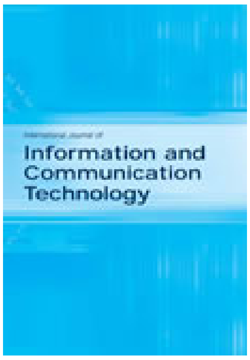

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Electronic component fault diagnosis based on cross-domain features and deep contrastive learning

Yun Liu

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Electronic component fault diagnosis based on cross-domain features and deep contrastive learning

Yun Liu

School of Big Data and Automation,
Chongqing Chemical Industry Vocational College,
Chongqing, 401220, China
Email: ly_cqcivc@163.com

Abstract: With the extensive use of electronic components in contemporary industry, fault diagnosis technology is more important in preserving equipment operation and improving output. Conventional fault diagnosis techniques limit their application in complicated fault situations by means of cross-domain feature extraction, which suffers limitations. This work thus suggests an electronic component fault diagnosis model called Cross-DeepContrastNet, which combines cross-domain feature extraction with deep contrastive learning and uses a series of training strategies to effectively extract discriminative features from many sources and types of data and acquire accurate fault diagnosis. Cross-DeepContrastNet beats conventional techniques in several respects, according to different experimental findings. Finally, further paths of investigation are suggested to solve the constraints of the use of the model in actual industries.

Keywords: electronic components; fault diagnosis; cross-domain features; deep contrastive learning.

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Biographical notes: Yun Liu received his Bachelor of Engineering Degree at Southwest Institute of Technology in 1998. He is currently a Senior Engineer at the Professor Level at Chongqing Chemical Industry Vocational College. His research interests include automated measurement and control, system reliability and motion control algorithm.

1 Introduction

1.1 Background of research

Rapid progress of electronic technology makes electronic components indispensable in many types of equipment. Modern manufacturing, communication, medical and other sectors depend more and more on electronic components; thus, their absence could cause system failure, financial loss, or even safety hazards (Badri et al., 2018). Thus, accurate fault diagnostic technology is rather important to guarantee the stability of equipment operation, lower maintenance costs, and increase manufacturing efficiency.

Although successful in some fields, traditional electronic component fault diagnosis techniques mostly rely on expert experience, rule-based reasoning, and model-driven approaches, which, as system complexity increases, especially in large-scale, heterogeneous environments, present many challenges. Data-driven based approaches have progressively taken front stage in electronic component problem diagnostics in recent years as deep learning technology has emerged (Jieyang et al., 2023). By increasing the distance between similar samples and reducing the distance between dissimilar samples, deep contrastive learning which is an efficient feature learning methods showcases enormous potential in unsupervised learning and representation learning. For instance, the failure modes of electrical components may show distinct traits in different operating conditions, which makes traditional models unable to migrate between several domains to efficiently diagnose data from many sources.

Though deep contrastive learning shows amazing performance on many tasks, the actual application of electronic component fault diagnosis still suffers with data transfer across domains. Usually influenced by a range of elements including environmental considerations, testing conditions, and usage history, the operational state of electronic components causes notable variations in the defect data acquired under various circumstances. In this discipline, a major challenge is now how to efficiently transfer and distribute features between several domains.

This work proposes a cross-domain feature and deep contrastive learning-based fault diagnosis method for electronic components to enhance the fault diagnosis performance under various operational environments by means of a cross-domain feature learning framework and combining of the advantages of deep contrastive learning. This work intends to overcome the limitations of current methods and offer a more efficient and strong solution for electronic component problem diagnostics by properly migrating and fusing traits from cross-domain data.

1.2 Research questions

This work intends to solve various important problems in electrical component fault diagnosis, particularly in the framework of merging cross-domain feature learning with deep contrastive learning. First, data on electronic component failure usually come from various operating settings, equipment models and histories, which causes appreciable distributional variations between the data (Kamsu-Foguem et al., 2023). A fundamental difficulty in electronic component problem diagnosis is how to extract discriminative features from cross-domain data and move them between several domains. Thus, in order to overcome the feature mismatch problem between source and target domains, thereby enhancing the stability and accuracy of the diagnostic model in various working contexts, this work will investigate the cross-domain feature learning method. Second, as a self-supervised learning approach, deep contrastive learning has shown amazing outcomes in the fields of picture and voice and can efficiently mine the similarities and differences between samples. Still, in the field of electronic component fault diagnosis, how to automatically extract effective fault features from complex sensor data by deep contrastive learning and optimise the contrast loss function to improve the discriminative ability of the model. One of the main objectives of this work will be to apply deep contrastive learning with minimal labelled data to raise the accuracy and robustness of defect identification.

Furthermore, both deep contrastive learning and cross-domain feature learning have independent benefits; but one of the primary problems of this work is how to naturally merge these two and efficiently fuse and optimise them in electrical component fault diagnostics. One of the main difficulties of this work will be designing a cross-domain feature fusion method so that the model may exchange effective features over several domains and further improve the feature discrimination ability utilising deep contrastive learning. Under the context of collaborative optimisation, this paper will investigate how to raise the general performance of defect diagnosis models. Traditional fault diagnosis algorithms demonstrate low generalisation capacity when confronted with unknown fault types or highly variable test data since electronic component defects are varied and frequently influenced by ambient elements (Choudhary et al., 2022). This work will concentrate on how to increase the generalisation ability and robustness of the model so that it may sustain high accuracy and stability under many operating environments, equipment types, and fault modes, so ensuring the effectiveness of the proposed diagnostic method in practical applications.

