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RESEARCH ARTICLE

Deep-Learning-Based Lithium Battery Defect Detection via Cross-Domain Generalization

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ABSTRACT This research addresses the critical challenge of classifying surface defects in lithium electronic components, crucial for ensuring the reliability and safety of lithium batteries. With a scarcity of specific defect data, we introduce an innovative Cross-Domain Generalization (CDG) approach, incorporating Cross-domain Augmentation, Multi-task Learning, and Iteration Learning. Leveraging a steel surface defect dataset as foundational knowledge, our approach compensates for the limited lithium-specific data and enhances model generalization. We also introduce the Lithium Electronic Surface Defect Classification (IESDC) dataset, demonstrating significant accuracy improvements over baseline methods. Our comprehensive evaluation covers model interpretability, robustness, and adaptability. Beyond battery technology, this methodology offers a framework for data scarcity challenges in various industries, emphasizing the importance of adaptable learning methods.

INDEX TERMS Lithium electronic surface defect classification, cross-domain generalization, multi-task learning, iteration learning.

I. INTRODUCTION

In the rapidly evolving landscape of lithium battery technology, the reliability and quality of electronic components stand as paramount concerns. Among the many aspects influencing these components, the detection and classification of surface defects in lithium electronic parts emerge as critical factors. These defects, which can range from microscopic fissures to subtle material inconsistencies, have the potential to significantly compromise the performance and safety of lithium batteries. Thus, the accurate identification and classification of these defects represent not only a vital endeavor but also a formidable challenge, particularly given the scarcity of specific defect data for training classification models [1], [2], [3]. This paper introduces an innovative approach to lithium electronic surface defect classification, meticulously designed to achieve remarkable accuracy even in scenarios with minimal training data.

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Surface defects in lithium batteries loom large on the radar of manufacturers and users alike. Imperfections such as cracks, impurities, and irregularities can lead to a plethora of problems, ranging from diminished battery life and efficiency to severe safety hazards, including overheating and the dreaded potential for explosions. As lithium batteries continue to gain prominence across a wide array of applications, the necessity for efficient and reliable defect detection methods becomes increasingly pressing. This demand is further underscored by recent research studies, such as those conducted by [4] and [5], which illuminate the critical role that accurate defect detection plays in enhancing battery safety and performance.

Traditional methods for surface defect classification traditionally rely on the availability of extensive and diverse datasets for training machine learning models. However, in the context of lithium electronic components, such datasets are a rare commodity. The rarity and specificity of defects in lithium batteries make the collection of comprehensive training data a formidable challenge. Moreover, standard datasets, which are often designed for more general applications, often prove inadequate for the specialized task of lithium defect classification, as noted in the research by [6] and [7].

To rise to these challenges, our study puts forth an innovative Cross-Domain Generalization (CDG) approach for lithium electronic surface defect classification. First and foremost, we implement Cross-domain Augmentation, leveraging the NEU dataset [8] designed for steel surface defect detection as a foundational learning resource. This dataset serves as a bedrock upon which our model can learn broader defect recognition patterns, thereby compensating for the scarcity of extensive, lithium-specific defect data. The efficacy of such cross-domain learning strategies has already been demonstrated in similar contexts, as evidenced by the work of [9].

Secondly, our approach incorporates Multi-task Learning [10], [11], an ingenious strategy that involves simultaneously training the model on both the augmented NEU dataset and the lithium electronic surface defect source dataset. This approach amplifies the model's defect detection capabilities across different contexts while preserving its accuracy for lithium-specific defects. The concept of multi-task learning harmonizes perfectly with recent advancements in machine learning, where models are increasingly trained to perform multiple tasks, thereby enhancing their overall performance and robustness.

The final, critical component of our methodology is Iteration Learning [12], [13]. This strategic approach involves iteratively training the model across different data sources, thus preventing it from overfitting to a single dataset and bolstering its ability to generalize across diverse scenarios. Iteration Learning is of particular significance in scenarios where data diversity is limited, as it equips models with the adaptability needed to handle new and unseen data effectively. This approach is firmly in line with the findings of [6], which underscore the pivotal role of adaptable learning methods in defect classification.

In addition to addressing the critical challenge of lithium electronic surface defect classification, our research also introduces a dataset, the Lithium Electronic Surface Defect Classification (IESDC) dataset. Our experimental results demonstrate the superiority of our proposed method over baseline approaches. We achieved remarkable performance gains in defect classification accuracy, underscoring the effectiveness of our Cross-Domain Generalization (CDG) approach. Furthermore, our research goes beyond mere performance metrics. We conducted a comprehensive analysis of our model's effectiveness, delving into various aspects. This in-depth evaluation not only validates the practical utility of our approach but also provides valuable insights into its strengths and limitations.

