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Construct a garbage recognition model using automatic machine learning based on EasyDL

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Abstract. In modern times, machine learning has become an indispensable part of various industries. As the amount of data increases, reducing the time cost of manual annotation is crucial. AutoML emerges as a solution that effectively automates labor-intensive tasks like image annotation. In this article, we use Tencent's EasyDL to develop a garbage recognition function. The garbage recognition model completed through EasyDL achieved an average of over 90% in terms of accuracy and F1 score. This indicates that autoML can greatly reduce manual participation while ensuring a certain level of accuracy.

Keywords: AutoML, EasyDL, image annotation, waste sorting.

1. Introduction

In the contemporary era, machine learning has evolved to become a fundamental component of various applications that permeate daily life. Its applications span diverse fields, encompassing facial recognition, image classification, automotive sensing, and fingerprint recognition, among others. The rapid advancement of embedded systems and the Internet of Things (IoT) has further propelled the demand for machine learning across sectors such as smart vehicles, intelligent furniture, virtual reality devices, and medical instrumentation [1].

However, this burgeoning demand and the escalating requirements for these technologies have concomitantly led to an increase in the volume of data that must be processed. Automated Machine Learning (AutoML) has emerged as a solution to this challenge [2]. AutoML streamlines many labor-intensive tasks, such as image annotation and prediction, which previously consumed substantial time and effort. It enables the intelligent annotation of existing data and the formation of preliminary models for user testing and manual modification [3]. This approach not only reduces human annotation time significantly but also achieves accuracy levels comparable to human annotation. Furthermore, intelligent annotation adheres strictly to guidelines, thereby eliminating human errors. The entire process necessitates minimal human intervention, resulting in considerable time savings [4].

In the context of this research, we employ EasyDL to develop a garbage identification model, primarily addressing the real-world problem of waste sorting [5]. EasyDL, a customized high-precision image application AI model, is developed by Baidu, based on the Wenxin Big Model[6]. It is part of the world's first 100 billion yuan Meta-knowledge enhancement model released by Baidu, encompassing a wide array of data processing functions. Our work focuses on utilizing EasyDL's image classification function to train waste classification models based on EasyDL's waste classification database, followed by a rigorous evaluation of the model's performance.

The structure of this article comprises three main sections. The first section, the Literature Review, involves a comprehensive examination of pertinent literature, where we analyze the practical significance of this model and explore potential solutions. The second section, the Waste Sorting Model, elucidates the training process in detail, providing an in-depth analysis of the results. Finally, the third section, the Discussion, summarizes the challenges encountered during the training process and evaluates the performance of the trained model, engaging in a critical discussion of the findings.

2. Literature review

2.1. Automated machine learning (autoML)

With the goal of automating various steps in the creation of a machine learning system, autoML has become a vital field. It includes feature extraction, model design, preprocessing, post-processing, and other processes. The following sections delve into the key studies, methodologies, applications, and challenges in the field of AutoML. Chen, et al. [7] provide a comprehensive review of the techniques used in AutoML, categorizing them into three main areas: automated feature engineering (AutoFE), and automated deep learning (AutoDL), automated model and hyperparameter learning (AutoMHL). They present cutting-edge techniques like Bayesian optimization, reinforcement learning, evolutionary algorithms, and gradient-based approaches, lay out well-known AutoML frameworks, and they draw attention to ongoing AutoML challenges. Escalante [8] summarizes the key discoveries from the early years of the field and provides a historical overview of the development of AutoML. The chapter introduces AutoML for supervised learning, describes the key paradigms, and outlines potential areas for future research. The goal of Truong, et al.'s [9] investigation into the state of AutoML tools is to automate processes like data preprocessing, feature engineering, model selection, hyperparameter optimization, and prediction result analysis. They conduct evaluations on various datasets, comparing the advantages and disadvantages of different tools on different test cases. Elshawi, et al. [10]present a comprehensive survey of the state-of-the-art efforts in tackling the Combined Algorithm Selection and Hyper-parameter tuning (CASH) problem in AutoML. Additionally, they highlight the work being done to automate the entire complex machine learning pipeline, from data understanding to model deployment, and they talk about some of the future research directions and unresolved issues. Zöller and Huber [11] analysis of popular AutoML frameworks on real datasets is combined with a survey of current AutoML methodologies. They provide an overview of key AutoML techniques for each stage of creating an ML pipeline and evaluate a number of AutoML frameworks on 137 datasets from well-known AutoML benchmark suits.