This work intends to present a unique electrical component fault detection approach based on cross-domain features and deep contrastive learning by tackling the above problems and to give significant technical support for related domains.

1.3 Research contributions

Aiming to solve the problems of conventional fault diagnosis techniques when confronted with cross-domain data and variable settings, in this work we offer an electronic component fault diagnosis model based on cross-domain characteristics and deep contrastive learning. More especially, this work mostly adds:

1 Cross-domain feature fusion and joint optimisation strategy proposed: This work presents a cross-domain feature fusion and joint optimisation technique combining deep contrastive learning with cross-domain feature learning to improve the general defect diagnosis model performance via co-optimisation. The approach not only increases the model's adaptability in several contexts but also considerably increases its diagnostic capacity in challenging situations.

2 Innovative introduction of deep contrastive learning to optimise feature extraction: In this work, the deep contrastive learning method is used in the field of electrical component fault detection, which maximises the similarity and difference between samples by contrastive learning and automatically learns discriminative features without much annotated data. Optimising the contrast loss function increases the feature representation ability of the model, therefore strengthening its accuracy and resilience in defective diagnosis.

3 Enhanced generalisation ability and robustness of diagnostic models: In this work, under unknown defects, various devices, and changing surroundings, the combination of cross-domain feature learning and deep contrastive learning considerably increases the generalisation capacity of the model. Strong robustness and accuracy in various real-world application scenarios are shown by the experimental findings of the proposed model, which exceeds conventional fault diagnosis techniques.

This work mostly proposes an electronic component fault diagnostic model combining cross-domain feature learning with deep contrastive learning, thereby creatively addressing the primary issues of cross-domain data migration, feature optimisation, and model fusion. This method gives theoretical support and technical approaches for intelligent fault diagnosis in real applications, so greatly improving the accuracy, robustness, and generalisation ability of fault detection.

2 Relevant technologies

2.1 Troubleshooting techniques for electronic components

Electronic component fault diagnostic technology is the application of monitoring and analysis to determine whether an electronic component has a fault. Usually depending on manual experience and test equipment, traditional electronic component fault diagnosis techniques directly detect and analyse a flaw in the device to manually identify whether one exists. But this approach has several drawbacks, particularly in the context of complicated systems and hidden flaws; conventional diagnostic techniques are sometimes unable to timely and precisely identify the problem. Thus, with the fast expansion of information technology, diagnostic technology based on automation and intelligence has progressively taken the front stage in study and application.

Electronic component defect detection today mostly consists of model-based, data-driven, signal processing-based approaches. By gathering and analysing the functioning signals of components, such voltage, current, power, and other characteristics, signal processing-based techniques ascertain whether a device is defective (Long et al., 2021). Simple implementation, strong real-time speed, and the capacity to somewhat detect clear failure signals define the benefits of this kind of approach. For some small, initial or hidden flaws, though, signal processing techniques' diagnostic power is usually insufficient.

Conversely, model-based fault diagnosis techniques use the deviation between a mathematical model of an electronic component and perform fault diagnosis by means of this process. Although these techniques usually depend on the operating rules and historical data of the equipment, the complexity and variety of the equipment make it quite challenging to build a correct mathematical model. Furthermore, model-based approaches could have significant mistakes when the equipment's running environment changes (Badihi et al., 2022).

Data-driven fault detection systems based on data have progressively taken the stage in recent years as big data and artificial intelligence technologies develop. Using sophisticated algorithms including machine learning and deep learning and gathering a lot of historical data from the operation of the equipment allows one to automatically extract important aspects from the data to detect failure mechanisms and generate forecasts. Particularly in multi-dimensional and multi-variable data, this kind of method has great benefits and can adjust to more complicated failure scenarios (Lin et al., 2021). Though the training and optimisation phase of the model involves high computer resources, this also necessitates that the quality and quantity of data must be suitably adequate.

Modern data-driven methods still have several difficulties even although they have made great progress in raising the accuracy and efficiency of defect diagnosis. For instance, how to ensure the robustness of the model under various operating conditions, how to handle the accurate identification of multiple fault modes, and how to perform effective fault diagnosis with insufficiently labelled data or poor data quality. These are still hot issues that must be constantly investigated in this field.

2.2 Cross-domain learning and feature transfer

Particularly when the destination domain has limited or incompletely labelled data, cross-domain learning and feature transfer methods are generally employed to solve the distributional variations between the source and target domains. The performance of the model in the target domain can be raised by transferring the knowledge or features gained in the source domain. Particularly in machine learning and deep learning, this method is extensively applied, especially when handling various work settings, tools, or devices.

Cross-domain learning's fundamental challenge is how to move beneficial characteristics between the source and destination domains. Though in actuality the source and target domains often have distinct data distribution, traditional learning approaches presume that the data distribution of the source and target domains is the same. This leads to unsuccessful models in the target domain. By methods of feature transfer and model migration, cross-domain learning approaches reduce the distributional discrepancies between several domains, therefore enabling learning in the target domain to be more effective.

