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Annotation Methods for Object Detection: A Comparative Analysis from Manual Labeling to Automated Annotation Technologies

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***Abstract*—With the rapid development of artificial intelligence technology, data annotation plays an increasingly important role in fields such as machine learning and deep learning. This article aims to comprehensively review the research status, applications, and challenges of data annotation tools and technologies, in order to provide a reference for researchers in related fields. Data annotation refers to the process of processing, organizing, and marking raw data to facilitate the learning and analysis of data by machine learning algorithms. This article first introduces the basic concepts of data annotation, then analyzes in detail the current mainstream data annotation tools and technologies, including manual annotation, semi-automatic annotation, and automatic annotation. Next, this article explores the applications of data annotation in various fields and points out the current challenges and future development trends.**

Keywords-Data annotation; Artificial intelligence; Machine learning; Tools and technologies

I. INTRODUCTION

Data annotation, as a fundamental task in the field of machine learning and artificial intelligence, is crucial for converting raw data into valuable resources for model training. It involves marking, categorizing, and processing data so that it can be interpreted by machine learning algorithms. With the advent of the big data era, the volume, velocity, and variety of data have increased dramatically, resulting in a soaring demand for data annotation[1]. In the realm of artificial intelligence, high-quality data annotation serves as the foundation for developing accurate and robust models. From image classification and object detection in computer vision to sentiment analysis and machine translation in natural language processing, data annotation enables these models to learn and generalize effectively. The quality and quantity of annotated data directly impact the performance of artificial intelligence systems, serving as a critical factor in their success or failure. Furthermore, the diversification of application scenarios has further elevated the complexity and specificity of data annotation needs. Different domains, such as healthcare[2], finance[3], and autonomous driving[4], possess unique data characteristics and annotation requirements. Therefore, there is an urgent need for innovative data annotation tools and techniques to efficiently adapt to these varied needs. Diagram for Data Annotation as Fig 1.

Figure 1. Diagram for Data Annotation

The research on data annotation tools and techniques is of great significance:

- Improving Efficiency: In the context of big data, manual annotation has become impractical due to its time-consuming and labor-intensive nature[5]. Automated and semi-automated annotation tools can significantly speed up the processing, enabling researchers and practitioners to handle larger datasets more efficiently.
- Reducing Costs: The high cost of data annotation is one of the major obstacles hindering the widespread adoption of artificial intelligence technologies. Developing cost-effective annotation solutions, such as crowdsourcing or leveraging pre-trained models for transfer learning, can help alleviate this issue and make artificial intelligence more accessible.
- Enhancing Model Performance: High-quality annotated data is crucial for training high-performance

models. By ensuring accurate and consistent annotations, researchers can improve the accuracy, generalization capability, and robustness of artificial intelligence systems. This is particularly important in sensitive fields such as healthcare, where incorrect predictions can have severe consequences.

- Promoting Artificial Intelligence Innovation: Advances in data annotation tools and techniques can drive new applications and use cases of artificial intelligence. By making it easier to annotate and process different types of data, researchers can explore new research areas and develop innovative solutions to real-world problems[6].

II. Overview of Data Annotation Tools and Techniques

A. *Classification of Data Annotation Tools*

Data annotation tools are tools used to mark and categorize datasets such as digital images, audio, video, or text. These tools can automatically or manually label objects, faces, objects, text, etc., within datasets so that machine learning models can understand and recognize this data. Data annotation tools are typically developed and used by developers or data annotation teams to better organize and label datasets[7].

Data annotation tools can be classified based on functionality and usage scenarios. From a functional perspective, data annotation tools can be divided into image annotation tools, video annotation tools, text annotation tools, and audio annotation tools. These tools cater to different types of data annotation, meeting diverse machine learning needs. From a usage scenario perspective, data annotation tools can be classified into lightweight tools suitable for beginners and small projects, tools suitable for medium-sized projects that support multiple annotation types and semi-automated annotation, and complex tools suitable for large-scale, multi-user collaborative projects[8]. These tools vary in their emphasis on annotation accuracy, annotation efficiency, team collaboration, and data management.

