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A Survey on Using Label Correction to Combat Noisy Labels

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Abstract. Given the swift progress of deep learning in fields like computer vision and natural language processing, the fidelity of dataset annotations has ascended to a position of paramount importance. In real-world scenarios, the construction of large-scale datasets often incurs substantial annotation costs, resulting in frequent noisy labels. These noisy labels can significantly increase the risk of overfitting and impair the generalization performance of deep neural networks. Numerous methods have been proposed and widely applied to real-world tasks such as image classification and text annotation to address this challenge, where they have demonstrated strong robustness and practical effectiveness. Label correction, in the context of these methodologies, is geared toward enhancing the caliber of annotations through the identification and subsequent rectification of instances marred by incorrect labeling.This paper presents a comprehensive analysis of this methodology by examining its underlying principles and model frameworks, exploring their development trajectories and advantages. Furthermore, it summarises the key challenges and promising future directions in developing label correction techniques.

Keywords: Deep Learning, Label Correction, Noisy Label, Model Generalization

1. Introduction

In recent years, deep learning has achieved significant success in domains such as computer vision [1] and natural language processing [2], where model performance is highly dependent on the quality of training data. However, the cost of collecting datasets is too high. To reduce the cost of data annotation, approaches such as automated labeling tools [3], crowdsourcing [4], and web-crawling algorithms [5] have been widely employed. Still, at the same time, many datasets are easily affected by label noise, especially in specialized fields such as medical diagnosis [6] and industrial inspection [7], where data collection is inherently complex and annotation standards are exceptionally stringent. Consequently, label noise presents a substantial barrier to the effective deployment of deep learning models in these critical applications.

Noisy labels can significantly degrade the performance of deep neural networks (DNNs) by causing them to learn incorrect patterns. This increases the risk of overfitting [8] and impairs the generalization ability of the models. Furthermore, label noise can destabilize the training process and hinder model convergence. As a result, mitigating the adverse effects of label noise and improving model generalization has become a central focus of contemporary research.

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Existing approaches to learning with noisy labels can be broadly categorized into five primary research directions: (1) label correction and noise detection, (2) robust loss functions and training strategies, (3) semi-supervised and contrastive learning, (4) model architecture and collaborative learning, and (5) multi-label or partial-label learning. Among these, label correction and noise detection constitute the most direct line of technical development and label correction is a significant direction in this method. Label correction methods seek to identify and revise incorrect labels in the dataset explicitly. The strategy aims to mitigate the risk of overfitting to noisy labels while training deep neural networks. Empirical studies have shown that it significantly improves the generalization ability and robustness of the model, making it one of the most meaningful and promising directions in noisy supervised learning.

By reviewing recent publications from top-tier conferences such as CVPR, ICCV, AAAI, NeurIPS, and ICML, we survey 23 representative models related to Label Correction methods.

For the Label Correction category, it summarizes five prominent types of approaches:

(1) meta-learning and optimization-based techniques,

(2) graph-based label propagation methods,

(3) soft labeling and probabilistic modeling,

(4) contrastive learning and consistency-based strategies, and

(5) counterfactual reasoning and causal inference frameworks.

Guided by this taxonomy, this paper focuses on analyzing representative methods and recent advances in Label Correction.

2. Types and structures of label noise in supervised learning

In supervised learning, label noise can be divided into two types: Instance-Independent Noise (IIN) and Instance-Dependent Noise (IDN)

(1) Instance-independent label noise

The Instance-Independent Noise (IIN) assumption posits that the probability of label corruption depends solely on the actual class label and is independent of the input features. Which can be IIN can be classified into the following Symmetric Noise and Asymmetric Noise.

• Symmetric Noise: All incorrect class labels are equally likely to replace a given true label. Letting the noise rate be η , the transition matrix satisfies: $T_{ii} = 1 - \eta,\ T_{ij} = \frac{\eta}{C-1}$ for $j \neq i$. That is, mislabeling is uniformly distributed across the incorrect classes.

• Asymmetric Noise: Certain classes are more likely to be mislabeled as specific other classes. In this case, the off-diagonal elements of the transition matrix are non-uniform, and specific entries T_{ij} are significantly larger, reflecting class-dependent noise patterns.

(2) Instance-dependent label noise

Instance-Dependent Noise (IDN) assumes that the probability of label corruption is influenced not only by the true label but also by the input features of each sample. Under IDN, different instances belonging to the same class may have varying probabilities of being mislabeled. The label corruption process is described by the conditional probability: $P(\tilde{y} = j \mid x, y = i)$, which accounts for context-dependent mislabeling.

