The EMF-PNet framework has been further validated for diagnosing other fault types and applied to additional motor systems, with specific tests conducted on electrical faults (focusing on power quality disturbances) and non-linear motor systems (specifically brushless direct current motor (BLDCM)), as detailed below:

1) Testing on Electrical Faults: Power Quality Disturbance Diagnosis

To verify its adaptability to electrical faults, EMF-PNet was tested on power quality disturbance diagnosis (Fig. 1), a typical category of electrical faults involving voltage sags, swells, harmonics, and transients.

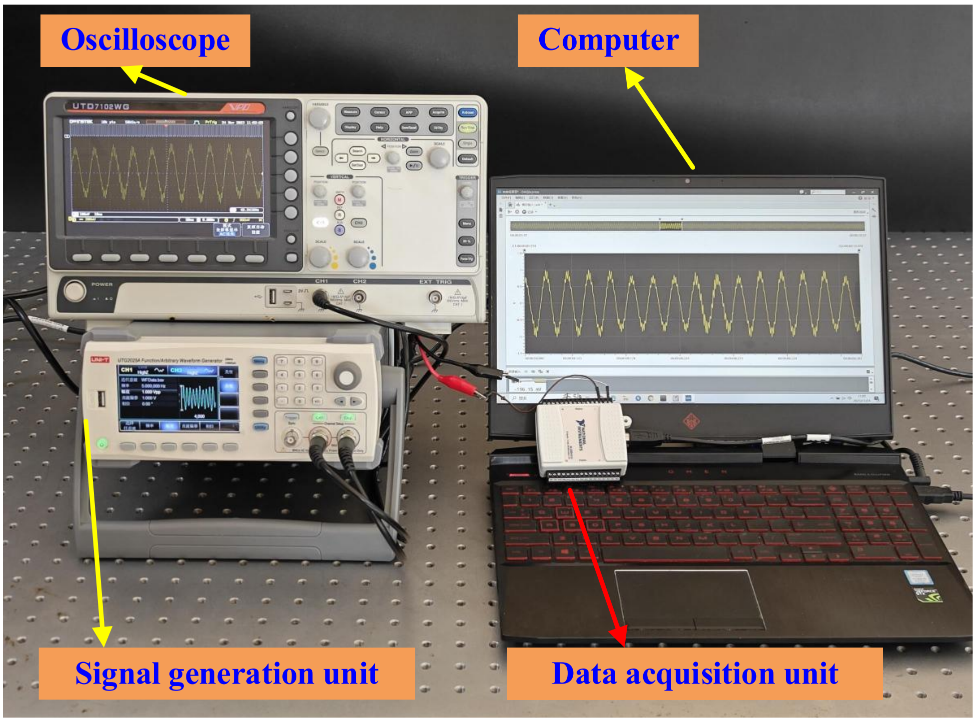

Fig. 1. Established experimental prototype platform of power quality disturbance diagnosis.

A. Dataset: A dataset of 3,000 power quality signals was constructed, including 10 disturbance types (normal, interruption, sag, swell, harmonics, oscillatory transient, impulsive transient, spike, notch, flicker) with varying severity levels.

B. Feature Processing: As shown in Fig. 2, Signals were converted into 2D ORP images using the same parameter settings (embedding dimension m=3, time delay t=60) as in the PMSLM AAF diagnosis, preserving time-frequency characteristics of transient disturbances.