B. *Introduction to Mainstream Data Annotation Tools*

Data annotation tools play a vital role in the field of artificial intelligence and machine learning. Choosing the right data annotation tool is crucial for improving annotation efficiency and accuracy. This paper summarizes the characteristics, applicable scenarios, advantages, and disadvantages of current mainstream data annotation tools such as LabelImg, VGG Image Annotator, brat, etc.

- LabelImg: Features intuitive user interface, supports bounding box annotation, runs quickly, and supports multiple output formats (such as XML, TXT, CSV, etc.). It can run on Windows, Mac, and Linux, facilitating cross-platform use. Application Scenario: Suitable for beginners or small projects that require fast, lightweight annotation, mainly for simple bounding box annotation. Advantages and Disadvantages: Advantages include simplicity, ease of use, lightweight nature, and cross-platform compatibility; disadvantages include limited functionality, only supporting bounding box annotation, not supporting complex shapes such as polygons, lines, or points, and lacking support for multi-user collaboration and automated annotation.

- VGG Image Annotator (VIA): Supports multiple annotation shapes such as polygons, rectangles, and circles, suitable for various image annotation scenarios. Application Scenario: Suitable for image annotation tasks that require multiple annotation shapes and flexible annotation[9]. Advantages and Disadvantages: Advantages include support for multiple annotation shapes and applicability to various scenarios; disadvantages include potentially less sophistication in some aspects compared to other specialized tools.

- brat: A Python-based natural language annotation tool designed for flexibility and practicality. It supports multiple annotation specifications and hierarchies, suitable for various natural language processing tasks. Application Scenario: Suitable for natural language processing tasks that require flexible annotation types and custom attributes. Advantages and Disadvantages: Advantages include support for multiple annotation specifications and hierarchies, and high flexibility; disadvantages include potential unsuitability for projects requiring efficient annotation.

In addition, there are some commonly used annotation tools, which are specifically shown in Table 1.

TABLE I. Comprehensive Performance of Annotation Tools

Tool	**Comprehensive Performance of Annotation Tools**		
	Key Features	***Application***	***Pros and cons***
LabelImg	Boundary box, Fast	Beginners, Small	Easy, Light/ Limited function
VIA	Multiple shapes	Flexible annotation	Versatile/ Less refined than specialized
brat	NLP, Flexible	Custom attributes	High flexibility/ May not be efficient
VoTT	Multiple types, Semi-auto	Technical users	Semi-auto, Multi-format/ Resource-intensive, Complex
Labelme	Powerful, Customizable	Various tasks	Powerful, Open-source/ No automation teamwork
CVAT	Powerful, Teamwork	Large-scale projects	Teamwork, Semi-auto/ Resource-intensive

C. *Key Techniques in Data Annotation*

- Manual Annotation Tools: Manual annotation tools are basic tools in the field of data annotation. They provide user-friendly interfaces and rich annotation functions, enabling annotators to conveniently process and label data. Common manual annotation tools include image annotation tools, text annotation tools, and speech annotation tools. These tools typically support multiple annotation methods, such as point annotation, line annotation, box annotation, etc., meeting the needs of different application scenarios. However, manual annotation tools also have some limitations. Firstly, the annotation process requires the participation of professional personnel, which incurs high costs; Secondly, the efficiency of annotation is influenced by the experience and skills of annotation personnel, making it difficult to ensure consistency and accuracy of annotation; Finally, for large-scale datasets, the time cost of manual annotation is too high to meet the needs of practical applications.

- Semi-Automated Annotation Techniques: To overcome the limitations of manual annotation tools, researchers have proposed semi-automated annotation techniques. These techniques combine the advantages of manual and automated annotation, improving annotation efficiency by introducing auxiliary tools and techniques[10]. For example, pre-trained deep learning models can perform preliminary classification and annotation of data, which is then revised and refined by annotators. Additionally, some semi-automated annotation tools support interactive annotation processes, allowing annotators to interact with models in real-time, further improving annotation efficiency and quality. Schematic diagram of semi-automatic annotation process as Fig 2.