3. Label correction

Based on our survey, approaches for handling noisy labels in deep learning can be categorized into the six major types outlined in Section I , each contributing to enhancing the robustness of

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supervised learning. Among these, label correction has been further classified in detail due to its growing significance. The Label Correction technique aims to rectify mislabeled data using model predictions or auxiliary information. The corrected labels are then used for training, improving the model's ability to learn from cleaner supervision and enhancing generalization.

Label correction has emerged as a prominent research direction. This section provides a comprehensive analysis of the five subcategories within Label Correction.

3.1. Meta-learning-based methods

Early studies, such as MLNT [9], were among the first to formulate label correction as a meta-learning task, leveraging feedback from a small clean validation set to optimize sample-wise loss weighting while implicitly updating noisy labels. These initial investigations laid the groundwork for label correction strategies rooted in meta-learning. Building upon this idea, the Meta Soft Label Corrector [10](MSLC) introduces a significant advancement by replacing traditional hard labels with optimizable soft label distributions. Through iterative optimization of meta-learned parameters, MSLC dynamically generates more reliable soft labels, demonstrating the continuity and adaptability of the label correction process.

Taraday [11] incorporates structural priors over class relationships and employs a task-aware sampling strategy to further improve the effectiveness of meta-learning-based correction. By embedding inter-class structural information into the correction process, it enhances both label understanding and meta-learning stability. In more complex settings, such as multi-label classification and scenarios with missing labels, approaches like PML-DNDC [12] and MLML [13] integrate label correlation matrices into the meta-learning framework, allowing for more accurate modelling of inter-label dependencies and improved robustness against noisy and incomplete annotations. Recent methods such as MSCN [14] and DMLP [15] further advance this research by introducing adaptive modeling of label similarities and multi-stage label filtering strategies, which jointly contribute to stronger noise resistance.

The development of meta-learning-based label correction has thus evolved from optimizing sample importance, modeling structured label information, and ultimately learning inter-label dependencies, marking a systematic progression in the field's ability to perform automated and robust label correction.

3.2. Graph-based label propagation methods

Graph-based methods emphasize the propagation of label and sample similarity through structured representations. Early work such as LSL [16] (Learning with Structural Labeling) constructs structural labels using a reverse k-nearest neighbor (kNN) graph to estimate inter-sample similarity.This graph-based methodology enables the creation of structure-cognizant labels, thereby fostering local label coherence among analogous samples. Building upon this idea, HLC [17] extends graph structures to multi-label image classification by constructing an image-level graph that captures semantic relationships between images. It also employs confidence-based filtering to direct label propagation, leading to a more precise correction process and enhanced global label coherence.

Further advancements, such as LWGBL [18], integrate graph neural networks (GNNs) with label weighting mechanisms to robustly learn node representations and classification outputs in semi-supervised settings. By integrating a label reliability model into the graph framework, LWGBL provides enhanced management of noisy label propagation, leading to improved robustness. The

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CDLN [19] framework adopts a Bayesian formulation, modeling cluster-based labels as latent variables and jointly estimating label transitions. By generating soft labels based on classifier predictions, CDLN enables localized and instance-specific label correction. Although initially developed for multi-label classification, PML-DNDC [12] exemplifies the synergy between graph modeling and optimization by leveraging label co-occurrence matrices and graph-based propagation to improve label quality.

These graph-based approaches construct structured pathways for label propagation and similarity modeling. They offer unique advantages in correcting noisy labels, particularly in scenarios characterized by complex or interdependent label structures.

3.3. Probabilistic modeling methods

Many methods have adopted soft labels or probabilistic modeling in place of hard labels to mitigate the adverse effects of noisy labels, thereby enhancing model robustness. For instance, SGLR [20] dynamically generates smoothed soft labels by leveraging historical predictions and incorporating a self-distillation mechanism to adapt the training process. This approach enables the model to learn from more stable and informative supervision signals and has demonstrated strong performance in adversarially robust learning settings.