The implications of our study extend far beyond the realm of lithium battery technology. Our methodology, rooted in Cross-Domain Generalization, Multi-task Learning, and Iteration Learning, represents a robust framework for addressing data scarcity challenges in specialized fields. This framework can be applied across various industries where quality control is paramount, yet hindered by the limited availability of training data.

The contributions of this research are multi-faceted and can be summarized as follows:

1) Our study presents a novel CDG approach for lithium electronic surface defect classification. We use cross-domain augmentation, multi-task learning, and iteration learning to address the scarcity of lithium-specific defect data and improve model generalization.
2) We introduce the Lithium Electronic Surface Defect Classification (IESDC) dataset as a benchmark for this classification task.
3) Our experimental results show significant improvements in defect classification accuracy compared to baseline methods, highlighting the effectiveness of our CDG approach for lithium electronic surface defect classification.
4) Beyond superior performance, we thoroughly evaluate our model's interpretability, robustness, and adaptability to provide a comprehensive understanding of its strengths and limitations.

In the following sections, we review existing research in lithium electronic surface defect classification, introduce our innovative methodology involving Cross-Domain Generalization (CDG), Multi-task Learning, and Iteration Learning to address data limitations, and present our experiments, including setup, data sources, and evaluation metrics. Finally, we summarize our findings and discuss their broader implications for defect classification and data scarcity challenges in the field.

II. RELATED WORK

A. INDUSTRIAL SURFACE DEFECT IDENTIFICATION

The field of industrial surface defect identification has seen significant advancements with the integration of machine vision and deep learning techniques, addressing challenges in quality control across various sectors. This section provides an overview of recent developments in this area, referencing key contributions from literature. Traditional feature-based detection methods in machine vision have focused on texture, color, and shape features for identifying surface defects in industrial products [14]. These methods laid the groundwork for more advanced techniques, but faced limitations in handling complex defect patterns and variations in industrial scenarios. Recent years have witnessed a shift towards deep learning-based approaches, which offer enhanced capabilities in handling complex defect scenarios. Supervised, unsupervised, and weakly supervised learning paradigms have been explored to improve detection accuracy and adaptability. Deep learning methods have tackled key challenges such as real-time processing, small sample learning, detection of small targets, and dealing with imbalanced datasets [14]. These advancements have proven particularly beneficial in sectors like semiconductors, steel, and textiles, where defect detection plays a crucial role in quality assurance.

A comprehensive review of deep learning techniques in surface defect inspection reveals the progress in automated visual detection, encompassing both hardware and software aspects [15]. This includes a summary of traditional algorithms, ranging from statistical methods to model-based and learning-based approaches, and their evolution into deep learning-based algorithms. These advancements have been successfully applied in key industries, demonstrating the versatility and effectiveness of deep learning in surface defect detection. Innovations in unsupervised learning, particularly through dual attention-based methods [16], have shown promise in enhancing defect detection. By employing channel and pixel attention mechanisms, these methods achieve robust image reconstruction, facilitating the differentiation between defective and non-defective images. Additionally, the introduction of consistency loss functions leverages differences in image modalities to further improve detection performance. Another significant development [17] has been the adaptation of the YOLOv5 framework for industrial surface defect detection. Addressing challenges like detecting small and less distinct features, this approach integrates convolutional networks with coordinate attention and BiFPN for multi-scale feature fusion. Incorporating Transformer structures within the network, it demonstrates improved prediction capabilities in complex scenarios. This method has achieved a substantial increase in recall rates for anomaly categories and notable improvements in real-time detection performance. Finally, the emergence of deep regression neural networks presents a novel approach [18] that combines regression and classification for general industrial defect detection. This framework, comprising deep regression-based detection models, pixel-level mis-detection reduction, connected component analysis, and deep network-based defect type classification, offers a comprehensive solution. By generating label data from annotations to capture the severity of defects, this method showcases state-of-the-art performance in both accuracy and efficiency on various benchmark datasets. The evolution of industrial surface defect detection technologies underscores the pivotal role of deep learning and machine vision. These advancements not only enhance detection accuracy but also cater to the specific needs of different industrial applications, paving the way for more efficient and reliable quality control processes.