2.2. Garbage identification

Given the growing difficulties in waste management around the globe, garbage identification has become a key field of research. The use of artificial intelligence and machine learning in this area has created new opportunities for accurate and effective waste management. The important research and approaches in the topic of trash identification are covered in the sections that follow. A number of methods for identification and evaluation in intelligent garbage classification are proposed by Wang, et al. [12], including material identification based on thermal theory and non-destructive laser irradiation, profile identification using scenery thermal image after PCA and histogram correction, and a coupling algorithm for thorough evaluation of garbage sort. Plyukhin and Agha [13] provide a low-overhead delayed reference listing approach (DRL) for termination detection in actor systems as they examine the idea of autonomous garbage collection (GC) in the context of actor systems. By creating a new open benchmark dataset for household trash picture classification, dubbed 30 Classes of Household trash Images (HGI-30), Wu, et al. [14] solve the issue of inadequate and unstable home garbage datasets. They also conduct experiments and performance analysis of state-of-the-art deep CNN methods on HGI-30. They also run tests and analyze the performance of cutting-edge deep CNN techniques. The approach

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Bansal, et al. [15] suggest employs artificial intelligence algorithms to find rubbish and uses a camera to determine its location. With over 95% certainty, the system can discriminate between jewels and trash in real-time.

3. Research methods

3.1. AutoML

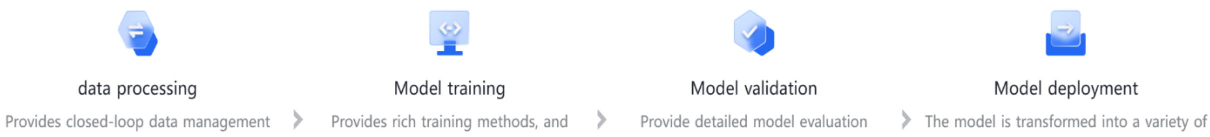

Figure 1. The process of AutoML.

As shown in Figure 1, the learning process of the proposed model is systematically organized into four distinct phases, each of which plays a crucial role in the development and deployment of the model. The following subsections provide a detailed description of each phase.

3.1.1. Data processing

Data processing constitutes the foundational step of the entire modeling process, where the quality and management of the data significantly influence the accuracy of the resulting model. This phase encompasses three key activities:

Data Upload: This involves the transfer of data collected from practical applications to a cloud platform, thereby providing the essential raw materials for subsequent model training.

Data Annotation: This refers to the meticulous labeling of data to facilitate the model's comprehension of individual data items. For instance, in the context of image recognition, specific objects within an image may be identified and annotated.

Data Reflow: This pertains to the iterative optimization of the model based on feedback data obtained post-training. The feedback is utilized to refine the model's predictions, enhancing its overall performance.

3.1.2. Model training

Upon successful data processing, the next phase entails model training. Utilizing EasyDL's platform, users can access multiple training methodologies, enabling the creation of high-precision models without the necessity for specialized programming skills. These methodologies may encompass predefined model architectures, strategies for parameter optimization, and more. The culmination of this phase is a trained model capable of predicting new data.

3.1.3. Model verification

Subsequent to the completion of model training, it becomes imperative to assess the model's performance. EasyDL offers comprehensive model evaluation reports and facilitates online validation, thereby allowing for targeted model optimization based on the validation outcomes. These evaluation reports typically encompass various performance metrics, including but not limited to accuracy, precision, and recall, thereby providing users with a nuanced understanding of the model's actual performance.

