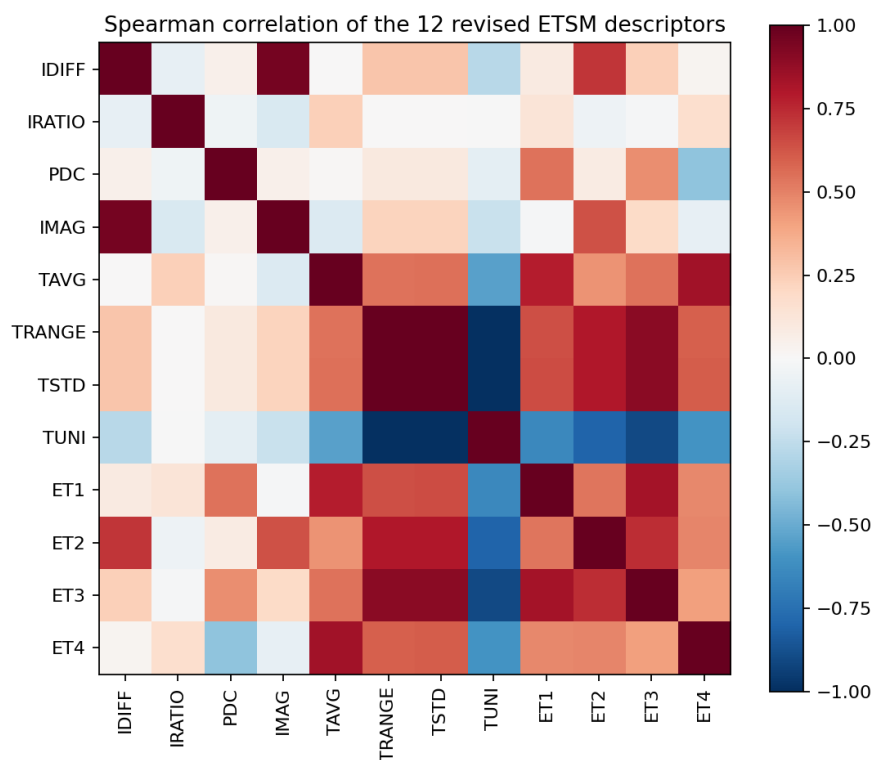


Fig. 5. Spearman correlation of the twelve revised ETSM descriptors.

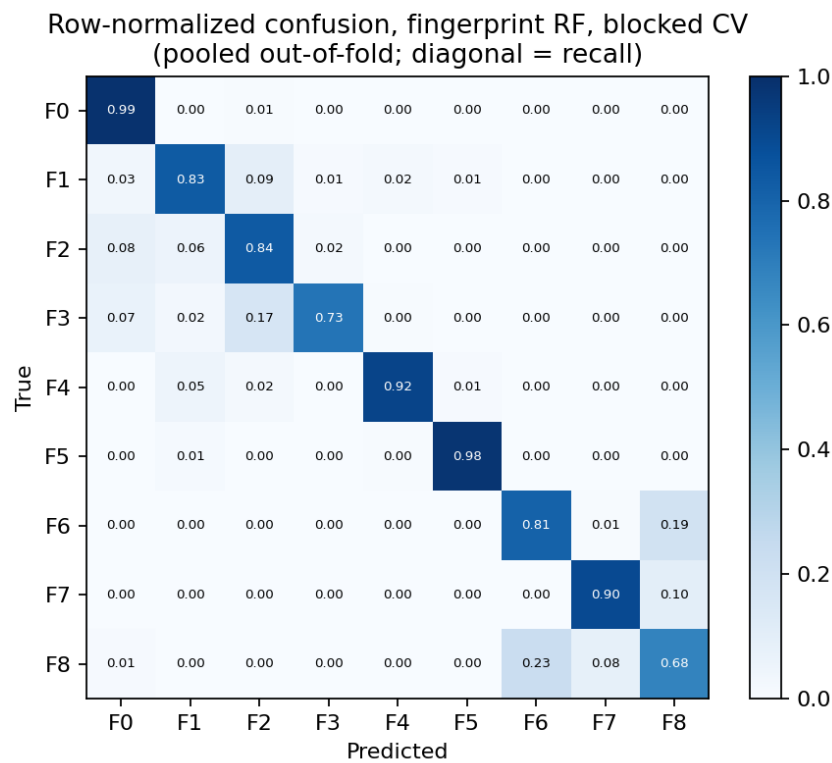


Fig. 6. Row-normalised confusion matrix of the fingerprint classifier (blocked CV).

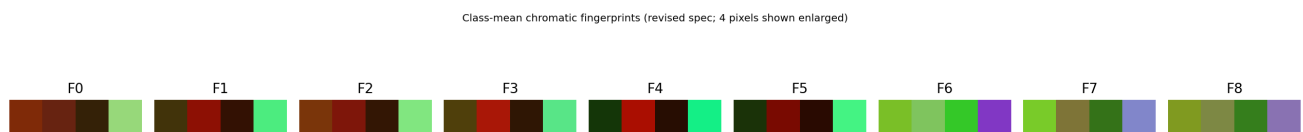


Fig. 7. Class-mean chromatic fingerprints.