B. LITHIUM ELECTRONIC SURFACE DEFECT IDENTIFICATION

The advancement in identifying surface defects in lithium electronic components is crucial for enhancing the quality and safety of lithium batteries. This section presents a review of various innovative methods employed in recent research to address the challenges in detecting and classifying surface defects in lithium batteries. The first significant approach, presented by [4], focuses on the automatic detection and identification of surface defects on lithium battery pole pieces. This method integrates multi-feature fusion with a Particle Swarm Optimization Support Vector Machine (PSO-SVM) algorithm. By combining texture, edge, and Histogram of Oriented Gradients (HOG) features, this approach extracts feature vectors from defect area images, which are then classified using PSO-SVM. The process involves image preprocessing, defect area extraction, feature extraction, and defect recognition. The experimental results demonstrate an impressive average recognition rate of 98.3%, proving the method's effectiveness in detecting various types of defects on lithium battery pole pieces. Another novel approach is described in [9], which employs an improved K-nearest neighbor algorithm and Euclidean clustering segmentation for lithium battery surface defect detection. This method uses a voxel density strategy for accelerating point cloud filtering and distinguishes defect features through clustering segmentation. The geometric features of each defect are determined using a least squares contour fitting algorithm, which aids in the classification of defect types. The approach encompasses point cloud filtering, defect area segmentation, defect feature extraction, and defect type classification. This method achieves a defect detection accuracy of 99.2% and an average data processing time of 35.3 milliseconds, highlighting its suitability for industrial applications in lithium battery production. In [6], an embedded machine vision-based approach is explored for detecting surface defects in lithium batteries. This approach aims to address the challenges of manual inspection in lithium battery production, such as high workload and error rates. The method leverages image processing techniques to locate and extract surface defects, followed by an adaptive threshold segmentation algorithm based on histogram reconstruction. The methodology includes image acquisition, area extraction, background compensation, defect localization, and defect detection. The results indicate a significant reduction in grayscale value fluctuations in the ROI background area, enhancing the effectiveness and speed of defect detection. Research presented in [5] introduces an automatic defect detection scheme for lithium-ion battery electrode surfaces. The goal is to achieve real-time online detection of electrode surface defects, thereby improving the actual industrial production quality of lithium-ion batteries. The method begins with conventional region extraction from captured electrode images, followed by a rapid background compensation algorithm to reduce grayscale value fluctuations in the ROI. It then employs simple threshold segmentation and bounding rectangle transformation for quick defect detection and extraction, culminating in an adaptive threshold segmentation algorithm based on histogram reconstruction for accurate and rapid defect detection. The experiment confirms the effectiveness of this scheme, especially in background compensation and threshold segmentation for defect detection. Lastly, [7] discusses the use of deep convolutional neural networks (CNNs) for detecting microstructural defects in lithium-ion battery electrodes from optical microscopic images of sliced cells. The challenge is to train deep CNNs with limited training images and design a highly sensitive and accurate

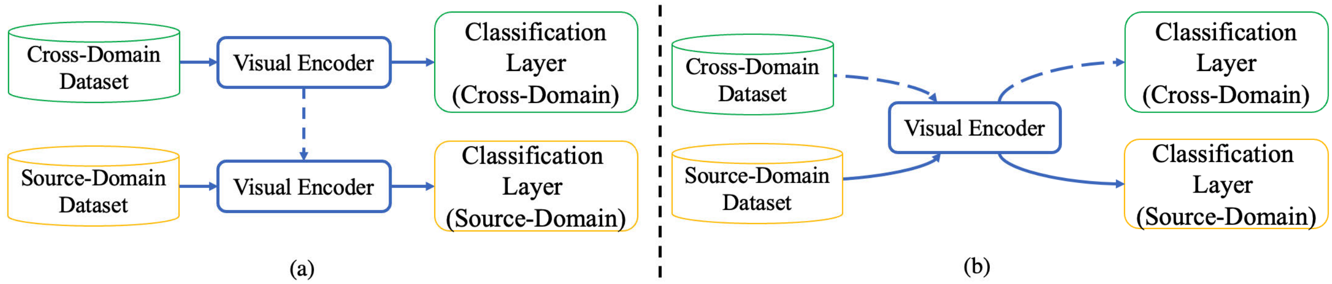


FIGURE 1. Different concepts between (a) Cross-Domain Pre-training and (b) Our Method. The solid line indicates the primary learning process for the model, while the dotted line represents the auxiliary learning process for the model.

defect detection scheme. This study adopts a multiscale image augmentation and classification approach, generating multiple scale image block samples from a few lithium-ion battery images. The two-stage classification scheme aims to differentiate and then identify specific defect types in the first and second stages, respectively. The method achieves a classification accuracy of 93.67% for defect image blocks and an average precision rate of 90.78% for defect type recognition, based on two enhanced multiscale datasets constructed from just 26 source images. These studies underscore the diverse and effective strategies employed in recent research for lithium electronic surface defect identification, utilizing a range of innovative algorithms and methodologies to enhance the quality and safety of lithium batteries. Besides, the robustness of models against difficult confusing examples and well-designed adversarial examples is a crucial consideration in developing methods for identifying surface defects in lithium electronic components. According to Dong et al. [19], models need to demonstrate resilience against restricted black-box adversarial attacks, a concept proven in their study on adversarial attacks against deepfake face swapping. Their findings reveal the importance of considering model robustness in the context of false surface defects detection, which could potentially be analogous to identifying deepfake anomalies. Dong et al. also argue for intrinsic adversarial robustness through probabilistic training [20]. The study underscores that by considering uncertainty and randomness in the training process, models could counter adversarial perturbations and thus enhance the precision of surface defect identification. This implies the need for developing lithium electronic surface defect detection methodologies that not only perform effectively but are also robust in the face of challenging adversarial samples.