3.1.4. Model deployment

Once the model has been verified and satisfies the stipulated performance criteria, it progresses to the deployment phase. EasyDL possesses the capability to transform the model into a format that aligns with user-specific business requirements, such as an Application Programming Interface (API). This

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transformation process may include a series of steps such as model exportation, importation, testing, optimization, and integration into practical applications.

3.2. Dataset source

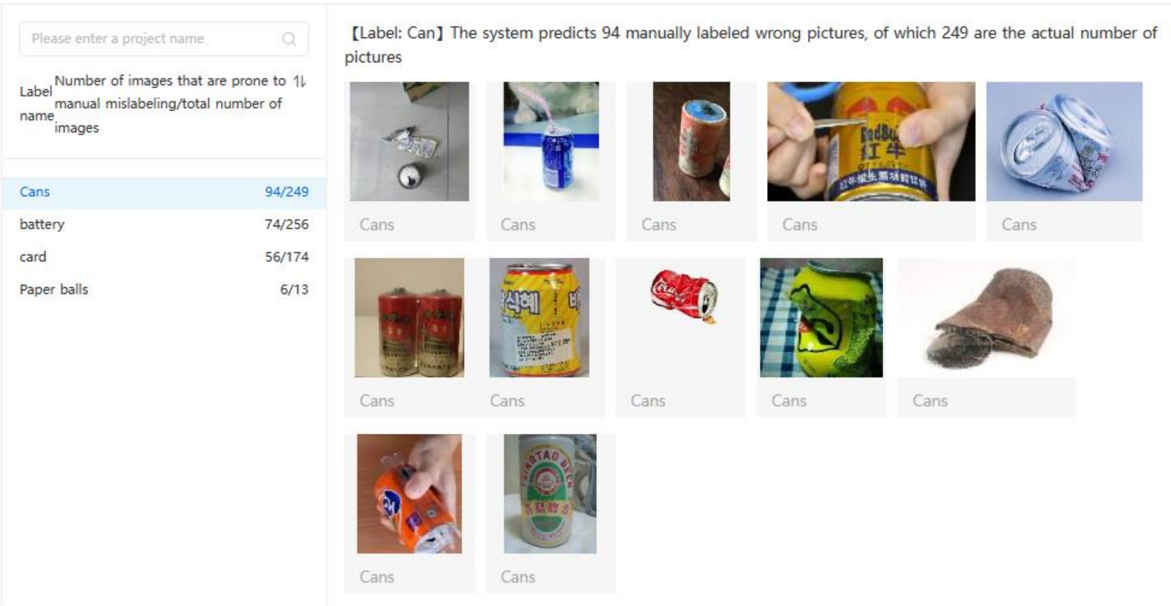

Figure 2. The example of datasets.

The dataset employed in this study is the Waste Sorting Dataset provided by EasyDL, comprising a total of 699 photographs, as shown in Figure 2. These images are categorized into specific waste types. There are 249 images dedicated to the category of drink cans, representing various forms and conditions. The category of batteries encompasses 256 images, illustrating different types and sizes. Additionally, the dataset includes 174 pictures of various cards, possibly representing credit cards, identification cards, or other similar items, and a smaller subset of 13 images is allocated to Paper Balls, capturing different shapes and sizes. Furthermore, there are seven images that do not correspond to any of the aforementioned four categories. These were identified as anomalies and were subsequently manually removed from the dataset to maintain consistency and relevance to the study's objectives.

3.3. Evaluation criteria

In the realm of image classification tasks, the performance of a model is typically evaluated using a set of computational metrics. These metrics, such as accuracy, precision, and recall, provide a quantitative understanding of the model's performance in classification tasks. The following are definitions and formulas for these commonly used metrics:

Accuracy: The percentage of samples that the model accurately predicts is measured by this metric. It is calculated as the total number of samples divided by the sum of true positives and true negatives, which is expressed mathematically as (True Positive + True Negative) / Total Samples.

