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AOI-OPEN: federated operation and control for DAO-based trustworthy and intelligent AOI ecology[*#]

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Abstract: Isolated data islands are prevalent in intelligent automated optical inspection (AOI) systems, limiting the full utilization of data resources and impeding the potential of AOI systems. Establishing a collaborative ecology involving software providers, hardware manufacturers, and factories offers an encouraging solution to build a closed-loop data flow and achieve optimal data resource utilization. However, concerns about privacy issues, rights infringement, and threats from other participants present challenges in establishing an efficient and effective community. In this paper, we propose a novel framework, AOI-OPEN, which first creates a trustworthy AOI ecology to gather related entities with decentralized autonomous organization (DAO) mechanisms. Then, a parallel data pipeline is proposed to generate large-scale virtual samples from small-scale real data for AOI systems. Finally, federated learning (FL) is adopted to use the distributed data resources among multiple entities and build privacy-preserving big models. Experiments on defect classification tasks show that, with privacy preserved, AOI-OPEN greatly strengthens the utilization of distributed data resources and improves the accuracy of inspection models.

Key words: Automated optical inspection; Decentralized autonomous organizations; Parallel data; Federated intelligence

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1 Introduction

Automated optical inspection (AOI) systems play important roles in the manufacturing industry and are widely used in automotive industry, consumer electronics, communication industry, aerospace, and other fields (Liao et al., 2018; Zhang WS et al., 2024). The development of robust and high-performance machine vision systems crucially depends on the availability of extensive and diverse datasets for training and validating visual models. Unfortunately, the construction of representative datasets is challenging due to the lack of effective collaboration mechanisms within the AOI ecology.

In the AOI industry, collaboration is often limited to product-level partnerships, leading to data islands, particularly in downstream processes like printed circuit board (PCB) manufacturing (Wang ZH et al., 2024). These data islands arise when production data are either not collected or not shared among stakeholders, hindering innovation. While AOI device users, such as factories, have access to extensive data, they typically lack the incentive to collect and use the data fully, as the data collection process can increase operational costs and does not align with their primary production objectives. This lack

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of data utilization creates significant barriers to developing advanced artificial intelligence (AI) models and optimizing system performance. Additionally, concerns over protecting business secrets prevent data sharing between factories and other stakeholders, like hardware and software providers. This limitation stifles the development of high-performance models and the fine-tuning of devices, obstructing collaborative advancements and the overall potential of AOI technology in industrial applications.

Building a collaborative ecology or community containing hardware manufacturers, software manufacturers, and inspection device users is promising to connect the data islands and achieve full utilization of data resources. Despite this attractiveness, there has been little attention and work on this kind of collaborative framework or community. Most of the existing work on AOI is focused on optical imaging and image processing methods (Reed and Hutchinson, 1996; Kim et al., 2017; Lu et al., 2018; Yang YT et al., 2020) and neglects the inclusion of as many participants as possible and the management of data. In this paper, we propose a collaborative framework to help construct an intelligent and trustworthy community. However, this goal is not easy to achieve, and several concerns including the leakage of private data, damage to own rights, and threats from other participants, have to be thoroughly considered before we can set up an effective collaborative mechanism.

The rise of decentralized autonomous organizations (DAOs) has garnered attention for enabling decentralized governance and collaboration among physical entities, addressing data sharing and utilization challenges in scenarios like AOI. This paper proposes a data-centric framework to construct a trustworthy, intelligent AOI ecosystem based on DAOs, comprising two modules: data mining and data management. The data mining module scales up data using metaverses for a parallel data approach (Liu et al., 2017), extracts features with federated intelligence technologies (Yang Q et al., 2019; Li T et al., 2020; Wang FY et al., 2021a, 2021b), and aggregates knowledge into global big models (Bommasani et al., 2021). Participants can then fine-tune their local models using knowledge distillation (Gou et al., 2021; Wang L and Yoon, 2022) or transfer learning (Pan and Yang, 2010; Weiss et al., 2016; Zhuang et al., 2021). The data management module, leveraging blockchain and smart contracts, enables federated operation, participant identification (Ouyang et al., 2023), and consensus on data resource usage, rewards, and penalties.

In this paper, we propose a trustworthy AOI ecology to thoroughly consider the interests of different participants so that they are motivated to join the community and contribute their resources. On this basis, closed-loop data flow is established, including the generation, transmission, management, as well as earnings of data, and data islands can be connected. With diverse and massive data resources, we deploy federated intelligence to achieve effective and privacy-preserving utilization of these data and train high-accuracy classification models. The main contributions of this paper are as follows:

1. A novel framework AOI-OPEN is proposed which develops a trustworthy and intelligent AOI ecology and is beneficial to facilitating the operations and collaborations of AOI industrial metaverse.

2. A DAO which effectively organizes the stakeholders and provides democratic decision-making and benefits-guaranteeing mechanisms, is proposed for the AOI community.

3. A data-centric pipeline incorporating virtual intelligence, real intelligence, and federated intelligence is proposed which strengthens the utilization of distributed data resources and improves the accuracy of defect classification models.