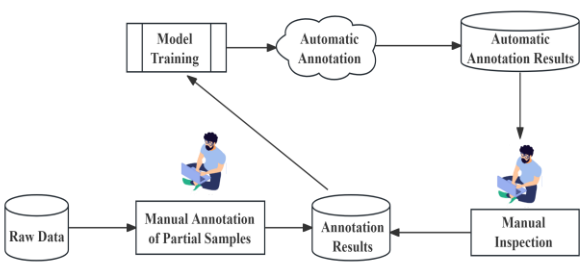

Figure 2. Schematic Diagram of Semi-Automatic Annotation Process

- Automated Annotation Techniques: Automated annotation techniques are cutting-edge research directions in the field of data annotation. They automatically complete data annotation tasks by training machine learning models, without human involvement. Automated annotation techniques are efficient, fast, and cost-effective, significantly shortening the data annotation cycle and improving annotation efficiency. However, due to the limitations of machine learning models, the accuracy and reliability of automated annotation techniques remain challenges. To improve the accuracy and reliability of automated annotation, researchers are continuously exploring new algorithms and models, and attempting to combine multiple techniques to achieve more efficient annotation processes. Diagram of automatic annotation process as Fig 3.

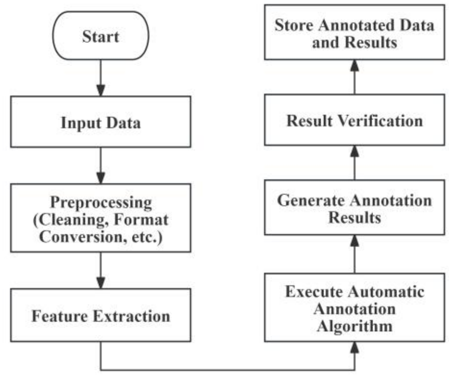

Figure 3. Schematic Diagram of Automatic Annotation Process

In order to compare the differences between these annotation techniques, an experiment was designed to further demonstrate this.

1.Experimental objectives:

Compare the differences between different annotation techniques (manual, semi-automatic, and fully automatic) in terms of annotation efficiency, accuracy, and quality, and demonstrate the annotation effects on the dataset.

Experimental hypothesis:

- Hypothesis 1: The annotation time of the automatic annotation tool is significantly shorter, but the accuracy is relatively low.
- Hypothesis 2: The annotation time and accuracy of the semi-automatic annotation tool are improved compared with the automatic annotation tool, but are still lower than manual annotation.
- Hypothesis 3: The manual annotation tool has the best accuracy, but the annotation efficiency is low.

Dataset selection:

Select a dataset containing 1,000 images, and the annotation task is "bounding box annotation" or "polygon annotation". Select COCO (contains rich object detection annotations) This dataset is a simple object detection task.

Labeling tool selection:

Manual labeling tool:

- LabelImg (commonly used for bounding box labeling)
- VGG Image Annotator (VIA) (supports multiple labeling types, commonly used for images and videos)

Semi-automatic labeling tool:

- CVAT (combined with pre-trained models, supports manual correction)
- Supervisely (provides semi-automatic labeling and task management functions)

Automatic labeling tool:

- YOLO (You Only Look Once) (real-time target detection model)
- Mask R-CNN (deep learning model suitable for instance segmentation tasks)

Task setting:

The experimental setting is as follows:

- Annotation type: bounding boxes (rectangles) and polygons of objects in the image.
- Dataset size: 1000 images, each containing 1 to 5 objects.
- Experimental subjects: Each tool uses the same set of annotators for annotation to ensure fairness.

Experimental steps:

Dataset preparation:

Select 1000 images from the public dataset, and the annotation tasks include object detection (bounding boxes) and instance segmentation (polygons).

Annotation process:

- Manual annotation: Use LabelImg for bounding box annotation and VIA for polygon annotation. Record the annotation time (minutes) and annotation accuracy of each image.
- Semi-automatic annotation: Use CVAT tool to automatically annotate through deep learning models (such as YOLO, Mask R-CNN), and then manually correct. Record the annotation time and accuracy.
- Automatic annotation: Use YOLO or Mask R-CNN to fully automatically annotate, and record the time and accuracy of automatic annotation.