A fundamental component of cross-domain learning, feature transfer moves the features of the source domain to assist the learning of the target domain (Gao et al., 2018). We wish to translate the features of the source domain to the feature space of the target domain by learning a mapping function f assuming X_s as the features of the source domain data and X_t as the features of the target domain data. This helps the model to attain improved performance on the target domain.

Minimising the variance in feature distribution between the target and source domains is a typical benchmark (Kouw and Loog, 2019). Common formula is the mean difference to gauge this variation:

$$\mathrm{MMD}\left(X_s, X_t\right) = \left| \frac{1}{n_s} \sum_{i=1}^{n_s} f\left(x_s^{(i)}\right) - \frac{1}{n_t} \sum_{j=1}^{n_t} f\left(x_t^{(j)}\right) \right| \tag{1}$$

where $x_s^{(i)}$ and $x_t^{(j)}$ are samples in the source and target domains respectively; $f(x)$ is the mapping function; n_s and n_t are the respective numbers of samples in the source and target domains. By computing the difference between the mapped feature means of the source and destination domains, the formula assesses their similarity; so, reducing this difference will help to attain effective feature transfer.

In addition to being feature level transfer, cross-domain learning can optimise at the deeper model level. Deep learning-based cross-domain learning approaches have lately allowed models to automatically learn the shared features across the source and target domains and optimise on the target domain by end-to-end training. Particularly in challenging and unpredictable data situations, this method can significantly raise the performance of cross-domain learning.

Cross-domain learning and feature transfer methods still present some difficulties even if they have made great advancement possible in many applications. Hot problems in present research are how to efficiently capture the common features between the source and target domains, prevent overfitting the data in the target domain, and increase the computing efficiency of the model (Xu et al., 2025).

2.3 Deep contrastive learning

Deep contrastive learning compares sample similarities and contrasts to learn data representations. The basic concept is to build pairs of positive and negative samples that push the representations of dissimilar samples farther away and bring the representations of similar ones closer together, hence obtaining differentiated feature representations.

Whereas in deep contrastive learning the model optimises a type of contrastive loss function to learn the relationship between samples. Positive sample pairings are those in which the feature space is comparable; negative sample pairs are those in which the feature space is dissimilar. Whereas dissimilar samples pull further apart, deep contrastive learning aims to make similar samples closer together in the feature space.

Two aspects define a commonly used contrast loss function: one for positive sample pairings and another for negative sample pairs (Xue et al., 2022). Considering a sample pair (x_i, x_j), its contrast loss may be stated as:

$$L_{\text{positive}} = y_i \cdot D^2(x_i, x_j) \tag{2}$$

where $D(x_i, x_j)$ is the Euclidean distance between samples x_i and x_j, $y_i = 1$ indicates that the sample pair is a positive one. The loss function for negative sample pairs ($y_i = 0$) is then defined as:

$$L_{\text{negative}} = (1 - y_i) \cdot \max\left(0, m - D(x_i, x_j)\right)^2 \tag{3}$$

where $D(x_i, x_j)$ still shows the Euclidean distance between sample pairs and m is a preset minimum distance criterion. Whereas the loss term L_{negative} for negative sample pairs guarantees that the distance between negative sample pairs is greater than the predefined threshold, so avoiding the model from producing meaningless features during the learning process, the loss term L_{positive} for positive sample pairs brings similar samples closer by minimising the distance between sample pairs.

The final comparison loss function is formed by aggregating the losses of the positive and negative sample pairs, therefore weighing and summing the whole loss function:

$$L_{\text{total}} = \frac{1}{2N} \sum_{i=1}^{N} \left(L_{\text{positive}} + L_{\text{negative}}\right) \tag{4}$$

where N is the overall count of pairs from samples. Deep contrastive learning can train efficient feature representations from data that distinguishes between several classes or patterns by minimising this loss function.

Deep contrastive learning finds extensive application in image processing, speech recognition, and natural language processing. Deep contrastive learning, for instance, can increase image retrieval accuracy in image retrieval tasks by mapping the features of like images to adjacent regions in the feature space, hence improving their accuracy. Deep contrastive learning allows relevant speech features from a lot of unlabelled voice data to be learnt in speech recognition systems, therefore enhancing their performance (Michelsanti et al., 2021).

Deep contrastive learning still has certain difficulties even if it has shown great performance in many fields. First, a major question is how to create positive and negative sample pairs with efficiency. Inappropriate selection of the sample pairs could compromise the stability and performance of the training process. Second, a pressing issue in deep contrastive learning is also how to build a better distance metric. How to use richer distance metrics to enhance the effect of contrast learning is a crucial direction in present research.

Furthermore, deep contrastive learning often requires a lot of processing resources, especially in relation to big-scale datasets and the computational load of training deep neural networks (DNNs) is significant. One more issue that must be addressed is how to lower the computational cost and increase training efficiency.