III. METHODOLOGY

Our methodology employs a multi-faceted approach to classify surface defects in lithium batteries. As shown in Figure 1, this approach is particularly designed to overcome the challenge of limited training data, a common issue in specialized domains. It should be highlighted that different from the previous cross-domain pre-training that regards both source-domain and cross-domain tasks equally as primary learning tasks, our method treats cross-domain data as the auxiliary knowledge resource and focuses on utilizing it to benefit the model learning for source-domain task. Below, we expand on each aspect of our methodology, incorporating detailed formulas and discussing the rationale behind each approach.

A. BASE MODEL

The foundation of our methodology is the base model, which utilizes a pretrained visual encoder. We opt for a pretrained encoder due to its proven effectiveness in feature extraction. This is particularly beneficial in our scenario, where domain-specific data is scarce. The pretrained encoder has been extensively trained on diverse datasets, enabling it to extract rich, generalized features. These features are crucial for our task, as they compensate for the limited data available in lithium battery defect images. Our architecture is as follows:

$$F = E(X) \tag{1}$$

$$Y = C(F) \tag{2}$$

where X is the input image, $E(\cdot)$ represents the visual encoder (a pretrained deep CNN), F is the extracted feature vector, $C(\cdot)$ is the classification layer, and Y is the output class. The use of this encoder allows us to leverage its powerful feature extraction capabilities, setting a strong foundation for accurate defect classification.

B. CROSS-DOMAIN AUGMENTATION

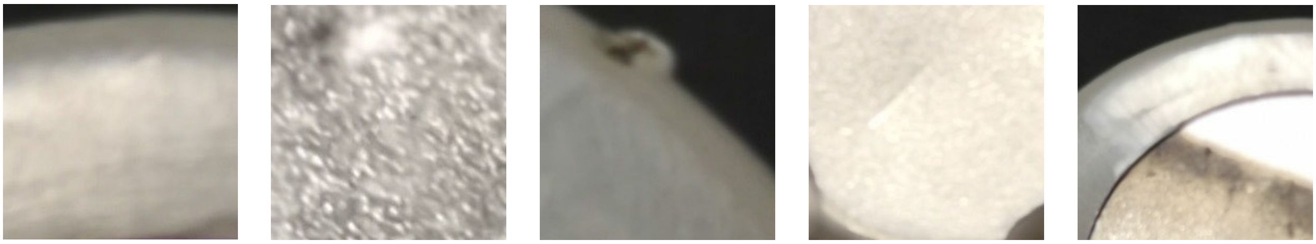
To address the scarcity of lithium-specific data, we employ Cross-domain Augmentation. This strategy involves augmenting our primary dataset (lithium battery images) with data from the NEU steel surface defect dataset. The rationale behind this is to enhance the model's exposure to a diverse range of defect patterns, which can be beneficial in learning more generalized features:

$$D_{augmented} = D_{lithium} \cup D_{NEU} \tag{3}$$

This augmented dataset broadens the learning scope of the model, enabling it to recognize a wider array of defect features. Such diversity in training data is instrumental in improving the model's ability to generalize to new,

TABLE 1. Sample number of our IESDC dataset.

Data Split	No Defect	Over Melting	Damaged	End Recess	Inked
Training	14	2	2	1	1
Test	56	8	8	5	5



(a) No Defect (b) Over Melting (c) Damaged (d) End Recess (e) Inked

FIGURE 2. Images and their classes in IESDC dataset.

unseen lithium defects, thereby enhancing its overall robustness and accuracy.

C. MULTI-TASK LEARNING

In our approach, Multi-task Learning is employed to enhance the model's performance across various types of defects. By simultaneously training the model on both lithium and NEU datasets, the model learns shared features that are relevant across different surface defect domains. This is based on the premise that certain defect characteristics are universal and can be learned more effectively when exposed to varied data sources:

$$L_{total} = \alpha L_{lithium}(Y, f(X)) + \beta L_{NEU}(Y, f(X)) \tag{4}$$

where α and β are weights balancing the importance of each task. This multi-task approach not only improves the model's performance on lithium defects but also endows it with the versatility and adaptability to handle a variety of surface defects.

D. ITERATION LEARNING

To further enhance the model's ability to generalize, we implement Iteration Learning. This involves training the model iteratively on different subsets or variations of the augmented dataset. Such a strategy minimizes the risk of overfitting, a common challenge in machine learning, particularly in scenarios with limited data:

$$L^{(i)} = \text{Loss for iteration } i \tag{5}$$

$$L_{overall} = L_{total} + \sum_{i=1}^{N} L^{(i)} \tag{6}$$

This iterative approach ensures a robust and comprehensive learning process, allowing the model to continuously adapt and refine its understanding of various defect types. This, in turn, significantly enhances its performance and generalization capabilities.