2 Related works

In this section, related works on AOI systems, blockchains, and federated intelligence are introduced.

2.1 AOI

AOI (Liao et al., 2018) is an integrated system of optics, mechanisms, electronic control, and software. It is often used in the manufacturing system to alleviate the workload of human inspectors. The application of AOI in manufacturing improves inspection consistency, speed, and accuracy while reducing labor costs. AOI has been used in several fields, such as fruits and vegetables (Cubero et al., 2011), mechanical part surfaces (Wang Y et al., 2015), and PCBs (Wang WC et al., 2017).

As the core of AOI, software algorithms have grown rapidly. In the early stage of AOI, machine learning methods are deployed to extract features and conduct inspections (Wu et al., 2008; Li ZY and Yang, 2011). Currently, deep learning methods are exploited to conduct more accurate inspections (Li YT and Guo, 2018). However, for deep learning methods, the lack of valuable data is becoming a serious obstacle to the development of AOI. Nowadays, metaverse has also been introduced into AOI systems to integrate inspection (Wang YT et al., 2022), which improves the manipulation efficiency of quality assurance.

The AOI-OPEN framework introduces a groundbreaking collaborative mechanism in the AOI sector by integrating DAO and federated learning (FL), enhancing user engagement and addressing the issue of rare data samples through novel virtual data generation. This approach improves existing FL systems by ensuring higher privacy and user rights protection, and fostering better collaboration among stakeholders. AOI-OPEN also features a robust feedback mechanism for continuous improvement and excels in generating diverse and robust training data. This integration effectively overcomes traditional data scarcity and privacy concerns, establishing a more secure and user-centric collaborative environment, as detailed in Table 1.

Table 1 Comparison of existing AOI systems and AOI-OPEN

System	Privacy security	Rights protection	Feedback mechanism	Data generation
Naive AOI	Low	No	No	No
FL-based AOI	High	Low	No	No
AOI-OPEN	High	High	Yes	Yes

2.2 DAOs and blockchains

DAOs represent a paradigm shift in governance and organizational structures, where decision-making processes are distributed among a set of members rather than centralized leadership (Zhang BY et al., 2024). This decentralized model operates through smart contracts that define the rules and automatically execute decisions based on predefined criteria. A well-known example of DAO is "The DAO," which was designed for venture capital funding, allowing members to collectively decide on fund allocation and modifications to the governing smart contract. DAOs provide a framework that promotes transparency, trust, and autonomy, leveraging blockchain technology to enforce rules without requiring traditional hierarchical oversight.

The structure of DAOs is typically composed of five key layers (Wang S et al., 2019): (1) the basic technology layer, which provides the underlying blockchain and smart contract infrastructure; (2) the governance operation layer, where voting and decision-making processes occur; (3) the incentive mechanism layer, designed to align the interests of participants and ensure their engagement; (4) the organization layer, which defines the roles and relationships among members; (5) the manifestation layer, where the outcomes of governance, such as funding decisions or operational actions, are executed. Recent studies on DAOs have explored their applicability in various domains, such as venture capital, social governance, and industrial ecosystems, demonstrating their potential to reshape traditional organizational models by enhancing efficiency, transparency, and decentralization. Nowadays, DAOs have been widely used in several applications such as metaverses (Goldberg and Schär, 2023), transportation systems (Yao et al., 2023), and logistics (Li JJ et al., 2023).

Blockchain is one of the most important technologies behind DAOs. A blockchain can be regarded as a distributed and secure database of transaction logs. To keep blockchain functioning properly, digital signature and commitment consensus are two basic and important capabilities. Blockchain (Monrat et al., 2019; Yu and Bai, 2024) employs digital signatures (Zhang R et al., 2020) to conduct identity verification during communication between two members. The smart contract (Wang S et al., 2018) is a chain of codes that executes the rules and policies of a contract between different interested parties.

2.3 Federated intelligence

Regarding federated ecology as infrastructure, federated intelligence aims at connecting data islands and achieving collective intelligence while protecting the privacy of different participants (Wang FY et al., 2021a; Tian et al., 2022; Yan et al., 2024). The federated intelligence framework for federated ecology is composed of federated service, federated management, federated control, and federated data (Wang FY et al., 2021b, 2021c). FL provides technical support for the framework in model training (Yang Q et al., 2019).

Federated service is the window of federated ecology for meeting external demands, and its purpose is to provide intelligent solutions applicable to different scenarios and problems for different organizations. Federated management comprehensively considers the actual situations of the systems to make plans for achieving the goals formulated by federated service. Federated control translates natural language generated by federated management into machine language to accomplish tasks such as the dynamic selection of nodes and the regulation of federated data. As the material basis for the operation of federated ecology, the federated data method proposes a distributed network for information exchange and collaboration between nodes, including various functions such as data collection, storage, computing, and communication.