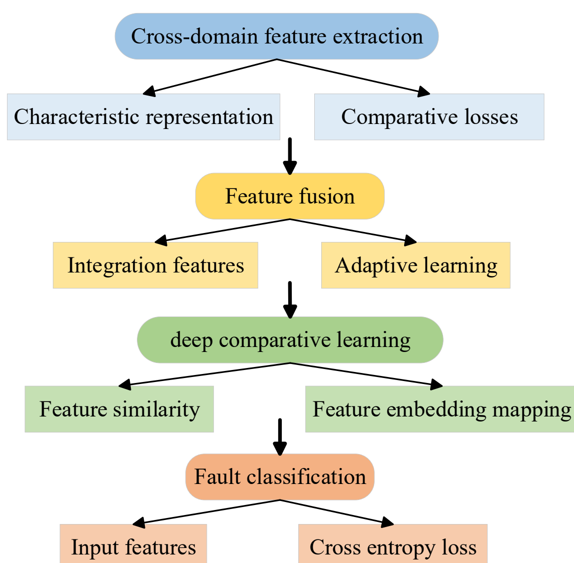
3 Electronic component fault diagnosis model

3.1 Model architecture

Combining the benefits of cross-domain feature learning with aims to automatically extract useful fault diagnosis features from multi-source data and optimise the feature representations using deep contrastive learning to achieve efficient and accurate fault diagnosis, thus the proposed electronic component fault diagnosis model in this paper is named Cross-DeepContrastNet.

See Figure 1 to find the following main components of the Cross-DeepContrastNet model:

Figure 1 Architecture of the Cross-DeepContrastNet model (see online version for colours)



1 Cross-domain feature extraction module

Cross-domain feature extraction module guarantees that the model can uniformly learn discriminative feature representations, regardless of the heterogeneity of the data sources, through the learning of a shared feature space since failures of electronic components are often manifested as different data patterns that may come from different sensors, devices or operating environments. The model initially transfers the features X_i of every data domain into the shared feature space Z employing a mapping function to reach this:

$$Z_i = f\left(X_i; \theta_i\right) \tag{5}$$

where Z_i represents the data in the i^{th} domain in the shared space; $f(\bullet)$ is the neural network mapping function; θ_i is the related learning parameter.

The Cross-DeepContrastNet model uses a contrast loss function, which is intended to ensure that the feature representations of faults of different classes are as far away as possible while the feature representations of faults of the same class are as close together as possible in the shared space, so optimising the feature representations. The loss function motivates the distance between each pair of feature samples Z_i and Z_j to be as small as feasible if they belong to the same class; it penalises their distance and expands the gap between them if they belong to different classes.

The loss function can be expressed as:

$$L_{\text{contrast}} = \frac{1}{N}\sum_{i=1}^{N} \mathbb{I}\left(y_i = y_j\right) \cdot \left\| Z_i - Z_j \right\|^2 \tag{6}$$

where $\mathbb{I}(y_i = y_j)$ is the indicator function and $y_i = y_j$ shows that the samples fall into the same category, the loss function minimises their distance to so promote their similarity (Huang et al., 2020). The loss function maximises the distance to guarantee their difference for samples of several kinds. The cross-domain feature extraction module constantly optimises this procedure so that efficient distinction of various fault kinds is at last obtained.

2 Feature fusion module

Using features from one domain alone may produce erroneous or insufficient fault pattern detection when features taken from several data sources have distinct semantic information. By weighing and merging features from several data sources, therefore fusing complimentary information from many data domains into a single feature space, the feature fusion module improves the defect diagnostic capacity of the model (Rong et al., 2019).

First, the module generates a complete fused feature representation Z_{fused} by weighted summation of feature representations from several data domains. One may define the weighted summation operation as follows:

$$Z_{\text{fused}} = \sum_{i=1}^{N} \alpha_i \cdot Z_i \tag{7}$$

where Z_i is the i^{th} domain feature representation; α_i is the weighting coefficient, therefore indicating the significance of the features in that domain. Especially in the context of electronic component fault diagnosis, the model can synthesise the data features from many sensors or devices, so improving the ability to identify fault patterns by means of weighted summation, which enables the combination of information from several domains.

By using an adaptive learning process, the feature fusion module also maximises the weighting coefficient α_i, hence enhancing the efficacy of the fused features. The model specifically automatically changes the weighting coefficients of every domain depending on the contribution of the features of every domain in the diagnostic task, so ensuring that features in important domains are given higher weights while those in unimportant domains are given lower weights. One can visualise this process by means of the following equation:

$$\alpha_i = \frac{\exp(\beta_i)}{\sum_{j=1}^{N} \exp(\beta_i)} \tag{8}$$

where β_i is a learning parameter connected with domain i, which regulates the weight of the features in that domain in the fused results. The model can automatically modify its weights amongst several data domains using this adaptive method to maximise diagnostic performance.

3 Deep contrastive learning module

By means of feature comparisons between similar and dissimilar failure samples, the deep contrastive learning module can enhance the capacity of the model to discriminate various failure modes since the failure modes of electronic components show considerable variations among cross-domain data sources, e.g., data from different sensors or devices.

The deep contrastive learning module is meant to decrease the distance between like fault samples and maximise the distance between dissimilar fault samples. Deep contrastive learning can assist the model to discriminate between various defect types by improving the sample relationships in the feature representation space (Xu et al., 2023). In this context, the feature representations of fault samples of the same class are brought closer together and those of different classes are brought further apart, hence improving the classification accuracy of fault diagnosis.