E. TRAINING

Finally, the training regimen is meticulously designed to synergize the various components of our methodology. The comprehensive loss function guides the model in effectively learning from both datasets and through iterative learning processes. The optimization of the overall loss function:

$$\text{Optimize } L_{overall} = L_{total} + \sum_{i=1}^{N} L^{(i)} \tag{7}$$

ensures that all elements of our methodology are cohesively integrated, leading to a robust and effective model for lithium battery surface defect classification.

IV. EXPERIMENTS

A. DATASET

In our experiments, we utilized two datasets: one that we collected ourselves, known as the Lithium Electronic Surface Defect Classification (IESDC) dataset, and another dataset containing six typical surface defect categories in hot-rolled steel strips, referred to as NEU-CLS [CLS]. Due to the high cost associated with data collection, our IESDC dataset offers only a limited number of training samples. The dataset comprises five categories: "End Recess", "Over Melting", "No Defect", "Inked", and "Damaged", with specific quantities as outlined in Table 1. Furthermore, visual representations of samples from our dataset are presented in Figure 2. To facilitate the understanding to challenges of such defects, we provide corresponding introduction and analysis as follows:

- **No Defect**: Amidst defect categories, the No Defect classification serves as a crucial baseline. The challenge lies in discerning between minute, non-critical anomalies and actual defects, thereby preventing false positives that could lead to unnecessary wastage or rework.

- **Over Melting**: Over Melting defects are aberrations caused by excessive heat application, usually resulting in localized deformations. Identifying these defects involves distinguishing between typical heat-induced variations and genuine structural compromises, often complicated by heterogeneous surface reflections.
- **Damaged**: Damage can present in a multitude of forms, from cracks to scratches, and is perhaps the most visually diverse category. Pinpointing these defects requires a keen eye for detail and context-aware analysis, as the signs of damage can be highly irregular and unpredictable.
- **End Recess**: Manifesting typically at the material edges, End Recess defects can be characterized by their subtle indents, which often escape standard detection due to lighting angles and shadowing effects. Accurate identification of these defects is essential to ensure structural integrity.
- **Inked**: Inked surfaces involve unintended markings that must be differentiated from inherent textural patterns. The identification challenge here is primarily around separating purposeful design elements from accidental ink spills, which can be particularly tricky in varying lighting conditions.

B. EXPERIMENTAL SETTING

During the model training process, we set the batch size to 16, the learning rate to 0.001, and the number of epochs to 10. We utilized the Adam optimizer [21]. Our proposed CDG method was trained on the NEU-CLS dataset for 50 steps and the IESDC dataset for 10 steps, followed by iterative alternating training. In the multi-task learning setting, both α and β were set to 1.0. We trained the model using a single Tesla T4 GPU with a memory capacity of 15GB. For the dataset images, we initially resized them to a size of 224×224 and applied random horizontal flipping and random rotation as data augmentation preprocessing steps.

C. RESULTS

The presented table 2 showcases a comparison of various methods on the IESDC dataset, utilizing accuracy (ACC) as the primary evaluation metric. The methods under examination encompass widely recognized deep learning architectures, including ResNet18, ResNet50, MobileNetV2, and the Vision Transformer (ViT). Additionally, the table incorporates variants of the CDG (Cross-Modal Generalization) method, denoted with their respective backbone models.

Among the baseline architectures, we have ResNet18, ResNet50, MobileNetV2, and ViT: These are well-established deep learning architectures with distinct characteristics. ResNet18 and ResNet50 are renowned for their depth, MobileNetV2 for its efficiency, and ViT for its transformer-based architecture's success in image classification tasks. A detailed analysis of the performance of the baseline models reveals the following: ViT achieves the highest accuracy of 82.5%. This outcome underscores the potential of transformer-based architectures, like ViT, for image classification tasks. ResNet18 follows closely with an accuracy of 72.5%, while ResNet50 and MobileNetV2 achieve accuracies of 71.25% and 70%, respectively. These results suggest that deeper architectures like ResNet50 may not always guarantee superior performance, and efficiency-focused models like MobileNetV2 may exhibit limitations in specific tasks.

TABLE 2. Comparison result on IESDC dataset.