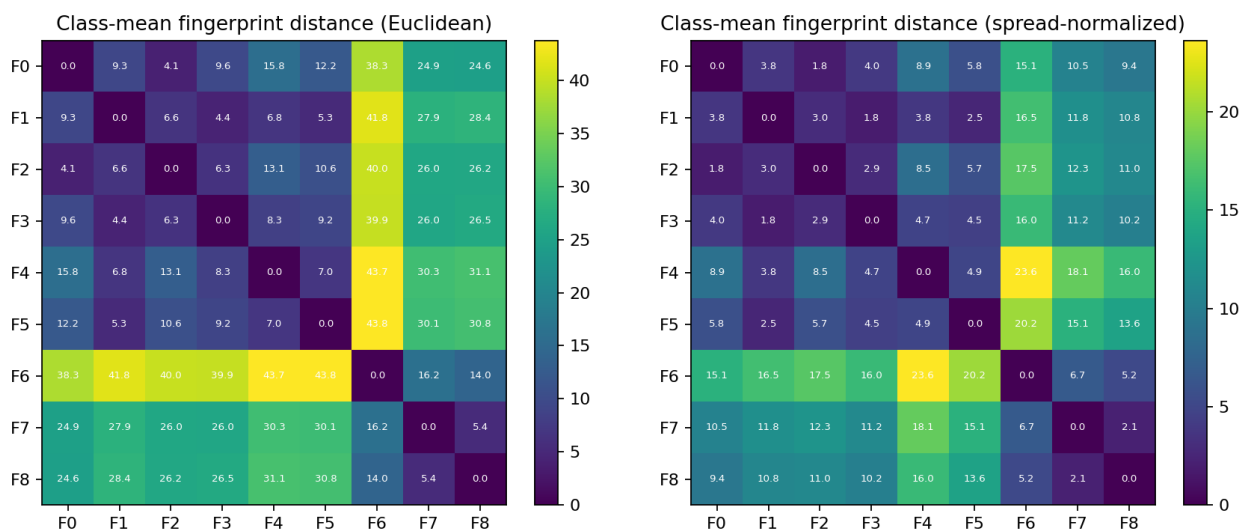


Fig. 8. Class-mean fingerprint distance matrices (Euclidean and spread-normalised).

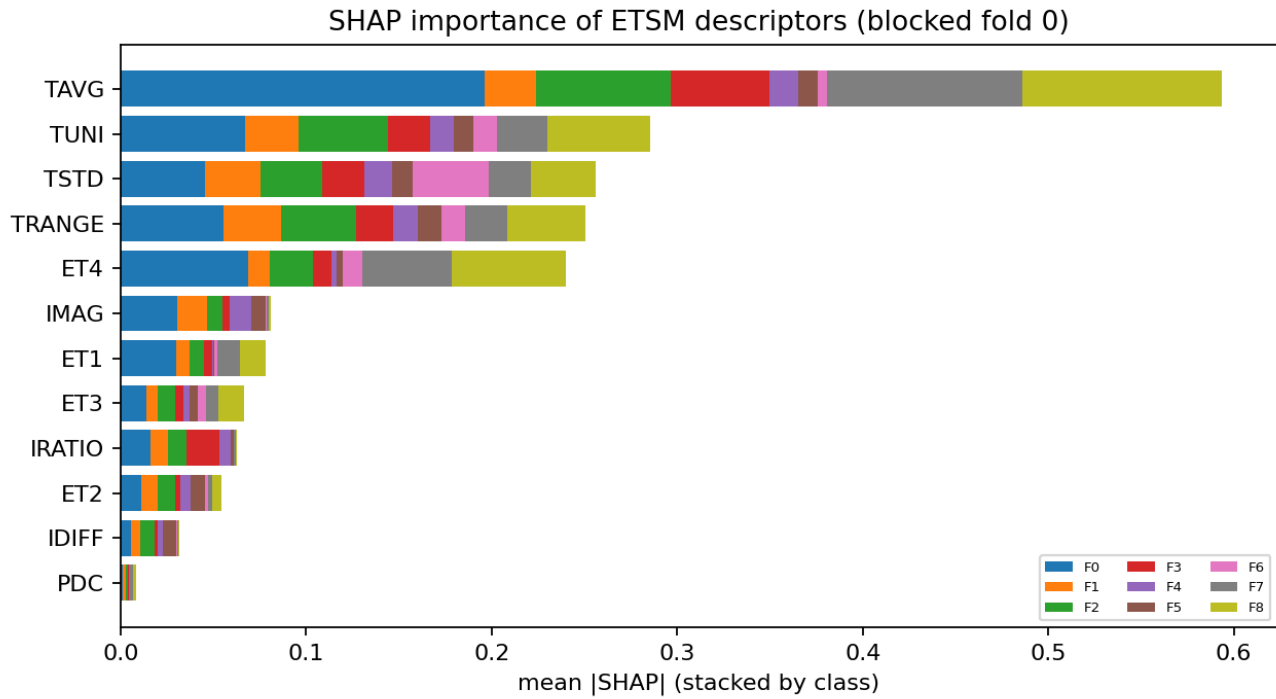


Fig. 9. Global SHAP importance of the ETSM descriptors (blocked fold 0).