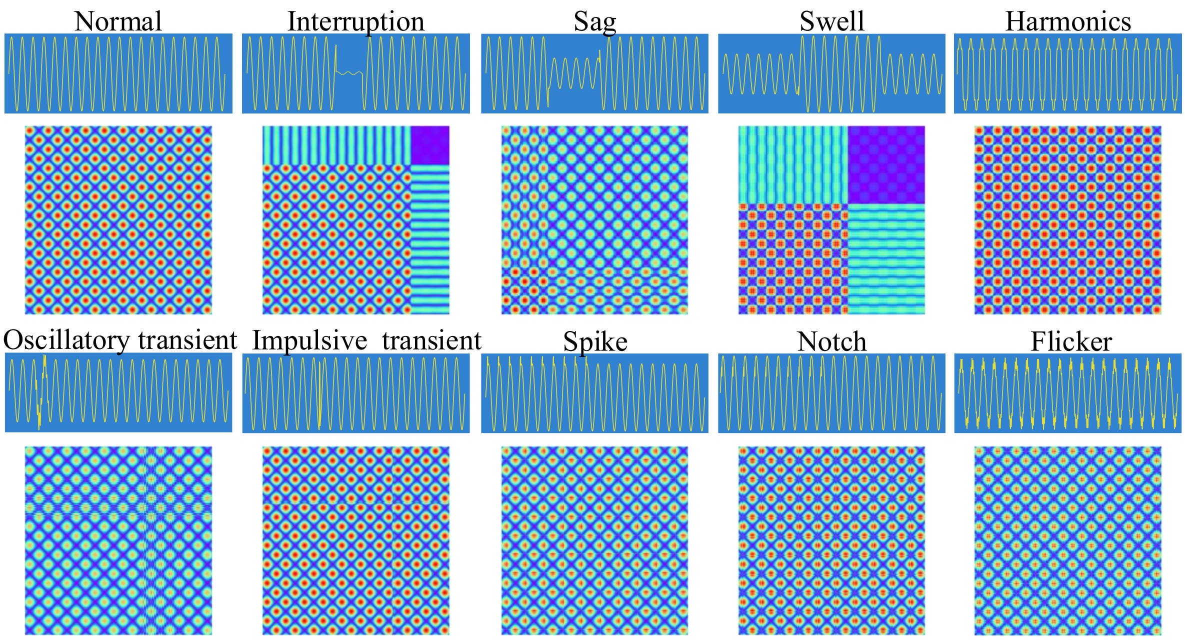

Fig. 2. 1D waveform and ORP images of different type PQDs.

C. Training and Test Configuration: To evaluate the performance of the proposed EMF-PNet framework under conditions of varying data scarcity, three training set sizes were employed: 400, 1000, and 2000 samples. A fixed independent test set (500 samples) was used for all evaluations to ensure fairness in comparisons. And 10 independent trials were conducted: in each trial, the training set (of the specified size) and the fixed test set were randomly partitioned from the total dataset without overlap. The model was trained on each training set and tested on the 500-sample test set, and the values in Table I correspond to the average test performance metrics across these 10 trials.

Table I

CLASSIFICATION RESULTS OF THE PROPOSED EMF-PNET ON ELECTRICAL FAULTS

Training set sizes	400		1,000		2,000	
Classification index (%)	Accuracy	F1	Accuracy	F1	Accuracy	F1
EMF-PNet	**96.85**	**96.97**	**97.05**	**97.72**	**98.51**	**98.43**

D. Results: The classification results in Table I demonstrate the exceptional performance of the proposed EMF-PNet framework in power quality disturbance (PQD) diagnosis, particularly under data-scarce conditions. Even with a relatively small training set of 400 samples, EMF-PNet achieves a high accuracy of 96.85% and an F1-score of 96.97%, highlighting its remarkable ability to learn discriminative features from limited data. As the training set size increases to 1,000 and 2,000 samples, the framework further improves its performance (accuracy: 97.05% and 98.51%; F1-score: 97.72% and 98.43%), confirming its robustness and scalability.

2) Application to Non-Linear Motor Systems: BLDCM Fault Diagnosis

To evaluate its generalization to non-linear motor systems, EMF-PNet was applied to fault diagnosis of brushless direct current motor (BLDCM) (Fig. 3), which exhibit non-linear characteristics due to commutation ripples and magnetic saturation.

A. Dataset: 4,000 vibration signals were collected from a BLDCM motor test rig (1.5 kW, 3,000 rpm) under 10 healthy and faulty conditions including series resistance fault (HRC), open phase (OP), hall sensor fault (HSF), rotor unbalance (RU), bearing inner race fault (BIRF), and bearing outer race fault (BORF). BIRF and BORF are classified into two categories and three categories, respectively, according to fault width, converted into 2D ORP images for model input.

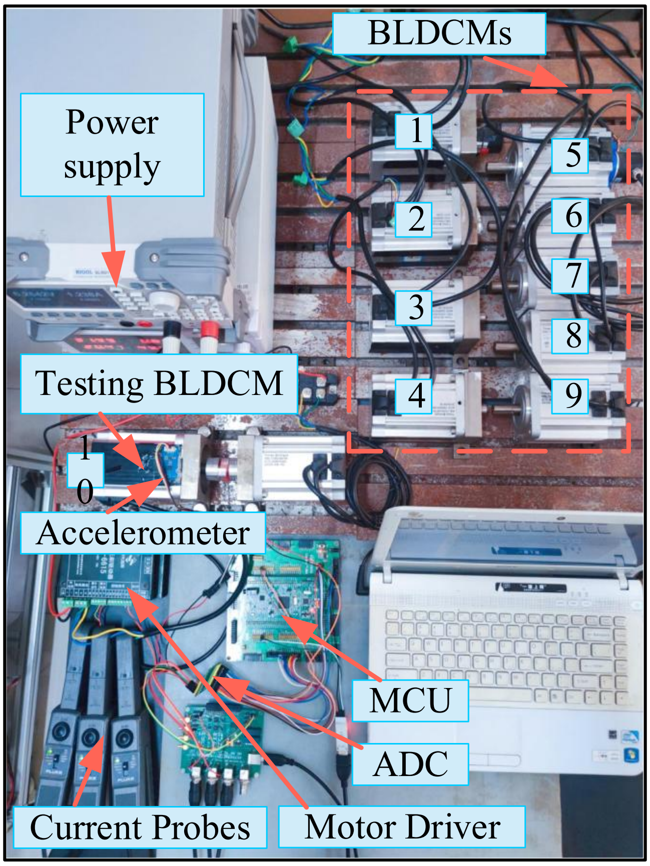

Fig. 3. Established experimental prototype platform of BLDCM fault diagnosis.