Precision: This metric counts the number of samples that actually tested positively among those the model predicted would. It is determined by dividing the quantity of true positives by the total of true positives and false positives, which is expressed as True Positive / (True Positive + False Positive).

Recall: This metric, also referred to as sensitivity, indicates the percentage of true positive samples that the model accurately predicts. It is determined by dividing the quantity of true positives by the total of true positives and false negatives, which is expressed as True Positive / (True Positive + False Negative).

These metrics provide a comprehensive evaluation of the model's performance, each highlighting different aspects of its predictive capabilities.

4. Experimental result

Table 1. Experimental results.

Types	Accuracy	F1-score
Total	94.69%	
Battery	96.10%	0.955
Cans	96.30%	0.963
Card	95.35%	0.932
Paper Balls	50.00%	0.677

As shown in Table 1, the performance of the model in classifying different types of waste was evaluated using two key metrics: Accuracy and F1-score. The overall accuracy of the model is 94.69%, reflecting the model's average performance across all categories. Although a total F1-score is not provided, the individual categories' F1-scores offer insights into the model's overall precision and recall.

In the Battery category, the model achieved an accuracy of 96.10% and an F1-score of 0.955. These figures indicate an excellent performance by the model in identifying and classifying batteries, with minimal false positives and false negatives.

For the Cans category, the model's accuracy is 96.30%, with an F1-score of 0.963. This high accuracy and F1-score demonstrate that the model also performs exceptionally well in recognizing and classifying cans.

The Card category has an accuracy of 95.35% and an F1-score of 0.932. While these numbers are slightly lower than the Battery and Cans categories, they still indicate a robust ability of the model to recognize and classify cards.

The Paper Balls category presents a noticeable challenge, with an accuracy of 50.00% and an F1-score of 0.677, significantly lower than the other categories. This may indicate challenges in the model's ability to recognize and classify Paper Balls, possibly requiring further optimization and tuning.

These results provide an in-depth understanding of the model's performance in various waste classification tasks. Overall, the model performs exceptionally well in most categories, but further research and improvement may be needed in the Paper Balls category. By analyzing these results in detail, the strengths and weaknesses of the model can be identified, providing direction for future research and development.

5. Discussion

The study embarked on an ambitious task of employing machine learning techniques, specifically using EasyDL, to create a garbage identification model. The results, as detailed in the previous sections, provide a multifaceted view of the model's performance.

The high accuracy and F1-scores in categories such as Battery, Cans, and Cards demonstrate the model's robustness and efficiency in classifying these types of waste. The utilization of 699 images, carefully annotated and processed, likely contributed to this success. The model's ability to achieve over 95% accuracy in these categories is indicative of its practical applicability in real-world waste sorting scenarios.

However, the Paper Balls category presented a significant challenge, with an accuracy of only 50% and a lower F1-score. This discrepancy may be attributed to various factors, such as the limited number of samples (only 13 images), potential issues in data annotation, or inherent complexities in distinguishing Paper Balls from other waste types. Further investigation into this category, possibly including additional data collection and model tuning, could enhance the model's performance.

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The study also highlights the importance of metrics like accuracy, precision, and recall in evaluating a model's performance. These metrics provided a comprehensive understanding of how the model performed across different categories, guiding future improvements.

6. Conclusion

This research successfully demonstrated the application of machine learning, specifically using the EasyDL platform, in the critical area of garbage identification. The model's high accuracy in most categories underscores its potential as a valuable tool in waste management and recycling efforts.

However, the challenges encountered in the Paper Balls category serve as a reminder that machine learning models are not without their limitations and complexities. Future work should focus on addressing these challenges, possibly through more extensive data collection, refined annotation processes, and tailored model optimization techniques.

The study contributes to the growing body of knowledge in automated waste sorting and offers a promising direction for leveraging machine learning in environmental sustainability efforts. Its insights and methodologies can serve as a foundation for future research and practical applications in waste management.

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