FL (Yang Q et al., 2019) is a distributed learning approach developed to protect data privacy while jointly training a model on data from different sources. In FL, edge devices with the same data structure collaboratively learn a global model on a cloud server, and the data do not leave their owner's device. First, each edge device uses its own data to train a local model and compute gradients, and then it masks a selection of gradients and sends masked results to the cloud server. Second, the cloud server performs secure aggregation with additional measures such as differential privacy (Dwork and Roth, 2014) to avoid unanticipated privacy leaks and generate a new model. Third, the edge devices download the parameters from the cloud server and retrain their respective models. FL has been widely applied in many scenarios such as industry (Zhang WS et al., 2022) and energy (Zhang WS et al., 2023), where data resources are effectively used to build global AI models.

3 Framework of AOI-OPEN

The overall framework of AOI-OPEN is shown in Fig. 1. It includes mainly two parts: the intelligent system (in the red dotted box) which focuses on the construction of high-performance AOI devices, and the trustworthy organization (in the green dotted box) which focuses on the construction of collaborating mechanisms within the AOI ecology.

3.1 Operations of AOI-OPEN

AOI-OPEN is centered around three kinds of entities, i.e., software manufacturers, hardware

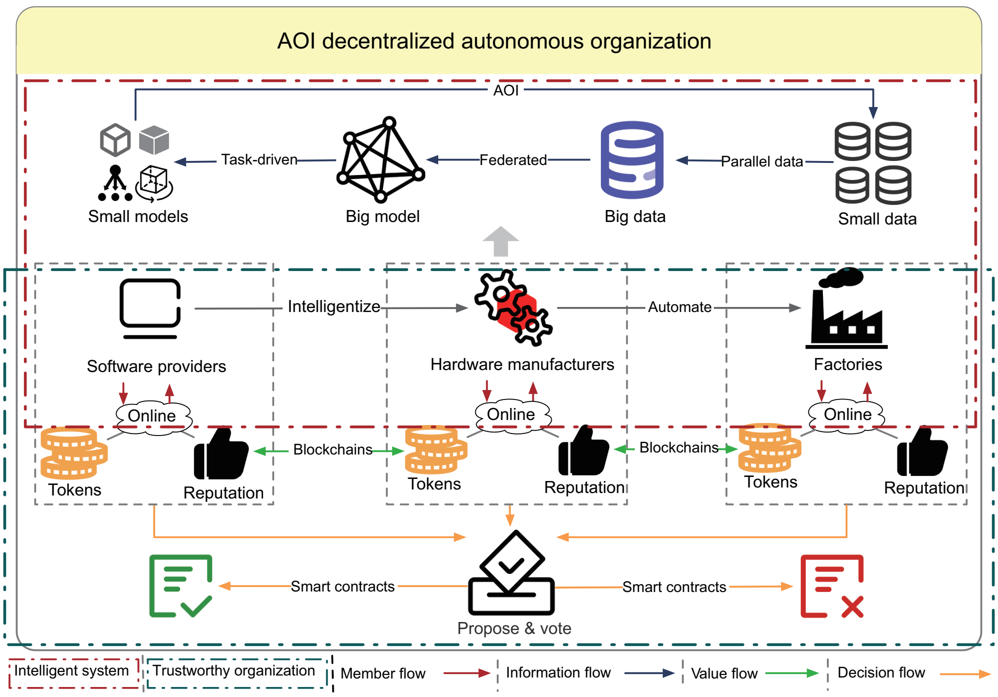

Fig. 1 Overall framework of AOI-OPEN (References to color refer to the online version of this figure)

manufacturers, and factories. AOI-OPEN aims at aggregating possible stakeholders to provide democratic and intelligent decision-making for the operation of the AOI ecology and combining scattered resources for intelligent AOI products. To do that, we design the member flow (red arrow) to provide access for different entities, the decision flow for event resolution (yellow arrow), the value flow for incentives of participation, and the information flow for the construction of AI models. In AOI-OPEN, members can be transformed from offline to online, information can be aggregated into intelligent models, value can be created and spread inside, and decisions can be made democratically for the effective management of the community. Therefore, member flow, information flow, value flow, and decision flow constitute the mechanisms of federated operation and control in AOI-OPEN. Technologies behind them include artificial identification, parallel data, FL, big models, and blockchains. Details of the operations are provided in the supplementary materials.

In the AOI-OPEN framework, DAO serves as the foundational structure enabling transparent, decentralized governance and collaborative decision-making among all participating entities, including software providers, hardware manufacturers, and factories. DAO is responsible for the management of community resources, the enforcement of rules, and the coordination of activities across the AOI ecology. By using smart contracts, DAO facilitates democratic decision-making processes, allowing members to propose, vote on, and execute decisions related to data sharing, model development, and operational policies. Based on DAO, AOI-OPEN achieves the effective operation of the trustworthy community in a federated way via decision flow, to realize the goal formulated by federated services such as acquiring high-performance AOI devices. Federated control accomplishes various tasks such as the selection of members and the regulation of federated data via member flow, information flow, and value flow.

3.2 Parallel data

In AOI systems, data with defects are rare; therefore, the collected dataset is highly biased toward normal data. Taking the manufacturing of PCB as an example, the rate of images with defects in datasets representing random production sampling is typically very low. Such an imbalance will greatly hinder the learning process of inspection models.

