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Enhancing urban cycling safety: The role of automated helmet compliance monitoring with EasyDL

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Abstract. With an increasing emphasis on individual safety in urban transportation, our study addresses the critical issue of bicycle helmet compliance. Helmets play an essential role in preventing cycling-related injuries, yet their usage often falls short of safety standards. We utilize Baidu's EasyDL, an automated machine learning tool, to detect the use of bicycle helmets in varied urban environments. This approach leverages a large, annotated dataset dedicated to bicycle helmets, achieving high precision in identifying helmet usage. Our preliminary tests in simulated urban settings show the method's capability to enhance safety measures effectively. This tool aids in real-time monitoring and pinpointing areas where helmet usage is neglected, aiming to elevate safety consciousness among cyclists. The study demonstrates the practicality of using automated helmet detection to improve urban cycling safety, providing a user-friendly option for those without a deep programming background. Our work underscores the value of EasyDL in analyzing bicycle helmet datasets and its potential role in reinforcing essential safety practices in urban cycling scenarios.

Keywords: Bicycle Helmet Compliance, Automated Machine Learning (AutoML), Urban Cycling Safety

1. Introduction

The increasing adoption of bicycles as a primary mode of transportation in urban areas has brought a renewed focus on cyclist safety [1]. Urban cycling, while beneficial for personal health and environmental sustainability, presents unique safety challenges. Among these, the use of bicycle helmets stands out as a crucial factor in preventing serious injuries. Studies have consistently shown that helmets can reduce the risk of head injuries by a significant margin, yet the rate of helmet usage among urban cyclists remains alarmingly low [2]. This discrepancy highlights a critical gap in safety compliance, exacerbated by the lack of effective monitoring and enforcement mechanisms.

In addressing this gap, our study explores the application of automated machine learning (AutoML) to improve helmet usage monitoring and compliance in urban environments. The choice of AutoML, specifically Baidu's EasyDL platform, is driven by its user-friendliness and accessibility, making advanced analytical capabilities available to those without extensive programming expertise. This democratization of technology is key to widespread implementation and can play a transformative role in urban safety initiatives.

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The importance of this research extends beyond the immediate context of cycling safety. It contributes to a larger conversation on the role of technology in enhancing urban transportation systems and how automated monitoring can complement existing safety measures. The integration of AutoML in safety compliance monitoring is relatively unexplored, particularly in the context of cycling, and presents an opportunity to set a precedent for technology-enabled urban safety solutions.

Our study specifically focuses on analyzing a comprehensive dataset of bicycle helmets, employing EasyDL to identify helmet usage in various urban cycling scenarios accurately. This methodological approach is novel in its application and holds significant potential for improving real-time monitoring and enforcement of safety regulations. By demonstrating the efficacy of AutoML in accurately detecting helmet usage, our research aims to bridge the gap between technological innovation and practical safety applications. We anticipate our findings will provide valuable insights for urban planners, policymakers, and technology developers, driving the agenda forward for safer cycling environments in urban settings.

2. Related work

2.1. Bicycle Helmet Compliance in Urban Cycling

Urban cycling, as an increasingly popular mode of transportation in cities, has brought cyclist safety, particularly helmet usage, into sharp focus. Among all European countries, Poland has the largest increase in the number of people riding bicycles on weekdays (45%), followed by Italy (33%) and France (32%), while in Portugal, Finland, and Ireland, the number of people riding bicycles in 2022 was lower than the previous period. Many cities have many bike lanes, and currently, there are over 35000 kilometers of bike lanes throughout the Netherlands [3]. In the capital, Amsterdam, the total length of bicycle lanes has exceeded 500 kilometers - a considerable figure for a city of 219.3 square kilometers with a population of less than one million. Research conducted by Hoshizaki, et al. [4] has shown that helmets significantly reduce the risk of head injuries. A survey shows that bicycle helmets can reduce the risk of head injury by 69% and severe brain injury by 79% [5]. Despite this clear benefit, actual helmet usage in urban areas is inconsistent. There are several possible reasons for this phenomenon: firstly, the helmet is too heavy and stuffy to wear, making it inconvenient for cycling. Secondly, some people believe wearing a helmet can ruin a well groomed hairstyle and affect one's image. Thirdly, some people lack safety awareness and do not understand the importance of wearing helmets.

The challenge in ensuring helmet compliance is exacerbated by the limitations of traditional monitoring methods. Traditional monitoring methods cannot accurately and efficiently distinguish whether riders are wearing helmets during resource-intensive times, and traditional monitoring cannot monitor and operate in real-time, resulting in low efficiency [6]. Gaps in monitoring and enforcement contribute to the overall low adherence to helmet safety norms among urban cyclists, highlighting the need for more efficient and scalable solutions.