Evaluation metrics:

- Annotation efficiency: Annotation time per 1,000 images, in minutes.
- Annotation accuracy: Compare the accuracy of each annotation (such as the IoU (Intersection over Union) of the bounding box or polygon) and the F1 value by comparing with the manual annotation.
- Annotation quality: Check for mislabeling (wrong bounding box position or wrong object classification), missing labels (unlabeled objects), and duplicate annotations.

2. Experimental Results

The experimental results are shown in Fig. 4.

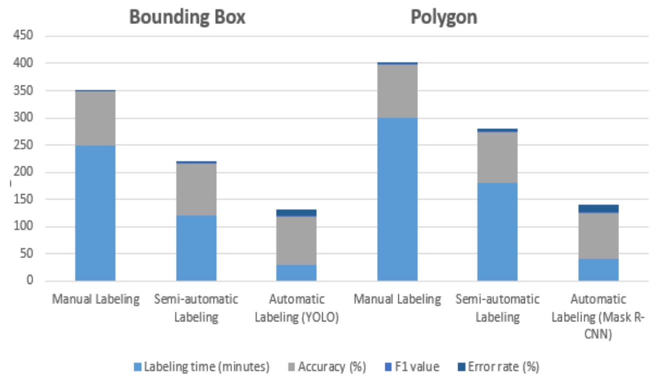

Figure 4. Experimental data table

Detailed description:

Annotation time:

- Manual annotation: Since each annotator needs to annotate each image one by one, it takes a long time, especially when annotating polygons.
- Semi-automatic annotation: Since automatic annotation can reduce the workload of annotators, the time is significantly reduced, but manual correction is still required, especially in complex scenes.
- Automatic annotation: Automatic tools such as YOLO and Mask R-CNN significantly improve the annotation speed, but due to the limitations of the model itself, the annotation accuracy is reduced.

Accuracy and F1 value:

- Manual annotation: The highest accuracy, manual annotation can avoid mislabeling and missing labels. The IoU value of the bounding box is close to 100%, and the accuracy of the polygon is also very high.
- Semi-automatic annotation: The accuracy of semi-automatic annotation is relatively high, but there are still some mislabeling and missing labels, and the F1 value decreases, especially when annotating complex objects, the model predicts more errors.
- Automatic annotation: The accuracy of automatic annotation tools is low, especially in more complex scenes, automatic annotation is prone to mislabeling and missing labels.

Error rate:

- Manual labeling: The error rate is the lowest, because humans can accurately determine the position and shape of objects and avoid most errors.
- Semi-automatic labeling: The error rate is relatively high. Although the pre-trained model helps some labeling work, model errors may lead to mislabeling or missing labels.

- Automatic labeling: The error rate is the highest, especially in complex scenarios, the error of deep learning models is obvious and there are many errors.

3. Results Analysis and Discussion

(1) Comparison of Labeling Efficiency:

- Automatic labeling tools significantly improve labeling speed. The labeling time of YOLO and Mask R-CNN is much lower than that of manual labeling and semi-automatic labeling tools.
- For large-scale data sets, automatic labeling tools have a huge advantage in time efficiency, especially for scenarios that require fast labeling.

(2)Comparison of Labeling Accuracy:

- Manual labeling has the highest accuracy and is suitable for small-scale projects that require high-precision labeling, especially for complex data sets or high-precision requirements.
- Semi-automatic labeling tools provide a certain degree of accuracy and high labeling efficiency, and perform well in medium-sized projects.
- Although the automatic labeling tool is the fastest, its accuracy is relatively low and requires post-correction to meet high-quality requirements.

(3) Error Analysis:

- The error rate of the automatic labeling tool is high, especially at the edges and details of objects, the IoU and accuracy of the automatic labeling decrease significantly.
- The semi-automatic labeling tool can greatly reduce the error through manual correction, but it also requires more manual intervention.
- Manual labeling has almost no error and is the most accurate labeling method.