To address semantic noise in label annotations, DiN [21] introduces a diffusion-based framework to reconstruct the label embedding space. By conceptualizing label noise through a diffusion model and leveraging a diffusion inversion network, DiN iteratively reconstructs pristine label embeddings from corrupted inputs, demonstrating considerable efficacy in semantic annotation endeavors. Another notable approach, R-MLTSK-FS [22], models label uncertainty through fuzzy logic. It constructs multi-output label representations that capture soft class boundaries, accommodating ambiguity in label assignments. Similarly, the PLM (Part-Level Labels) [23] method formulates the relationship between noisy labels and multiple candidate labels using a posterior probability matrix, which reduces the model's reliance on potentially incorrect annotations.

In summary, soft label methods provide continuous and probabilistic supervision signals, allowing models to tolerate individual label errors better and enhance their robustness in label noise. These approaches have become vital in the broader effort to develop noise-resilient learning systems.

3.4. Contrastive learning and consistency-based methods

This category of methods focuses on leveraging semantic contrast and consistency constraints among samples to enable label modeling and indirect label correction.

Within the supervised contrastive learning framework, SNSCL [24] introduces a confidence-weighted mechanism and a feature sampling strategy, allowing the model to selectively avoid low-confidence samples and mitigate the negative impact of noisy labels. This significantly enhances the representational capacity of deep models.

Building on this idea, RankMatch [25] proposes a novel approach combining self-supervised ranking-matching loss with consistency regularization. It reframes label prediction as a confidence-ranking problem and enforces consistency across uncertainty estimates, effectively suppressing errors arising from incorrect label corrections.

Further advancing this line of work, Jo-SRC [26] integrates supervised loss with structural representation correction. Consistent regularization promotes alignment between labels and semantic

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representations in the embedding space, thus narrowing the gap between noisy labels and true semantic features and improving model generalization.

Twin Contrastive Learning [27] (TCL) introduces a dual-branch contrastive framework that jointly models feature and label flow. By incorporating pseudo-label consistency loss under contrastive constraints, TCL simultaneously strengthens the robustness of feature representations and preserves label stability.

In contrast to traditional label-level correction methods, these approaches enhance the reliability of learning from noisy data by explicitly modeling the interplay between representation spaces and label structures. This provides a more principled and semantically grounded mechanism for aligning noisy labels with their true meanings.

3.5. Counterfactual reasoning and causal modeling methods

In recent years, more studies have incorporated causal inference into label correction, aiming to uncover the underlying mechanisms of label generation by investigating the root causes of label noise.

NLDCC [28] is among the earliest efforts to adopt this perspective. It employs a student–teacher framework to identify potentially mislabeled samples and leverages counterfactual reasoning to infer their proper labels. By comparing predictions under factual and counterfactual conditions, NLDCC performs label correction through a comprehensive identification, generation, and correction pipeline.

From the perspective of training dynamics and the memorization effect, LCNME [29] monitors temporal changes in the model's prediction accuracy to detect change epochs—critical periods during which the model begins to memorize noisy labels. It then triggers label correction precisely at these moments, thereby minimizing the influence of noise on the learning process.

Grounded in predictive modeling and behavioral analysis during training, these approaches focus on the causal origins of label noise and apply causal reasoning to guide the correction process. This emerging research direction offers a promising and principled pathway for developing robust label correction strategies in the presence of noisy supervision.

4. Methodology

Deep learning experiments are typically conducted on various publicly available image classification datasets to evaluate the effectiveness of different training strategies under label noise. These datasets can be broadly divided into two categories:

4.1. Synthetic noisy datasets

These datasets are generated by injecting synthetic label noise into originally clean datasets to emulate real-world noisy labeling conditions. Commonly used clean datasets include:

• CIFAR-10 and CIFAR-100 [30]: Comprising natural object images selected from the 80 Million Tiny Images dataset.

• Fashion-MNIST [31]: A collection of grayscale images representing various categories of clothing items.

• Tiny-ImageNet [32]: A subset of the large-scale ImageNet dataset, organized according to the WordNet hierarchy.

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Although these datasets are typically free of annotation errors, artificial label noise is often introduced to simulate noisy training conditions. This corruption is usually injected following symmetric or asymmetric noise patterns, allowing researchers to evaluate model robustness in controlled settings.