Method	ACC
ResNet18 [22]	72.5
ResNet50 [22]	71.25
MobileNetv2 [23]	70
ViT [24]	82.5
CDG (ResNet18)	82.5
CDG (ResNet50)	82.5
CDG (MobileNetv2)	73.75
CDG (ViT)	**91.25**

The CDG method, with different backbone models (ResNet18, ResNet50, MobileNetV2, ViT), consistently outperforms the baseline models, showcasing the effectiveness of the proposed CDG method for enhancing cross-modal generalization: CDG with ViT as the backbone leads with the highest accuracy among all methods, at an impressive 91.25%. This result underscores the synergy between the CDG method and transformer-based architectures, resulting in exceptional performance. CDG with ResNet18, ResNet50, and MobileNetV2 as backbones all achieve identical accuracies of 82.5%, indicating that the CDG method effectively mitigates the performance disparities between different backbone models, making the choice of the backbone less critical when CDG is applied. The comparative analysis of the results reveals: CDG with ViT significantly outperforms all other variants and baseline models, highlighting the transformative impact of the CDG method on ViT, which already performed well as a baseline. This emphasizes the potential of CDG in enhancing the capabilities of state-of-the-art architectures.

The experimental results suggest that the CDG method, particularly when paired with a transformer-based architecture like ViT, can substantially elevate the performance of image classification tasks on the IESDC dataset. The superior performance of the CDG method when paired with a ViT backbone can be attributed to the ability of transformer models to process images as sequences, enabling them to capture global context and intricate inter-pixel relationships more effectively than traditional CNNs. The self-attention mechanisms in ViT are particularly synergistic with the CDG approach, which aims to leverage features relevant across different domains for enhanced generalization.

This combination allows the method to discern nuanced patterns in surface defects within the IESDC dataset, leading to a significant increase in detection accuracy.

D. ABLATION STUDY

The ablation study Table 3 provides valuable insights into the effectiveness of different methods for cross-modal generalization (CDG) using different backbone models (resnet50 and ViT) on the NEU-CLS and IESDC datasets. We also examine the impact of pre-training on NEU-CLS, multi-task learning, and our proposed CDG method.

TABLE 3. Ablation study.

Method	ACC
ResNet50	71.25
Pre-trained (ResNet50)	78.75
Multi-Task Learning (ResNet50)	72.5
CDG (ResNet50)	**82.5**
ViT	82.5
Pre-trained (ViT)	81.25
Multi-Task Learning (ViT)	81.25
CDG (ViT)	**91.25**

First, let's focus on the resnet50 backbone. The baseline resnet50 model achieved an accuracy of 71.25% on the IESDC dataset. Pre-training resnet50 on the NEU-CLS dataset improved the performance significantly to 78.75%. This result demonstrates the benefits of pre-training, which helps the model capture more general features that can be fine-tuned for the target dataset. However, when applying multi-task learning with both NEU-CLS and IESDC datasets simultaneously, the accuracy dropped to 72.5%. This suggests that combining datasets without proper adaptation can lead to performance degradation due to domain shift. The key contribution comes from our CDG method with the resnet50 backbone, which achieved an impressive accuracy of 82.5%. CDG leverages the NEU-CLS dataset during training and employs iteration training to enhance traditional multi-task learning. This approach demonstrates the effectiveness of our proposed method in mitigating domain shift and improving cross-modal generalization. In addition, the baseline ViT model initially outperformed resnet50 with an accuracy of 82.5%. Pre-training ViT on the NEU-CLS dataset yielded a slightly lower accuracy of 81.25%, indicating that ViT might not benefit as much from pre-training as resnet50. Multi-task learning with ViT also resulted in an accuracy of 81.25%, similar to pre-training, which suggests that ViT might already possess a better generalization capability. However, the most remarkable result in this study is the performance of CDG with the ViT backbone, achieving an accuracy of 91.25%. This highlights the superiority of CDG in adapting ViT to the IESDC dataset, showcasing its ability to bridge the domain gap effectively. CDG's iterative training approach appears to be particularly beneficial for ViT, as it achieves a substantial improvement over the baseline. From the results above, each module contributes uniquely to the overall performance of surface defect classification. Pre-training captures general features from one dataset, which enhances the model's ability to adapt when fine-tuned on a target dataset, as shown by the improvement with ResNet50. However, combining datasets for multi-task learning without consideration for domain discrepancies can negatively impact performance due to domain shift. The CDG method helps rectify this by leveraging domain-specific training and iterative updates, leading to improved generalization across different datasets. For ViT, the inherent strengths of the architecture may minimize the benefits of pre-training and multi-task learning, but CDG methodology maximizes its potential, particularly through iterative training that significantly boosts its adaptability and accuracy on challenging datasets.

E. TRAINING LOSS

As shown in Figure 3, two prominent deep learning models, *resnet50* and *Vision Transformer (vit)*, were trained on two distinct datasets: IESDC, represented as LiImages, and NEU-CLS, represented as GImages. The training loss curves for both datasets were observed over a course of 10 epochs.