4. Experimental conclusion

(1) Manual labeling: suitable for small-scale data sets with high precision requirements, but the labeling speed is slow and the efficiency is low.

(2)Semi-automatic labeling: suitable for medium-sized projects, which can balance the labeling time and accuracy to a certain extent. It is suitable for scenarios with limited resources and high accuracy requirements.

(3) Automatic labeling: suitable for large-scale data sets, especially time-sensitive scenarios. Although it requires later correction, it greatly improves the labeling efficiency.

III. Current Development Status of Data Annotation Tools and Techniques

In recent years, data annotation tools and techniques have made significant progress, mainly reflected in algorithm improvements, tool upgrades, and the introduction of new features.

A. *Algorithm Improvements*

Automated annotation techniques leverage deep learning and machine learning algorithms to significantly improve annotation efficiency and accuracy. For example, in image annotation, object detection and image segmentation techniques are widely used to quickly identify and annotate objects in images. In speech annotation, speech recognition and natural language processing techniques are employed to achieve automatic transcription and annotation of speech data. The introduction of these techniques has significantly reduced the workload of manual annotation and improved annotation quality.

B. *Tool Upgrades*

Comprehensive Annotation Platforms: Comprehensive data annotation platforms such as Label Studio and Supervisely support various data types including images, texts, audios, and videos. They also provide a rich array of annotation templates and export formats. These platforms typically integrate automated annotation features, support team collaboration, and offer permission control, making them suitable for data annotation projects in large enterprises and scientific research institutions[11]. Lightweight Annotation Tools: Tools like Make Sense and T-Rex Label are lightweight and user-friendly, making them suitable for rapid annotation of small-scale datasets or specific application scenarios. For example, T-Rex Label employs visual cues for annotation, which is ideal for objects that are difficult to describe with text. The classification of data annotation tools is shown in Table 2.

TABLE II. Classification of Data Annotation Tools

Tool classification	Key Features	applicable scenario
image annotation tool	Supports a variety of annotation shapes	Image classification, object detection and other tasks
Text Annotation Tool	Supports multiple annotation specifications and hierarchies	Natural language processing tasks such as sentiment analysis
Lightweight tools	Friendly interface and easy operation	Beginners or Small Items
Medium Project Tools	Support multiple annotation types, semi-automatic annotation	Items that require flexible labeling and multi-type labeling
Large Collaboration Project Tools	Powerful annotation capabilities to support team collaboration	Large-scale, multi-user collaborative projects

C. *Introduction of New Features*

Pre-annotation and Automatic Quality Inspection: Many modern annotation tools have integrated pre-annotation features that use machine learning algorithms to automatically identify and annotate some data, reducing the burden on manual labor. Meanwhile, automatic quality inspection features can detect annotation errors in real-time, enhancing annotation quality. For instance, Jinglianwen Annotation Platform possesses pre-annotation capabilities and automatic quality inspection functions, effectively improving annotation efficiency and quality. Multimodal Data Annotation: With the advancement of AI technology, multimodal data annotation has gradually become a trend. Future data annotation tools will support the joint processing and annotation of multiple modal data such as images, speech, and text, further enhancing data utilization efficiency and model performance.

IV. Current APPLICATION Status of Data Annotation Tools and Techniques

Data annotation tools and technologies have demonstrated their powerful application effects in various fields such as autonomous driving, medical imaging, customer service, and speech recognition. These application cases not only prove the crucial role of data annotation in driving the development of AI technologies but also provide strong support for the widespread application and innovation of AI technologies in the future.The application fields related to data annotation are shown in Fig. 5.