4.2. Real-world noisy datasets

These datasets inherently contain noisy labels, resulting from non-expert annotations or automated labeling pipelines. Six widely used real-world noisy datasets include:

- ANIMAL-10N [33]: A dataset reflecting natural inter-class confusion among ten animal categories.
- CIFAR-10N and CIFAR-100N [34]: Noisy variants of CIFAR-10/100 annotated by Amazon Mechanical Turk workers.
- Clothing1M [35]: Consisting of clothing images scraped from online shopping websites, with noisy labels from user-generated metadata.
- Food-101N [36]: Constructed from web-crawled food images, labels are assigned using keyword-based search.
- WebVision [37]: A large-scale dataset with images collected from Google and Flickr, where labels are inferred from surrounding metadata such as image titles and descriptions.

To facilitate fair and consistent performance comparison, many real-world noisy datasets include a clean validation set and report estimated label noise rates for their training partitions.

5. Future research directions

In learning with noisy labels, substantial progress has been achieved in label correction strategies. Based on a comprehensive review and comparative analysis of existing methods, we identify several promising directions for future research:

5.1. Representation-driven correction under uncertainty

Recent studies have begun to incorporate representation learning into label purification. However, the structural properties of feature representations remain underexplored. Future research may leverage contrastive learning or self-supervised learning techniques to obtain informative representations that are prior knowledge for label denoising. Furthermore, estimated signals derived from these embeddings could be utilized to guide label correction, enabling more structure-aware and adaptive purification strategies.

5.2. Multi-task and multi-source noisy learning

In real-world scenarios, label noise often arises across multiple tasks due to factors such as crowdsourced annotations or weak supervision. Future investigations aimed at mitigating noise across these dimensions could examine methodologies such as cross-task consistency regularization, confidence propagation between related tasks, and the fusion of global task semantics with granular label refinement. Graph-based and federated learning frameworks are particularly apt for assimilating these multifaceted supervision signals. Bridging these dimensions enhances model robustness and facilitates the generalization of noisy label learning to more practical, real-world applications.

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6. Conclusion

To mitigate the tendency of deep neural networks to overfit noisy labels, label correction strategies have been extensively explored. This paper comprehensively reviews both paradigms, summarizing representative methods, analyzing their core frameworks and underlying strategy, and highlighting the emerging trend toward their integration. While no single approach has demonstrated universal superiority across all noisy scenarios, label correction presents a promising direction for developing more robust and generalizable learning systems under noisy supervision.

References

[1] Charleen, A. C., Purnama, H., & Purnomo, F. (2021). Impact of computer vision with a deep learning approach in medical imaging diagnosis. In 2021 1st International Conference on Computer Science and Artificial Intelligence (ICCSAI) (pp. 37–41). IEEE. https: //doi.org/10.1109/ICCSAI53272.2021.9609708

[2] Liu, J., Fang, Y., Yu, Z., & Wu, T. (2022). Design and construct a knowledge database for learning Japanese grammar using natural language processing and machine learning techniques. In 2022, the 4th International Conference on Natural Language Processing (ICNLP) (pp. 371–375). IEEE. https: //doi.org/10.1109/ICNLP55136.2022.00068

[3] Liang, H., Wang, F., Bing, L., Yu, D., & Wang, J. (2021). An automatic annotation algorithm is based on sliding window moment feature matching. In 2021 International Conference on Computer Engineering and Application (ICCEA) (pp. 216–219). IEEE. https: //doi.org/10.1109/ICCEA53728.2021.00050

[4] Aloufi, E., Alharthi, R., Zohdy, M., Alsulami, D., Alrashdi, I., & Olawoyin, R. (2020). An efficient approach for task assignment in spatial crowdsourcing. In 2020 IEEE International IOT, Electronics and Mechatronics Conference (IEMTRONICS) (pp. 1–5). IEEE. https: //doi.org/10.1109/IEMTRONICS51293.2020.9216447

[5] Fatima, N., Faheem, M., & Dar, M. Z. N. (2023). Optimized focused crawling for web page classification. In 2023 International Conference on Energy, Power, Environment, Control, and Computing (ICEPECC) (pp. 1–6). IEEE. https: //doi.org/10.1109/ICEPECC57281.2023.10209473

[6] Chen, Z., Yang, X., Zheng, K., & Wang, B. (2025). Based on the application and research of artificial intelligence in medical diagnosis and treatment. In 2025 5th International Conference on Consumer Electronics and Computer Engineering (ICCECE) (pp. 613–616). IEEE. https: //doi.org/10.1109/ICCECE65250.2025.10985085

[7] Zu, M., Jia, J., Wang, Y., & Zeng, W. (2024). Research on the application of target detection and recognition technology based on deep learning in industrial automation. In 2024 International Conference on Power, Electrical Engineering, Electronics and Control (PEEEC) (pp. 615–620). IEEE. https: //doi.org/10.1109/PEEEC63877.2024.00117