Furthermore, the computation of feature similarity is introduced by the deep contrastive learning module, therefore strengthening the discriminative power of the model. Especially in Cross-Domain data sources, feature similarity is a crucial metric of similarity across samples in the Cross-DeepContrastNet model. Cosine similarity is used to determine the relationship in the common feature space of two samples thereby evaluating their resemblance (Kirişci, 2023). Cosine similarity has the formula shown below:

$$\text{sim}(Z_i, Z_j) = \frac{Z_i \cdot Z_j}{\|Z_i\| \|Z_j\|} \tag{9}$$

where $\| Z_i \|$ and $\| Z_j \|$ respectively indicate their vanes; Z_i and Z_j are respectively the feature representations of the i^{th} and j^{th} samples. The cosine similarity gauges the directional similarity between the two feature vectors; the value ranges from –1 to 1, the closer to 1 denotes the greater similarity between the two samples. The deep contrastive learning module guarantees that several failure modes are essentially separated in the feature space by enhancing the similarity between samples of the same class and decreasing the similarity between samples of other classes.

The Cross-DeepContrastNet model uses a feature embedding mapping technique to improve mapping of the input data to the shared low-dimensional feature space. One may write the feature embedding E_i as:

$$E_i = f(X_i) \tag{10}$$

where X_i is an input sample and $f(\bullet)$ is a deep network model, learning the mapping function of the input sample generates a low-dimensional feature representation. While offering a larger discriminative feature space for the next classification assignment, this embedding representation can efficiently capture the central information of the input data and avoid the redundancy of high-dimensional data.

4 Fault classification module

The primary responsibility of the fault classification module in the Cross-DeepContrastNet model is to categorise the input samples regarding the fault kinds depending on the feature vectors acquired from the aforesaid cross-domain feature extraction module and deep contrastive learning module. The major classification method selected for this aim is DNN. DNN demonstrates better performance in high dimensional data and has strong nonlinear modelling capacity, which helps it to properly manage complicated fault kinds (Duan et al., 2018).

Derived from the output of cross-domain feature extraction and deep contrastive learning in the preceding modules, the feature representation E_i provides input for this module. First, mapped and transformed across several hidden layers, the input features then pass through the output layer to generate the prediction of fault kinds. Specifically, the predicted probability distribution $\hat{y}_i$ for every category is the output of the neural network; so, a softmax function is utilised to process the raw score $W_c \bullet E_i + b_c$ of the network output to derive the final probability value for every category.

$$\hat{y}_i^c = \frac{e^{W_c \cdot E_i + b_c}}{\sum_{c'} e^{W_{c'} \cdot E_i + b_{c'}}} \tag{11}$$

where E_i is the input feature vector; W_c and b_c are respectively the weights and bias terms for category c. The softmax function guarantees that, over all categories, the probability values of the outputs add to 1, therefore enabling each forecast to be understood as the probability the sample falls into that category.

Using a cross-entropy loss function as the objective function which gauges the variation between the true labels and the model's projected distribution helps one train the neural network and maximise the model parameters (Ho and Wookey, 2019). The cross-entropy loss function has as its expression:

$$L_{\mathrm{CE}} = -\sum_{c \in C} y_i^c \log\left(\hat{y}_i^c\right) \tag{12}$$

where $\hat{y}_i^c$ is the projected probability of the model for the category c corresponding to the sample i and y_i^c is the actual label which is usually 0 or 1, indicating whether the sample belongs to the category or not). By minimising the cross-entropy loss function, the model can help to categorise the errors in the category c. Reducing the cross-entropy loss function helps the neural network to modify its weights and biases such that the gap between the projected probability and the actual label is as minimal as feasible, hence enhancing the accuracy of fault classification.

By means of close collaboration among the four above-mentioned modules, Cross-DeepContrastNet can efficiently process multi-source data, extract important features, and finally accomplish successful electronic component problem diagnosis.

3.2 Training strategies

First, a basic stage of the training plan is data preparation. Normalising the input data helps to guarantee that the scales of various features are constant, therefore enabling the convergence of the model and increasing its resilience. Usually, mean decentering and standard deviation normalisation are part of data preparation. The normalised data helps the optimisation process better fit to various feature distributions and avoid the scale variation between features.

Cross-DeepContrastNet aggregates the cross-entropy loss function with the contrast loss function to build the loss function for design. Targeting to improve the feature consistency across cross-domain data, the contrast loss function is utilised in the cross-domain feature extraction and deep contrastive learning module. The cross-entropy loss function is utilised to maximise the classification accuracy in the fault categorising module. Simultaneous optimisation of these two loss functions helps the model to raise the local and global diagnosis performance.

The Adam optimiser is employed in the choice of optimisation method; it is an adaptive learning rate optimiser with higher convergence and capable handling of the sparse gradient problem. By dynamically changing the learning rate of every parameter throughout the training process, the Adam optimiser can avoid the issue of gradient disappearance or gradient explosion and has a great robustness, which can hasten the training process and raise the convergence efficiency (Chen et al., 2022).

Early halting techniques can find application in the training process. The early stopping technique tracks the change of the loss function of the validation set to avoid the model from overfitting throughout the training process (Anam et al., 2024). Early stopping of the training will prevent the waste of computing resources and guarantee the performance of the model on the validation set when the loss of the validation set does not show appreciable improvement within a given period.