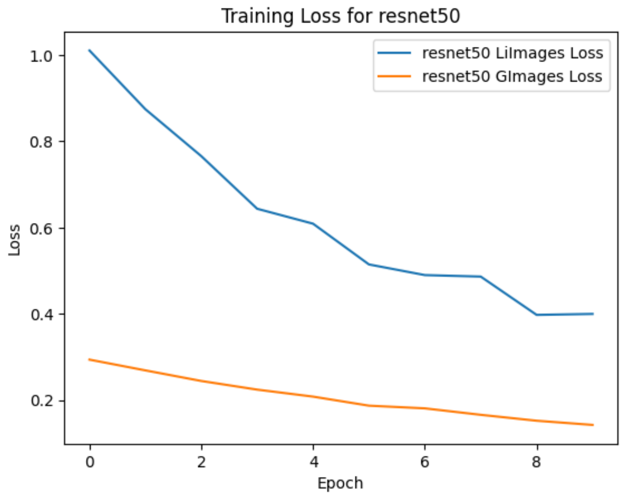
For the *resnet50* model, the LiImages loss started at approximately 1.0, showing a steep decline in the initial epochs and then plateauing after epoch 6, ending at around 0.3. In contrast, the GImages loss began at a lower value, close to 0.4, and exhibited a more gradual descent, finalizing near the 0.2 mark. This pattern indicates a faster convergence on the NEU-CLS dataset compared to the IESDC dataset for the *resnet50* architecture.

The *Vision Transformer (vit)* demonstrated a similar trend with LiImages loss initiating at around 1.4 and descending sharply until epoch 2, then continuing to decrease at a slower rate, stabilizing close to 0.2 by epoch 10. The GImages loss for *vit* started just above 0.4 and dropped steadily to just below 0.1. The Vision Transformer model achieved a lower loss on the NEU-CLS dataset more rapidly than on the IESDC dataset, suggesting a better fit to the former.

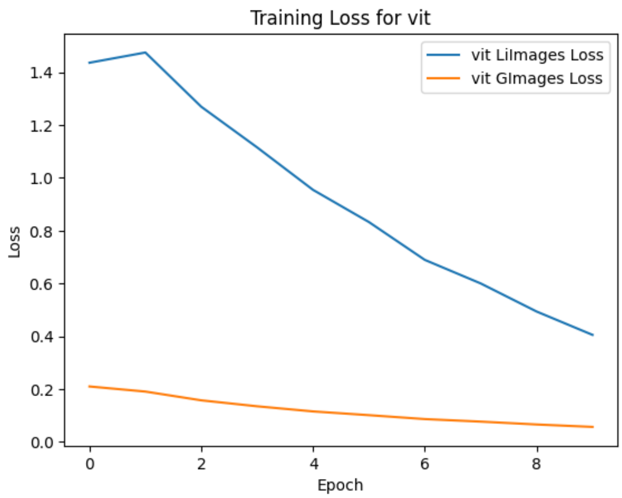
The concurrent reduction in loss for both LiImages and GImages across epochs for each model suggests compatibility and effective learning from both datasets. The more significant loss reduction for GImages indicates that both models could capture the NEU-CLS data characteristics with greater ease or that the NEU-CLS dataset might be less complex or more consistent in its features compared to the IESDC dataset.

F. IMPACT OF DOMAIN AUGMENTATION

The performance comparison between our proposed Contextual Domain Generalization (CDG) method and the baseline across different classes is illustrated in the Figure 4. The left figure represents the accuracy of our CDG method, while the right figure depicts the baseline performance. From the left figure, we observe a significant improvement