In AOI-OPEN, we increase the number of data samples with defects by using the parallel data approach (Liu et al., 2017; Wang KF et al., 2017). The core ideas behind parallel data are artificial data and virtual–real interaction. Parallel data help transform small-scale data into large-scale data and back to task-specific small-scale data (Miao et al., 2023). For AOI systems, the parallel data approach adopts two steps to improve the quality and quantity of data according to the applications, i.e., data generation mechanism and data refinement mechanism. A general pipeline of the generation of AOI data with the parallel data approach is shown in Fig. 2. It starts from small-scale real data that can be collected from the PCB production lines. Both data with and without defects are used for the training of generative models or methods such as digital twins (DT) (El Saddik, 2018), variational autoencoder (VAE) (Kingma and Welling, 2013), and generative adversarial networks (GANs). Virtual data can be easily extended to form a large-scale dataset. To optimize the generated virtual data, we add a data refinement stage where experienced workers or AI engineers can manually filter unqualified data.

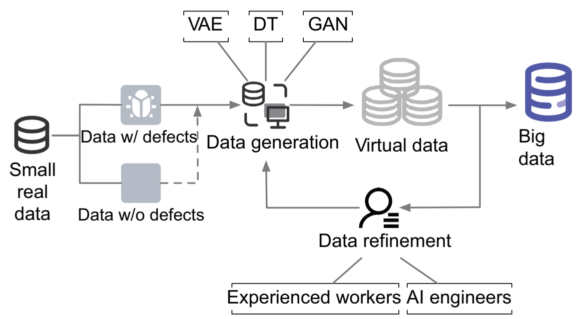

Fig. 2 A general pipeline of AOI data generation with a parallel data approach (AOI: automated optical inspection; DT: digital twins; GAN: generative adversarial network; VAE: variational autoencoder)

Different approaches to generating virtual defect data suit different situations in the AOI scenarios. For defects whose formation mechanism is clear, we can build a virtual production line with DT where several defect generation rules and the space of data generation parameters can be predefined. By randomly sampling inside the parameter space, we can generate diverse defects. The advantages of DT-based defect generation pipeline are high controllability and interpretability. Defects can be generated according to our demands, and the effectiveness of the virtual data can be guaranteed. However, the DT-based method works on the condition of a clear understanding of the defect generation mechanism, while in most cases the reason behind the formation of defects is complex and unclear, which makes it hard to precisely simulate real defects. Data-driven methods like VAE and GAN have a more powerful representation ability and can learn the hidden patterns of data with defects automatically. The advantages of data-driven methods include the elimination of hand-crafted features and ease of use in the generation of massive new data. However, data-driven methods have higher requirements on the training data, in both quantity and diversity.

Note that parallel data take the generation of virtual data as an iterative process and the key step is virtual–real interaction. It means that in the initial stages, the quality of generated virtual data might be unsatisfactory, but, with progressive optimization, the quality of generated data can be increasingly improved. During the optimization process, the deviation between generated virtual data and real data can be fed back to the generative models or digital process, and human knowledge has great importance in feedback generation. Human-in-the-loop optimization mechanism is an effective approach to handling embarrassing situations where we have neither massive and diverse data nor powerful models. It relies on both experienced workers from the production line and AI engineers to integrate the knowledge from the workers into machine learning systems. The advice from experienced workers on the production line is valuable because it contains an understanding of the formation mechanism of defects, and such advice is hard to model with current machine learning approaches.

3.3 Privacy-preserving big models in AOI-OPEN

Big models are used to learn general representations from large-scale data. They have powerful representation ability and adaptation ability and are the key to building intelligent AOI systems. With the help of the parallel data pipeline, the scale of data in each node can be significantly enlarged; however, the diversity is still insufficient due to the constriction of local scenarios. AOI-OPEN aggregates the information from distributed nodes. It adopts the FL mechanism to protect the privacy of different members and train global big models. Besides, blockchain is adopted to provide a secure platform for information exchange during the collaboration process. To apply big models in local applications, distillation and fine-tuning processes are proposed when transforming global big models into local small models. All these operations are executed on a blockchain system. Blockchain technology significantly enhances the trustworthiness and activity level of the AOI-OPEN model by providing a secure platform for information exchange and an effective incentive mechanism. It provides a distributed recording of the model parameters. Besides, the incentive mechanism of the blockchain can stimulate members to contribute their data and computation resources, and smart contracts help automatically coordinate the operation of the system. During the collaboration of multiple members in AOI-OPEN, data leakage and third-party attack are possible during the transmission of feature or gradient information. The encryption mechanism helps avoid leakage. In AOI-OPEN, homomorphic encryption and differential privacy can be adopted to prevent third-party attacks. Besides, by encoding the raw inputs, the information is transmitted in the form of high-dimensional features, which further reduces the risk of data leakage.