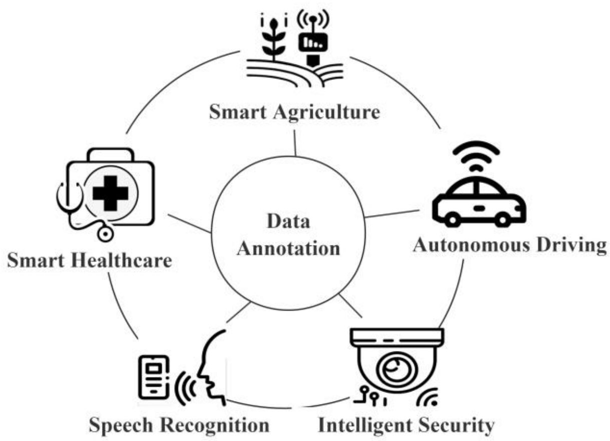

Figure 5. The Application Fields of Data Annotation

1) Autonomous Driving[12]: Data annotation is utilized to train autonomous driving models, enabling them to perceive the surrounding environment and move with minimal or no human input. In autonomous driving, data annotation involves pedestrian recognition, vehicle recognition, traffic light recognition, road recognition, and more, providing precise training data for related companies and safeguarding intelligent transportation.

2) Intelligent Security[13]: Data annotation expands the perception range of existing security systems by integrating and collaboratively analyzing data from various sources, thereby improving the accuracy of monitoring and alerting. Corresponding annotation scenarios include facial recognition, face detection, visual search, facial keypoint extraction, and license plate recognition.

3) Smart Healthcare: The application of artificial intelligence and big data analysis technologies in the medical industry provides deep insights into medical knowledge and data, assisting doctors and patients in solving challenges such as image recognition difficulties, high drug development costs, and poor cancer treatment outcomes in fields such as medical imaging, new drug development, oncology and genetics, and health management[14]. Corresponding annotation scenarios include surgical tool identification, prescription recognition, medical image annotation, voice annotation.

4) Smart Agriculture: Relying on precise data annotation, the location of crops and their maturity and growth status can be identified, enabling intelligent crop harvesting and solving the problem of precise pesticide application[15]. This reduces manpower consumption and improves pesticide utilization rates. Currently, data annotation scenarios in smart agriculture include cultivation management, precise water and fertilizer application, and safety monitoring[16].

V. Existing Issues and Future Development Trends

Despite significant advancements in data annotation tools and technologies, several challenges persist that hinder their widespread adoption and effectiveness. Firstly, annotation costs remain relatively high, posing a significant barrier, especially when dealing with large-scale datasets. These costs not only encompass the direct expenses related to labor and tools but also indirect costs such as time and resource allocation. Secondly, striking a balance between annotation efficiency and quality is particularly challenging, especially in complex application scenarios where the data may be diverse, nuanced, or require domain-specific expertise. This dilemma often leads to trade-offs that can compromise the overall quality of the annotated data. Lastly, while automatic annotation technologies have made strides, their accuracy and reliability still lag behind human-level performance, necessitating ongoing improvements and validations [14].

To overcome these challenges, researchers are continuously exploring new methods and technologies.

1) Technological Innovation and Automation Enhancement: It is anticipated that data annotation technology will achieve significant breakthroughs in automation in the future. Through continuous innovations in deep learning, Natural Language Processing (NLP), computer vision, and other fields, the accuracy of automatic annotation tools will significantly improve, reducing the dependence on human annotators.

2) Multimodal and Cross-Domain Integration: As multimodal data becomes more prevalent, future data annotation technology will focus more on the comprehensive processing of various data types such as images, text, and audio. This will promote cross-domain integration, enabling annotation tools to adapt to more diverse application scenarios.

3) Human-Computer Collaboration and Intelligent Assistance: Future data annotation will emphasize human-computer collaboration, utilizing intelligent assistance tools to improve the efficiency and accuracy of human annotators. These tools may include intelligent recommendation systems, automatic error detection and correction functions, etc. The human-computer collaboration model will promote the improvement of annotation quality while reducing the burden on human annotators and enhancing overall work efficiency.

VI. Conclusion

This paper reviewed the research progress and application status of data annotation tools and technologies. We discussed the advantages and disadvantages of manual annotation, semi-automatic annotation, and automatic annotation methods, analyzing their applicability in different application scenarios. At the same time, we also focused on current challenges and future development trends. In the future, with the continuous development of artificial intelligence technologies, data annotation tools and technologies will become more intelligent and automated. We believe that with the joint efforts of researchers, the field of data annotation will achieve more significant progress and breakthroughs.

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