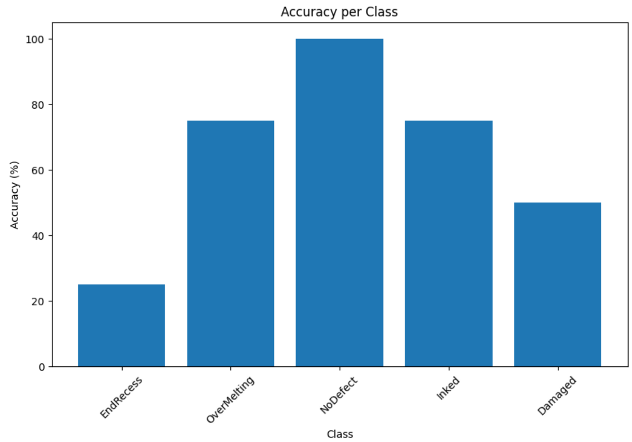


(a) Loss on ResNet50 Backbone

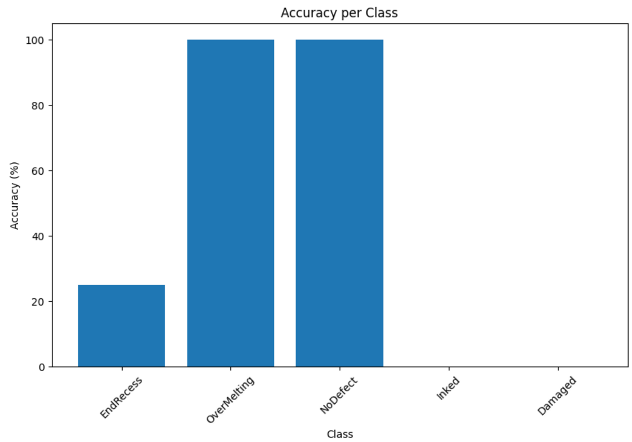


(b) Loss on ViT Backbone

FIGURE 3. **Impact of training loss.**



(a) Loss on ResNet50 Backbone



(b) Loss on ViT Backbone

FIGURE 4. **Impact of training loss.**

in accuracy for the 'Overmelting' and 'Nodefect' classes, where CDG achieves over 80% accuracy. This suggests that CDG effectively captures the underlying patterns within these classes, possibly due to enhanced feature representation or domain augmentation techniques that mitigate domain shift. In contrast, the 'Endrecess' class demonstrates a substantially lower accuracy of approximately 20%, indicating that this category may have a higher intra-class variability or less representation in the training data, which CDG struggles to generalize. Similarly, the 'Damaged' class also shows reduced performance, hinting at potential complexities in characterizing damage-related features that are not fully captured by the current model. On the other hand, the right figure shows the baseline model's performance. The baseline exhibits a more uniform distribution of accuracy across classes but underperforms compared to CDG in 'Overmelting' and 'Nodefect' by a noticeable margin. This uniformity may point to a lack of specialization towards specific classes, which CDG seems to counteract, likely through domain-specific feature alignment or regularization strategies. The 'Inked' class presents an interesting case where both CDG and the baseline have comparable accuracies, suggesting that features of the 'Inked' class are less affected by domain variations or are well-represented in the data.

G. CASE STUDY

As shown in Figure 5, we present a qualitative analysis of the samples that were correctly classified by our Contextual Domain Generalization (CDG) approach. The images represent instances of various classes, including 'EndRecess', 'OverMelting', 'NoDefect', 'Inked', and 'Damaged'. These samples reflect the diverse and complex nature of the classification task at hand. The 'EndRecess' class is characterized by subtle indentations or recesses on the surface. The sample image shows a faint, elongated depression which our CDG method has successfully identified. This success may be attributed to the method's ability to extract and generalize low-contrast features across different domains. The 'OverMelting' class depicts areas where the material has melted

FIGURE 5. **Case study of our CDG method.**

excessively. The correctly classified sample reveals a small, rounded protrusion with a distinct texture, indicating overmelting. CDG's adeptness in capturing textural differences seems to play a crucial role in identifying such defects. In the 'NoDefect' class, the sample portrays a uniform and defect-free surface. The CDG approach has correctly classified this example, demonstrating the model's capacity to distinguish between negative and positive instances effectively, a critical requirement for practical applications. The 'Inked' class comprises samples with ink or similar markings. The given image shows a clear demarcation with ink around the edge. Despite the potential for confusion with shadowed regions, CDG has successfully recognized the distinctive features of ink markings. Lastly, the 'Damaged' class involves more pronounced defects. The sample image illustrates a distinct anomaly on the surface, which CDG has identified as damage. The method's efficacy in detecting such conspicuous defects indicates robust feature learning and domain adaptability. The successful classification of these samples indicates that CDG is capable of discerning intricate patterns and variations within each class, confirming its robustness and generalization across domain-specific challenges.

V. CONCLUSION AND FUTURE DIRECTIONS

This paper presents a novel approach to lithium electronic surface defect classification, addressing the challenge of limited specific defect data. Our Cross-Domain Generalization (CDG) strategy, integrating cross-domain augmentation, multi-task learning, and iterative learning, has proven effective in enhancing model accuracy and adaptability. By leveraging the NEU steel surface defect dataset and the Lithium Electronic Surface Defect Classification (IESDC) dataset, we have demonstrated significant improvements in defect classification performance. The CDG approach's adaptability and robustness in handling diverse defect scenarios set a new benchmark in lithium battery defect classification. Our methodology's success not only provides a valuable tool for quality control in lithium battery manufacturing but also offers a framework applicable to other industries facing similar data scarcity challenges. Meanwhile, though the CDG marks a significant advance in surface defect classification, addressing adversarial examples remains an area ripe for further exploration. Such examples pose a considerable threat by exploiting model vulnerabilities to induce misclassifications—a challenge not fully tackled in the current model. Future iterations of our methodology could benefit from integrating adversarial training, a technique designed to enhance model robustness by exposing it to adversarially crafted inputs during the training phase. Additionally, exploring techniques for detecting and mitigating adversarial attacks in real-time could further reinforce the model's resilience. Through these enhancements, we aim to fortify our CDG strategy against worst-case scenarios, ensuring its effectiveness and reliability in diverse and adversarial environments.

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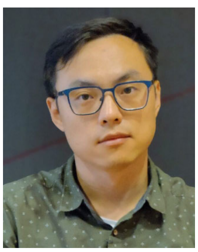

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