As shown in Fig. 3, the FL process of big models in AOI-OPEN contains two different modes on the condition of the computation ability of different nodes, i.e., full-model mode and partial-model mode. The former directly distributes the complete model in the training process as shown in the left part of Fig. 3, while the partial mode splits the model into several sub-models, which are then assigned to different members, as shown in the right part of Fig. 3. Big models contain a large number of parameters that will consume a great deal of memory. Not all members of the community in AOI-OPEN can afford it. For members with sufficient computation resources, the full-model mode can be applied where each node can obtain a copy of the big models and complete the forward pass as well as the backpropagation of gradients. Then, the updated parameters from different nodes will be uploaded to the server and combined after the evaluation process. The updated global models will be sent back to each node and a new iteration will start. For members with

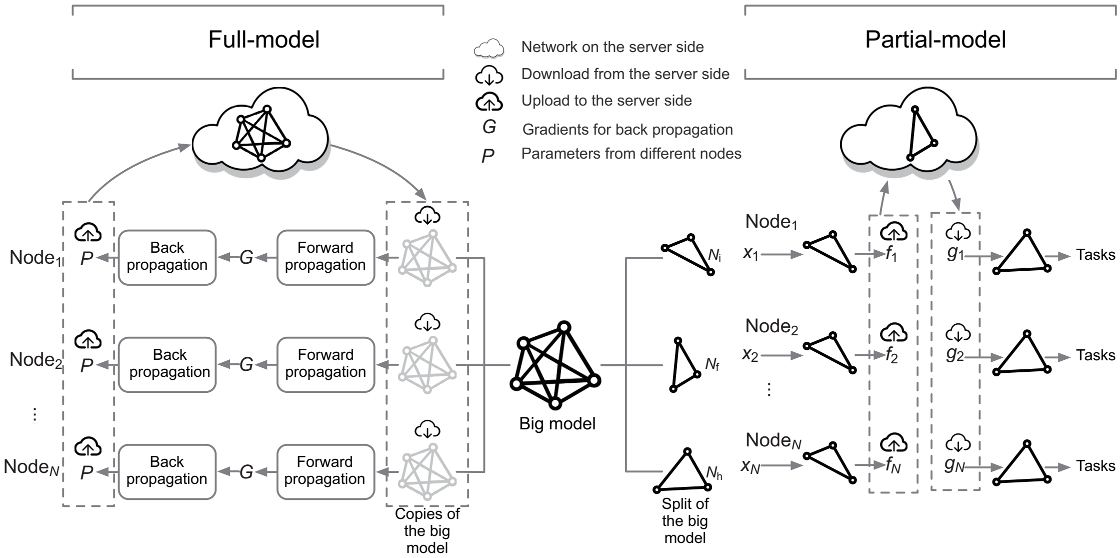

Fig. 3 Pipelines of full- and partial-model modes for the training of the big model

insufficient computation resources, a partial-model mode inspired by split learning (Vepakomma et al., 2018) can be applied. In partial-model mode, the global big model is split into different parts. Considering that the raw data and labels contain the privacy of each node, we split the big model into three sub-models, namely, input embedding model N_{i}, feature extraction model N_{f}, and task-specific head N_{h}. The input embedding model maps the raw inputs x_i to features f_i locally to prevent the leakage of personal information. The feature extraction model contains most of the parameters of the big models, and is deployed on the server. The feature extraction model further processes f_i and generates the intermediate features g_i. Then, g_i is sent back to the local node, and the task-specific head is used to generate the predictions. With the split of big models, the privacy of different nodes can be protected with an affordable computation cost. The pipelines of full- and partial-model modes are shown in Fig. 3.

Although big models have powerful representation ability, the model sizes are large and inference costs are high, which hinders the application of big models in AOI systems. Besides, the demands and tasks of different AOI systems are various. It is hard to meet the requirements of different applications. Therefore, transforming the knowledge in big models into light models is necessary. In AOI-OPEN, once the global big model is trained, members can get access to the global model and fine-tune it for personal usage with their local small dataset. Multiple approaches such as distillation, compression, and quantization can be used to develop a light model based on the global big model.

To stimulate the positivity of members and reduce malicious actions, AOI-OPEN adopts the incentive mechanism in the blockchain. First, a test dataset is constructed to validate the update of models from each node in the FL system, which is stored on the server and is unavailable to other members of the community. The construction of the server-side test dataset is based on the distributed proposal and voting mechanism of DAO. Every member can start a proposal and upload up to K data samples with defects to the data pool on the server (K is far less than the total number of data samples that the member has, so that the leakage of privacy is negligible) over a certain period of time. When the proposal stage ends, a smart contract will be activated to allocate each member in the community with M data samples randomly from the data pool (M is far less than the total number of data samples in the data pool). Each member can vote for the data they support. After the voting stage, top-N data samples with the higher approval rating will be used as the test dataset. With the test dataset, whenever a node uploads the updated parameters, the server will evaluate the new model from each member. Different levels of rewards or punishment will be given to different members based on the effectiveness of their models.

In summary, AOI-OPEN integrates FL, large-scale models, and blockchain technology, facilitating efficient and secure data processing. This integrative approach is key to handling a vast amount of data while maintaining privacy, crucial for the advancement of intelligent inspection of products such as PCB. Second, AOI-OPEN emphasizes the creation of a healthy ecosystem, balancing interests and fostering sustainable development through incentivization mechanisms and democratic decision-making processes. This method does not focus only on the technology itself, but considers the social and economic impacts of its practical application.