Furthermore, approaches are included in the training process for data improvement. By creating fresh training samples on the training data by means of transformations like rotation, scaling, and translation, the variety of the training set is expanded. This approach lowers the risk of overfitting, increases the generalising capacity of the model, and improves its classification performance on several fault kinds.

Still another often-utilised training tactic is learning rate decline. A higher learning rate is utilised to hasten the convergence of the model at the start of training (Yan et al., 2020). As the training advances, the learning rate is progressively lowered so that the model may adjust the parameters and converge to a better solution. Common approaches of learning rate reduction are:

$$\eta_t = \eta_0 \cdot \frac{1}{1+\lambda t} \tag{13}$$

where t is the number of training cycles; λ is the decay factor; η_0 is the starting learning rate. Learning rate decay helps early stage of training to converge rapidly and later stage to fine-tune the model parameters to prevent oscillation and over-adjustment.

Through suitable data preparation, loss function design, optimisation algorithm, early halting strategy, data augmentation and learning rate decay Cross-DeepContrastNet guarantees effective training of the model and powerful fault diagnosis capabilities. The model can have great accuracy and resilience in useful applications by means of an effective mix of all strategies.

4 Experimental results and analyses

4.1 Dataset

In this work, the NASA Bearing Data Center (Paderborn Bearing Data) dataset has been used as a main data source in the endeavor of electronic component diagnosis. One of the main parts utilised in industrial equipment, rolling bearings have vibration signal data available in this NASA dataset.

Table 1 Basic information of the NASA Bearing Data Center

Fault types	*Normal operation, outer race fault, inner race fault, rolling element fault*
Sensor type	Vibration sensor (accelerometer)
Data format	Time-series data, frequency range: 12 kHz
Number of samples	6000 samples, corresponding to different fault types and operating conditions
Sampling frequency	12 kHz
Label information	Each sample is labelled with fault type (normal, outer race fault, inner race fault, rolling element fault)
Fault modes	Outer race fault, Inner race fault, rolling element fault, Normal operation
Relevance to study	Bearing faults are common in electronic component diagnosis, suitable for cross-domain feature learning and fault classification

Many mechanical devices and electrical components depend on bearing failures; failure types that influence not only the normal operation of the equipment but also might cause more major systemic failures. The dataset lets researchers spot and classify several kinds of bearing failures: outer ring failures, inner ring failures, rolling element failures, and so forth. These fault kinds are quite useful, notably in activities like accurate diagnosis, prediction and early fault detection since they resemble frequent problems in electronic components. Table 1 exhibits the fundamental details of this dataset:

Several features of this dataset reflect the fit with electronic component fault diagnosis: First, especially in the mechanical part, bearing failure is a typical issue in electronic component fault diagnostics. Second, this dataset can offer rich sample data for cross-domain feature learning and features a broad spectrum of defects. For this reason, it is perfect to apply the Cross-DeepContrastNet model in this work. Furthermore, the multi-dimensional data acquired from vibration sensors may efficiently support the use of deep contrastive learning in fault diagnosis and assist the model extract cross-domain features for more effective problem detection and diagnosis.

4.2 Experimental setting

Data preparation marks the start of the experimental phase; the raw vibration signal is split into fixed-length sections with 1,024 data points apiece. To remove scale variations and guarantee that individual characteristics equally supported the learning process, all signals were normalised. Furthermore, several overlapping segments created using a sliding window approach help to guarantee that the dataset has enough training examples for model development. Time and frequency domain analysis techniques then transform every segment into a feature vector. The Cross-DeepContrastNet model drew inputs from these feature vectors.

Robust assessment of model performance and overfitting prevention were guaranteed during model training by using a 5-fold cross-valuation technique (Lee et al., 2021). Four of the randomly split datasets were utilised for training; each of the five subsets used in turn as a validation set. The model's training batch size is set at 32; the maximum number of training rounds is 50 (Liao et al., 2023). Using a learning rate decay approach, the Adam optimiser is applied, and the initial learning rate is set at 0.001 and changed in line with the number of training cycles. Several criteria are used to evaluate the model's performance so that its diagnostic powers may be properly analysed.

4.3 Experimental procedure

While comparing it with other popular algorithmic fusion models, experiment 1 seeks to reasonably assess the Cross-DeepContrastNet model inference time and accuracy in defect detection activities. The aim of the experiment is to test the efficiency and accuracy of Cross-DeepContrastNet in processing electronic component defect diagnosis data, particularly its responsiveness in real-time application scenarios.

This work presents a deep learning model called Cross-DeepContrastNet, which combines deep contrastive learning methods with cross-domain feature extraction to aim at effective electronic component fault diagnosis. The model first employs a deep contrastive learning module to optimise the representation of the important features extracted from various source domain data; subsequently, it uses a cross-domain feature extraction module to classify the features eventually in the fault classification module.