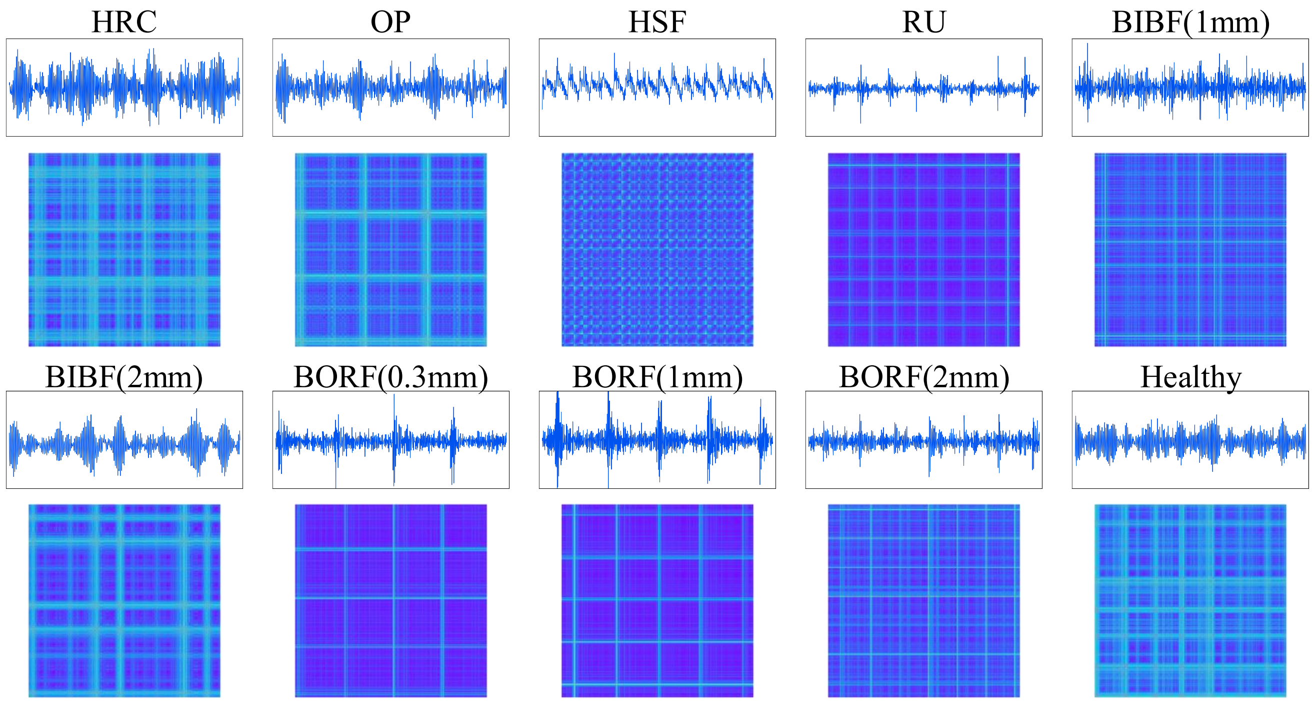

Fig. 4. 1D waveform and ORP images of different type BLDCM faults.

B. Feature Processing: As shown in Fig. 4, signals were converted into 2D ORP images using the same parameter settings (embedding dimension m=3, time delay t=60) as in the PMSLM AAF diagnosis, preserving time-frequency characteristics of transient disturbances.

C. Training and Test Configuration: To evaluate the performance of the proposed EMF-PNet framework under conditions of varying data scarcity, three training set sizes were employed: 400, 1000, and 2000 samples. A fixed independent test set (500 samples) was used for all evaluations to ensure fairness in comparisons. And 10 independent trials were conducted: in each trial, the training set (of the specified size) and the fixed test set were randomly partitioned from the total dataset without overlap. The model was trained on each training set and tested on the 500-sample test set, and the values in Table II correspond to the average test performance metrics across these 10 trials.

Table II

CLASSIFICATION RESULTS OF THE PROPOSED EMF-PNET ON BLDCM FAULT DIAGNOSIS

Training set sizes	400		1,000		2,000	
Classification index (%)	Accuracy	F1	Accuracy	F1	Accuracy	F1
EMF-PNet	**96.61**	**96.34**	**96.57**	**96.85**	**98.17**	**98.23**

D. Results: The classification results in Table II validate the outstanding performance of the proposed EMF-PNet framework in brushless direct current motor (BLDCM) fault diagnosis, with a particular emphasis on its superiority under data-scarce conditions. Even when trained on a relatively small dataset of 400 samples, EMF-PNet achieves a remarkable accuracy of 96.61% and an F1-score of 96.34%, demonstrating its strong capability to capture critical fault features from limited labeled data. This is particularly valuable for BLDCM motor diagnosis, where collecting large-scale fault samples is often challenging due to operational constraints and the complexity of fault replication. As the training set size increases to 1,000 and 2,000 samples, the framework maintains stable and improved performance (accuracy: 96.57% and 98.17%; F1-score: 96.85% and 98.23%), confirming its robustness and scalability.

In conclusion, these experiments demonstrate that EMF-PNet is not limited to PMSLM AAF diagnosis but can be generalized to electrical faults and non-linear motor systems, leveraging its few-shot learning capability and ORP-based feature enhancement.