Despite its notable advantages, the complexity of the AOI-OPEN method cannot be overlooked. Integrating various technologies and coordinating relationships among numerous participants may pose challenges during implementation. For instance, FL requires coordinating a vast amount of data across different nodes, and the implementation and maintenance of blockchain technology necessitate expertise and resources. Additionally, building and maintaining a healthy ecosystem requires continuous effort and dynamic management.

4 Experiments

In this part, we take defect classification as a reference task to validate the effectiveness of the proposed methods. We give an introduction to the data used for experiments and the performance of each part in AOI-OPEN.

4.1 Data description

In this work, we investigate the classification task on PCB with hole-type defects. Ten kinds of common defects are considered as shown in Table 2. Among these defects, subclasses C1 and C2 are negligible in most of the real applications and therefore classified as “OK,” while other subclasses from C3 to C10 are regarded as “NG” (not good).

Since most of the production lines in PCB factories are quite stable, the aforementioned defects are rare and therefore quite difficult to collect manually. To address this issue, we generated a substantial amount of virtual data using a parallel data generation process (Fig. 4). The total number of virtual data samples reached 108 577, while only 2215 real samples were collected. This resulted in a virtual-to-real data ratio of approximately 49:1, emphasizing the need for virtual data to support the training of our classification models. All real data were reserved for testing, while only the generated virtual data were used during training.

Table 2 The taxonomy and description of PCB defects

Class	Subclass	Description
OK	C0	Good images
OK	C1	Holes with slight shifts
OK	C2	Holes with shadows
NG	C3	Missing holes
NG	C4	Hole rings with nicks outside
NG	C5	Missing hole rings
NG	C6	Hole rings with protrusions
NG	C7	Short hole rings
NG	C8	Hole rings with nicks inside
NG	C9	Holes with serious shift
NG	C10	Open hole rings

PCB: printed circuit board; NG: not good

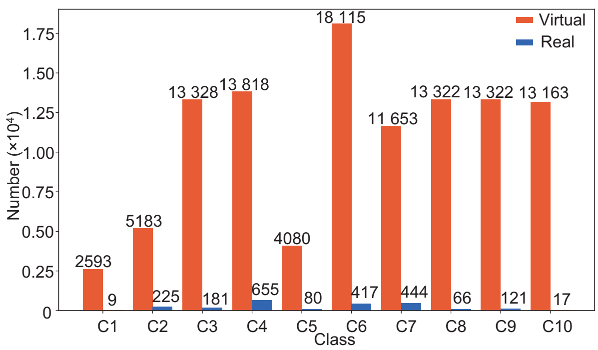

Fig. 4 Number of data samples before and after the parallel data generation process (References to color refer to the online version of this figure)

In Fig. 4, the numbers of virtual and real data samples for each defect class are presented. The red bars indicate the virtual data generated during the parallel data generation process, while the blue bars represent the real defect data collected from the production batch. For most defect classes, the number of virtual data samples significantly outweighed that of the real data samples. This disparity was most evident in classes such as C8 and C10, where the real data were especially scarce, further emphasizing the necessity of virtual data to build effective classification models. This parallel data generation ensures that the model is sufficiently trained across all defect types, despite the limited availability of real-world data.

4.2 Comparison with different image models

To evaluate the impact of different vision models on AOI-OPEN, we designed an experiment to compare various networks including VGG-11, VGG-16, VGG-19, ResNet-18, ResNet-50, and Vision Transformer (ViT). From the results shown in Table 3, it was evident that the VGG and ResNet models consistently achieved high accuracy, with VGG-16 and ResNet-50 performing slightly better than the other models, reaching accuracies of 88.01% and 88.50%, respectively. These models benefit from deeper architectures and residual connections, which allow them to capture more complex features while mitigating vanishing gradient issues in deeper networks. A notable observation was the performance of ViT (Dosovitskiy et al., 2021). Although ViT has demonstrated impressive results on large-scale datasets, achieving state-of-the-art performance in several tasks, its accuracy in this experiment on the smaller dataset was significantly lower (78.70%) compared to that of CNN-based models. This highlights a key limitation of the Transformer architecture: it tends to rely heavily on large-scale data for optimal performance (Yuan K et al., 2021; Yuan L et al., 2021). To validate this, we further conducted experiments with enhanced vision Tranformers such as T2T (Yuan L et al., 2021) and DeiT (Touvron et al., 2021). With improved local feature modeling ability, T2T and DeiT achieved competitive results compared to CNN-based methods. Considering the performance, we used ResNet-50 for the image backbone in our following experiments by default.