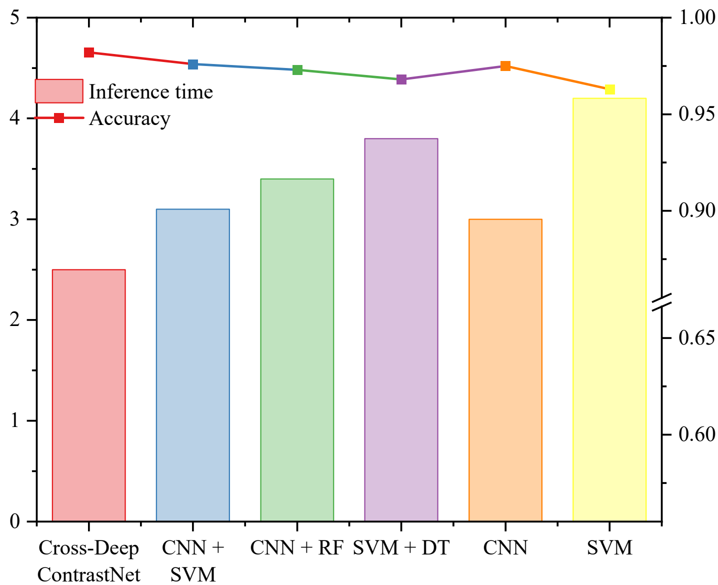
Apart from the conventional models used in the comparative studies, this work chooses three classical fusion algorithms for comparison:

- CNN-SVM: it is a feature extraction and classification tool combining support vector machines (SVM) with convolutional neural networks (CNN). While SVMs classify the acquired spatial characteristics, CNNs automatically extract them from unprocessed data.

- CNN-RF: it integrates random forest (RF) with CNN. CNN extracts features; RF serves as a classifier to categorise the features obtained by CNN.
- CNN-RF: it is a mix of SVM and decision tree (DT), SVM used for feature extraction and DT used for feature classification.

The benefits and constraints of merging deep learning with conventional machine learning algorithms may be assessed by comparing Cross-DeepContrastNet with similar fusion techniques, subsequently the performance advantages of Cross-DeepContrastNet in actual applications can be found. Figure 2 exhibits experimental outcomes.

Figure 2 Experimental results of the fault diagnosis task (see online version for colours)



Cross-DeepContrastNet clearly beats other models in both inference speed and accuracy based on experimental findings. Cross-DeepContrastNet has a processing time of 2.5 ms per sample, far less than other models, especially the SVM model, whose inference time is 4.2 ms. With evident benefits for industrial situations needing quick diagnosis, the difference inference time indicates Cross-DeepContrastNet can react more effectively in real-time applications.

Cross-DeepContrastNet achieves 98.2% accuracy, hence it performs equally well. This outcome shows the accuracy with which the model can classify electronic component failures, so indicating its efficiency in fault diagnosis chores. Though somewhat less than Cross-DeepContrastNet, fusion models such as CNN-SVM and CNN-RF demonstrated good classification ability with accuracy rates of 97.6% and 97.3%, respectively. Though less accurate, some conventional models such as SVM-DT keep a classification accuracy of over 96%.

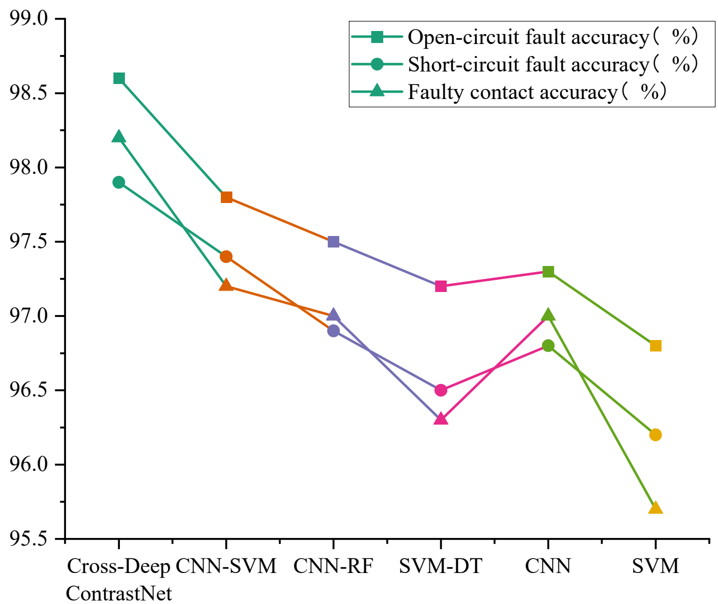
Moreover, in terms of the performance of the fusion models, especially in the SVM-DT combination with an inference time of 3.8 ms, which results in a decrease in their adaptability in real-time fault diagnosis, the inference time is considerably longer even if they combine several machine learning approaches and have some advantages in terms of accuracy. Cross-DeepContrastNet provides more consistent performance in accuracy in addition to a major benefit in inference speed. Consequently, in defective detection activities especially for applications with high real-time response needs, the Cross-DeepContrastNet model is obviously more competitive.

Based on experiment 1, experiment 2 investigates the performance variation between Cross-DeepContrastNet and other models under various fault kinds, therefore verifying the robustness of the model in several fault diagnostic situations.

Experiment 2 specifically intends to assess Cross-DeepContrastNet's performance in several kinds of electronic component problem diagnosis. The accuracy of any model in spotting several kinds of electronic component defects (e.g., open-circuit faults, short-circuit faults, defective contact, etc.) is tested by including several common sorts of problems. All models in the experiment use the same fault type dataset and are evaluated and compared under the same criteria.