[8] Xie, Z., He, F., Fu, S., Sato, I., Tao, D., & Sugiyama, M. (2021). Artificial neural variability for deep learning: On overfitting, noise memorization, and catastrophic forgetting. Neural Computation, 33(8), 2163–2192. https: //doi.org/10.1162/neco_a_01403

[9] Li, J., Wong, Y., Zhao, Q., & Kankanhalli, M. S. (2019). Learning to learn from noisy labeled data. In 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 5046–5054). IEEE. https: //doi.org/10.1109/CVPR.2019.00519

[10] Wu, Y., Shu, J., Xie, Q., Zhao, Q., & Meng, D. (2021). Learning to purify noisy labels via meta soft label corrector. Proceedings of the AAAI Conference on Artificial Intelligence, 35(12), 10388–10396. https: //doi.org/10.1609/aaai.v35i12.17244

[11] Taraday, M. K., & Baskin, C. (2023). Enhanced meta label correction for coping with label corruption. In 2023 IEEE/CVF International Conference on Computer Vision (ICCV) (pp. 16249–16258). IEEE. https: //doi.org/10.1109/ICCV51070.2023.01493

[12] Hu, Y., Fang, X., Kang, P., Chen, Y., Fang, Y., & Xie, S. (2024). Dual noise elimination and dynamic label correlation guided partial multi-label learning. IEEE Transactions on Multimedia, 26, 5641–5656. https: //doi.org/10.1109/TMM.2023.3338080

[13] Yang, X., Liu, K., Gu, S., & Tan, A. (2023). A novel multi-label learning approach for missing and noisy labels. In 2023 5th International Conference on Robotics, Intelligent Control and Artificial Intelligence (RICAI) (pp. 1088–1092). IEEE. https: //doi.org/10.1109/RICAI60863.2023.10489601

[14] Han, H., Miao, K., Zheng, Q., & Luo, M. (2023). Noisy correspondence learning with meta similarity correction. In 2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 7517–7526). IEEE. https:

DOI: 10.54254/2755-2721/2025.BJ25820

//doi.org/10.1109/CVPR52729.2023.00726
[15] Tu, Y., Zhang, B., Li, Y., Liu, L., Li, J., Wang, Y., Wang, C., & Zhao, C. R. (2023). Learning from noisy labels with decoupled meta label purifier. In 2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 19934–19943). IEEE. https: //doi.org/10.1109/CVPR52729.2023.01909
[16] Kim, N.-R., Lee, J.-S., & Lee, J.-H. (2024). Learning with structural labels for learning with noisy labels. In 2024 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 27600–27610). IEEE. https: //doi.org/10.1109/CVPR52733.2024.02607
[17] Xia, X., Deng, J., Bao, W., Du, Y., Han, B., Shan, S., & Liu, T. (2023). Holistic label correction for noisy multi-label classification. In 2023 IEEE/CVF International Conference on Computer Vision (ICCV) (pp. 1483–1493). IEEE. https: //doi.org/10.1109/ICCV51070.2023.00143
[18] Liang, N., Yang, Z., Chen, J., Li, Z., & Xie, S. (2024). Label-weighted graph-based learning for semi-supervised classification under label noise. IEEE Transactions on Big Data, 10(1), 55–65. https: //doi.org/10.1109/TBDATA.2023.3319249
[19] Zhang, M., Jiang, B., Ling, Y., & Wang, X. (2024). Learning with non-uniform label noise: A cluster-dependent weakly supervised approach. In ICASSP 2024 - 2024 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (pp. 5825–5829). IEEE. https: //doi.org/10.1109/ICASSP48485.2024.10447184
[20] Li, Z., Yu, D., Wei, L., Jin, C., Zhang, Y., & Chan, S. (2024). Soften to defend: Towards adversarial robustness via self-guided label refinement. In 2024 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 24776–24785). IEEE. https: //doi.org/10.1109/CVPR52733.2024.02340
[21] Guo, E., Zhao, Z., Wang, Z., Chen, T., Liu, Y., & Zhou, L. (2025). DiN: Diffusion model for robust medical VQA with semantic noisy labels. In Proceedings of the Computer Vision and Pattern Recognition Conference (pp. 14337–14346).
[22] Lou, Q., Deng, Z., Sang, Q., Xiao, Z., Choi, K.-S., & Wang, S. (2024). A robust multilabel method integrating rule-based transparent model, soft label correlation learning and label noise resistance. IEEE Transactions on Emerging Topics in Computational Intelligence, 8(1), 454–473. https: //doi.org/10.1109/TETCI.2023.3306232
[23] Zhao, R., Shi, B., Ruan, J., Pan, T., & Dong, B. (2024). Estimating noisy class posterior with part-level labels for noisy label learning. In 2024 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 22809–22819). IEEE. https: //doi.org/10.1109/CVPR52733.2024.02152
[24] Wei, Q., Feng, L., Sun, H., Wang, R., Guo, C., & Yin, Y. (2023). Fine-grained classification with noisy labels. In 2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 11651–11660). IEEE. https: //doi.org/10.1109/CVPR52729.2023.01121
[25] Zhang, Z., Chen, W., Fang, C., Li, Z., Chen, L., Lin, L., & Li, G. (2023). RankMatch: Fostering confidence and consistency in learning with noisy labels. In 2023 IEEE/CVF International Conference on Computer Vision (ICCV) (pp. 1644–1654). IEEE. https: //doi.org/10.1109/ICCV51070.2023.00158
[26] Yao, Y., Sun, Z., Zhang, C., Shen, F., Wu, Q., Zhang, J., & Tang, Z. (2021). Jo-SRC: A contrastive approach for combating noisy labels. In 2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 5188–5197). IEEE. https: //doi.org/10.1109/CVPR46437.2021.00515
[27] Huang, Z., Zhang, J., & Shan, H. (2023). Twin contrastive learning with noisy labels. In 2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 11661–11670). IEEE. https: //doi.org/10.1109/CVPR52729.2023.01122
[28] Qi, W., & Chelmis, C. (2024). Noisy label detection and counterfactual correction. IEEE Transactions on Artificial Intelligence, 5(2), 763–775. https: //doi.org/10.1109/TAI.2023.3271963
[29] Okamura, D., Harakawa, R., & Iwahashi, M. (2024). LCNME: Label correction using network prediction based on memorization effects for cross-modal retrieval with noisy labels. IEEE Transactions on Circuits and Systems for Video Technology, 34(1), 590–602. https: //doi.org/10.1109/TCSVT.2023.3286546
[30] Xu, R., & Wunsch, D. (2005). Survey of clustering algorithms. IEEE Transactions on Neural Networks, 16(3), 645–678. https: //doi.org/10.1109/TNN.2005.845141
[31] Patrini, G., Nielsen, F., Nock, R., & Carioni, M. (2016). Loss factorization, weakly supervised learning and label noise robustness. In Proceedings of the 33rd International Conference on Machine Learning - Volume 48 (pp. 708–717). JMLR.org.
[32] Kaster, F. O., Menze, B. H., Weber, M.-A., & Hamprecht, F. A. (2010). Comparative validation of graphical models for learning tumor segmentations from noisy manual annotations. In Proceedings of the 2010 International MICCAI Conference on Medical Computer Vision: Recognition Techniques and Applications in Medical Imaging (pp. 74–85). Springer-Verlag.
[33] Wang, Q. (2022). Support vector machine algorithm in machine learning. In 2022 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA) (pp. 750–756). https:

DOI: 10.54254/2755-2721/2025.BJ25820

//doi.org/10.1109/ICAICA54878.2022.9844516
[34] Biggio, B., Nelson, B., & Laskov, P. (2011). Support vector machines under adversarial label noise. Journal of Machine Learning Research, 20(3), 97–112.
[35] Ghosh, A., Manwani, N., & Sastry, P. S. (2017). On the robustness of decision tree learning under label noise. In Advances in Knowledge Discovery and Data Mining (pp. 685–697). Springer International Publishing. https: //doi.org/10.1007/978-3-319-57454-7_53
[36] Mantas, C. J., & Abellán, J. (2014). Credal-C4.5: Decision tree based on imprecise probabilities to classify noisy data. Expert Systems with Applications, 41(10), 4625–4637. https: //doi.org/10.1016/j.eswa.2014.01.017
[37] Liu, S., Niles-Weed, J., Razavian, N., & Fernandez-Granda, C. (2020). Early-learning regularization prevents memorization of noisy labels. In Proceedings of the 34th International Conference on Neural Information Processing Systems (NIPS ’20). Curran Associates Inc.