Table 3 Accuracy of different models

Model	Accuracy (%)
VGG-11	87.44
VGG-16	88.01
VGG-19	87.94
ResNet-18	86.46
ResNet-50	88.50
ViT	78.70
T2T	85.12
DeiT	85.38

4.3 Effectiveness of the parallel data approach

Based on the parallel data approach, we generated the virtual images for different kinds of defects, which greatly improved the number of training samples. Fig. 4 illustrates the number of samples before and after our parallel data approach. In our parallel data pipeline, we first located the position of holes in each normal image without defects. Then, random shapes were generated to create different kinds of defects by adding or removing specific pixels on the normal images. Several demos of the generated defects are shown in Fig. 5.

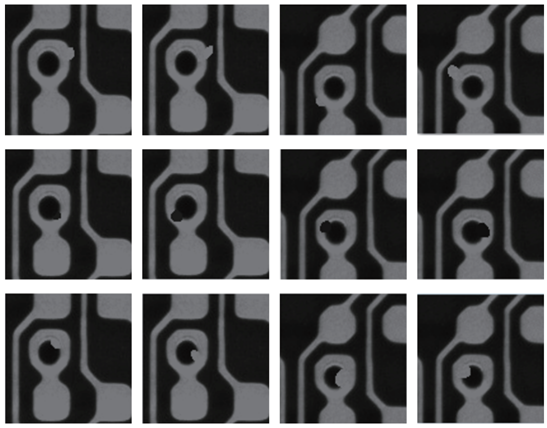

Fig. 5 Demo images with artificial defects generated by a parallel vision approach

To validate the quality and effectiveness of the generated virtual defects of PCB, we trained the networks with purely real images and purely virtual images, separately. The results are shown in Table 4. To train the classification model on a real dataset, we manually collected 500 real samples from another factory, which is different from the one described in Section 4.1, as the training set, and left others for testing. The experiments were denoted as “Real.” For experiments with models trained on virtual images (denoted as “Virtual”), we sampled 2500 data samples from each subclass. Besides, we added the experiments with unsupervised methods proposed in Defard et al. (2021), which directly used the good images without defects (subclass C0) to train the classification model.

Table 4 Classification results of the models trained with different strategies

Method	Accuracy (%)	Precision (%)	Recall (%)
Real	80.5 (±0.5)	66.3	30.6
Virtual	89.3 (±0.4)	92.4	90.5
Unsupervised (PaDiM)	80.2 (±1.1)	91.3	67.6

4.4 Open ecology with DAO and FL

Considering that direct sharing of data in real businesses is impractical, we leverage DAO to help with the aggregation of data resources for AOI applications. We assume that there exist several factories working on the same task, and each of them is denoted as a node in our experiments. We first analyze the advantage of the FL strategy in this scenario and then discuss the design of the incentive mechanism toward effective resource utilization.

Table 5 demonstrates the performance of models with and without federated operations. We predefined two kinds of data splits to simulate the distribution of AOI data in real applications, denoted as "Split-H" and "Split-V." For Split-H, one node has only several specific kinds of data but with the full amount of each type. For Split-V, each node has all kinds of data (Fig. 4), but with only a fraction of the amount of each type. Here, we conducted binary classification to validate the effectiveness of the proposed federated operations. We denote FL mode with "All" in Table 5 and individual learning mode with "Node$_x$" ($x = 1, 2, \cdots, 5$). As we can see, with federated operations, the classification performance got better than the model trained locally in each node. Besides, a more significant gap between FL and individual learning was witnessed in "Split-H," which illustrates that the diversity of data is important in the collaboration of building intelligent classification models.

Table 5 Classification results with different splitting strategies

Split	Node	Accuracy (%)
Split-H	All	85.6 (±0.3)
	Node$_1$	81.8 (±0.5)
	Node$_2$	77.0 (±0.6)
	Node$_3$	74.8 (±0.4)
	Node$_4$	83.7 (±0.3)
	Node$_5$	84.0 (±0.5)
Split-V	All	88.5 (±0.2)
	Node$_1$	84.7 (±0.2)
	Node$_2$	84.0 (±0.3)
	Node$_3$	86.8 (±0.4)
	Node$_4$	86.1 (±0.3)
	Node$_5$	86.4 (±0.2)

We conducted a comparison between the full-model mode and the partial-model mode in the FL process. In the partial-model mode, the weights of the image encoder were divided into splits and distributed across different nodes for training. To address the underutilization of data when nodes were trained only on independent splits, we proposed a cycle-training method. The method sequentially assigns different parts of the model to each node during each training epoch, ensuring that every node can train the model's different submodules over time. As shown in Table 6, the full-model mode achieved the highest accuracy of 88.5%. In contrast, the partial-model mode without cycle-training resulted in lower accuracies of 71.2% and 69.1% for two and three splits, respectively. However, with the introduction of cycle-training, the performance was improved to 79.5% and 77.4% respectively, indicating that the cycle-training approach helps better use the data across nodes and enhances model performance.