Figure 3 displays the experimental outcomes.

Figure 3 Experimental results of classification fault diagnosis (see online version for colours)



With an accuracy of 98.6%, which is much higher than previous models, Cross-DeepContrastNet shows great accuracy in the diagnosis of various fault kinds, especially in the detection of open-circuit faults, according to the experimental data. By contrast, CNN-SVM and CNN-RF have accuracy of 97.8% and 97.5%, respectively, which is greater but still less than Cross-DeepContrastNet in the recognition of open-circuit faults.

Cross-DeepContrastNet had 97.9% accuracy in the identification of short-circuit defects, also more than in all other compared models. While SVM-DT has 96.5%, CNN-SVM and CNN-RF have respective accuracy of 97.4% and 96.9%. These findings reveal high generalisation capacity and robustness of Cross-DeepContrastNet in the diagnosis of several defect kinds.

Furthermore, Cross-DeepContrastNet beats the other models with an accuracy of 98.2% when diagnosing defective contact failures. CNN-SVM has accuracy of 97.2% and CNN-RF of 97.0%; SVM-DT has accuracy of 96.3%. Cross-DeepContrastNet demonstrates great robustness in several kinds of defect identification in addition to being very accurate taken all around. Cross-DeepContrastNet so clearly performs well in multi-fault type diagnosis jobs, particularly for real-time fault diagnosis applications requiring great accuracy and vast adaptability.

Cross-DeepContrastNet so clearly performs well in multi-fault type diagnosis jobs, particularly for real-time fault diagnosis applications requiring great accuracy and vast adaptability.

5 Discussion and challenges

Aiming to overcome the frequent cross-domain feature and complicated data problem in electronic component failure diagnosis, this work proposes a cross-domain feature and deep contrastive learning based electronic component fault diagnosis model, called Cross-DeepContrastNet. Deep contrastive learning and cross-domain feature extraction help the model to perform accurate defect diagnosis via deep learning techniques and efficiently extract important features from many sources and diverse kinds of data. Under certain fault types, Cross-DeepContrastNet shows outstanding performance, particularly in terms of accuracy and inference speed, both of which demonstrate higher diagnostic efficiency and stronger robustness than other conventional approaches according to experimental results.

This study has some restrictions, though as well. First of all, even though Cross-DeepContrastNet shows good performance in many studies, its generalisation capacity in particular circumstances still have to be shown, particularly on electrical component datasets of varied domains and sizes. Furthermore, especially in large-scale data, the deep contrastive learning model applied in this work depends on high computational resources and may encounter significant training overheads and computational bottlenecks.

Furthermore, even if this work demonstrates great capacity in defect diagnosis tasks, in some useful application scenarios data imbalance, data noise, and real-time speed could still be issues. These elements will affect the practical application impact of the model to some degree. Cross-DeepContrastNet offers a fresh approach for electronic component failure diagnosis overall, but more optimisation and validation are still required to guarantee its dependability and usefulness in increasingly challenging surroundings.

6 Future work

Cross-DeepContrastNet has shown improved experimental outcomes in jobs involving electronic component problem identification, although some issues still need attention. Deeply in the following directions future studies can investigate to enhance the actual application capacity and performance of the model.

First, the model still has to have more generalising capability developed. By adding more cross-domain learning approaches to increase its generalisation capacity in real-world contexts, further study can improve the model's adaptability to several data distributions. Researchers might thus investigate ways to attain more accurate fault diagnosis using adaptive feature extraction techniques for the variety of different kinds of defects.

Second, a still major difficulty for the model is its computational resource consumption. By means of network architecture optimisation, lightweight neural networks (e.g., MobileNet, EfficientNet, etc.), or quantisation and pruning adoption, the computational resource consumption of the model can be lowered in the future (Musa et al., 2025), so enabling more efficiency in industrial applications. Furthermore, it is feasible to investigate how to integrate distributed computing architectures with hardware acceleration (e.g., GPUs, TPUs, etc.) to improve the training and inference speed of models for large-scale real-time fault diagnosis activities.

Moreover, one of the main elements influencing the performance of fault diagnosis models remains is the data issue. Future studies can investigate generative adversarial networks (GANs), data improvement strategies, or sample recalibration approaches to balance the dataset and lower the negative influence of noise on model performance. Furthermore, taken into consideration as further improving the performance and applicability of the model is a mix of unsupervised learning or semi-supervised learning approaches using a little amount of labelled data and a great number of unlabelled data for training.

Finally, the implementation of models in industrial environments depends much on their interpretability and real-time character. Future studies could aim to find a better balance between inference speed and accuracy and make the fault diagnosis process more transparent by introducing interpretable techniques (e.g., model visualisation, locally interpreted models, etc.) to enable engineers to understand and change the models (Mi et al., 2020).

To further promote the application of deep learning in the diagnosis of electronic component faults and to meet the needs in real industrial environments, future research directions can concentrate on improving the generalisation ability of models, optimising computational efficiency, solving data problems, and enhancing the real-time and interpretability of models.

Declarations

All authors declare that they have no conflicts of interest.

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