Table 6 Performance comparison between full-model mode and partial-model mode in the FL process

Mode	Number of splits	Cycle-training	Accuracy (%)
Full	1	No	88.5
Partial	2	No	71.2
Partial	2	Yes	79.5
Partial	3	No	69.1
Partial	3	Yes	77.4

4.5 Closed-loop refinement

In this subsection, we analyze the effectiveness and necessity of the closed-loop data pipeline where human factors as shown in Fig. 2 are introduced to provide advice and recommendations on the quality improvement of generated data. We invited five volunteers, including three experienced workers in PCB industry and two engineers from the AOI company, to check the quality of the generated virtual data. Performance change with the data refinement process is illustrated in Fig. 6. The model's accuracy evolved through iterative refinement: starting at 89.3%, it rose to 97.6% with strategic adjustments. Joint training with both virtual and real data boosted it to 92.4%, followed by image smoothing (95.3%) and diverse image inclusion (96.3%). Notably, introducing random crop sizes yielded the highest accuracy. This empirical progression highlights the effectiveness of thoughtful adjustments in optimizing defect classification models, providing insights for a broader research community.

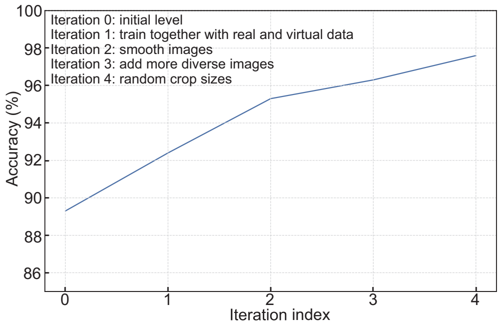

Fig. 6 Performance change with the data refinement process

4.6 Ablation studies

To analyze the role of each module in AOI-OPEN, we conducted ablation studies as shown in Table 7. We used simulated participants to model user enthusiasm in engaging with the AOI-OPEN community and mapped their enthusiasm to the available data volume. Degree of participation (DoP) was used to calculate the level of user engagement, with specific DoP values obtained through volunteer-based experiments (detailed experimental settings of the evaluation of the trustworthiness of AOI-OPEN are provided in the supplementary materials). The results indicated that both DAO and FL play significant roles in improving user participation. Specifically, the accuracy achieved was 88.5% when all three modules, i.e., DAO, parallel data (denoted as PD), and FL, were combined, while removing DAO reduced the accuracy slightly to 88.0%, suggesting that DAO's role in protecting user rights and enhancing transparency is crucial for maintaining high participation. This higher participation level likely contributes more data to the system, improving model training. Similarly, FL showed its importance in protecting user privacy, as seen by the drop of DoP to 0.2 when FL was removed. The inclusion of FL enhanced user confidence in the system's data handling, leading to higher participation. However, the distributed data utilization strategy adopted for privacy preservation in FL also resulted in a certain loss of accuracy. PD also proved to be an effective method for boosting model performance. Without PD, the accuracy dropped to 78.6% from 88.5%. This showed that PD contributes to better data generation and diversity, leading to more accurate model detection results.

Table 7 Ablation studies on the effectiveness of the proposed modules

DAO	PD	FL	DoP	Accuracy (%)
✓	✓	✓	0.35	88.5
	✓	✓	0.10	88.0
✓		✓	0.35	78.6
✓	✓		0.20	89.3

DAO: decentralized autonomous organization; PD: parallel data; FL: federated learning; DoP: degree of participation

In summary, the combination of DAO, FL, and PD not only increased user participation, with benefits seen in higher DoP, but also boosted the performance of the AOI system by providing more high-quality data for training. However, it still faces some challenges, which are discussed in detail in the supplementary materials.

5 Conclusions

To alleviate data loss and connect the data island in the automated optical inspection ecology, this paper proposes a data-centric framework to organize a DAO-based trustworthy and intelligent AOI ecology through federated operation and control. First, a trustworthy cooperation approach is developed with member identification, value transmission, and decision-making mechanisms to lay the foundation for secure and beneficial collaboration among different participants. Such a design significantly improves the willingness to participate in data and resource sharing. Second, in the collaborative community, virtual data generation and data utilization mechanisms are constructed to train representative big models, which can be easily transferred into different applications, thus leading to intelligent inspection systems. Experiments are conducted for image defect classification tasks. With the proposed parallel data approach, the scale of data with defects and model accuracy are largely improved. Besides, with the FL approach, we aggregate the data resources among different entities and improve the performance by comparison with the model trained with a single node. With the proposed data refinement stage, we continuously improve the accuracy to 97.6%. In the future, we will further extend the virtual data generation pipeline to a metaverse-based one. Based on the real production environment, virtual machines and virtual factories will be developed and integrated into the industrial metaverse to provide an interactive platform for AOI-related research.

Contributors

Yansong CAO, Yonglin TIAN, and Yutong WANG designed the research. Yansong CAO, Yutong WANG, Jing YANG, Yonglin TIAN, and Jiangong WANG processed the data. Yansong CAO and Yonglin TIAN drafted the paper. Yutong WANG, Jing YANG, and Jiangong WANG helped organize the paper. Yansong CAO and Fei-Yue WANG revised and finalized the paper.

Conflict of interest

Fei-Yue WANG is an executive associate editor-in-chief of *Frontiers of Information Technology & Electronic Engineering*, and he was not involved with the peer review process of this paper. All the authors declare that they have no conflict of interest.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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List of supplementary materials