2.2. Automated Machine Learning for Safety Monitoring

Integrating AutoML into urban safety monitoring represents a significant technological advancement [7]. Machine learning has shown tremendous potential and application value in various fields. However, traditional machine learning models' construction and optimization process often requires a large amount of manual involvement, which limits their widespread application speed and scale. In this context, fully automated AutoML technology has emerged and is considered an important direction for the future development of machine learning. AutoML has now been applied in classifying video images, users, and more. The work of Zhang, et al. [8] is a notable example, demonstrating how AutoML can effectively process and analyze large volumes of visual data to identify safety violations in real time. This capability is particularly relevant for helmet compliance monitoring, where the ability to quickly and accurately analyze visual data is crucial [9].

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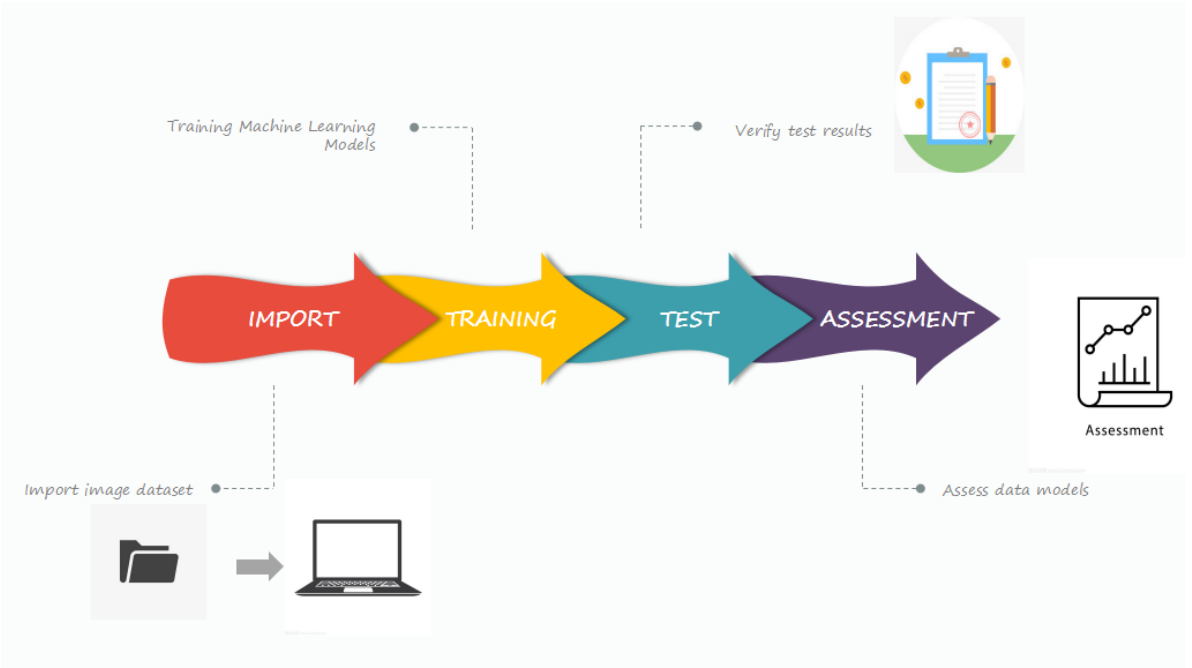


Figure 1. AutoML methods.

In the context of helmet detection, the introduction of user-friendly AutoML platforms such as Baidu's EasyDL has been a game-changer. EasyDL is very user-friendly, and this platform will provide you with guidance to complete the program step by step to achieve the final result. As shown in Figure 1, Non technical backgrounds can also use advanced analysis functions [10]. The practicality and efficiency of EasyDL in analyzing visual data make it an invaluable tool for identifying helmet usage patterns and areas of non-compliance. Such advancements in technology are key to implementing more effective safety measures and promoting helmet usage in urban cycling [11].

3. Methods

3.1. Data Collection and Preprocessing

The foundation of our study is a comprehensive dataset focused on bicycle helmets.The dataset used for this training is a publicly available helmet image dataset from Aliyun. The dataset comprises thousands of images featuring cyclists in various urban settings, both with and without helmets.This dataset contains 764 images from 2 different categories for helmet detection, with and without helmets [12]. The PASCAL VOC format provides bounding box annotations. Prior to analysis, the dataset underwent several preprocessing steps, including image resizing, normalization, and augmentation. This preprocessing included standardization of image dimensions, normalization of color scales, and augmentation techniques like rotation and scaling to enhance the dataset's robustness and reduce model overfitting .

3.2. Model Training with EasyDL

Leveraging Baidu's EasyDL, we trained a machine learning model to identify the presence or absence of helmets in the images. The training process involved feeding the preprocessed images into the EasyDL platform, where the model learned to distinguish between helmeted and non-helmeted cyclists. The deployment method used for this training is public API, V1 version, with a training set of 300 images.

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3.3. Model Validation and Testing

After the training phase, the model was subjected to a series of validation tests to assess its accuracy and reliability.During the verification test, another helmet dataset was used for testing, and the test results showed that this experiment achieved an accuracy rate of over 90%. We conducted tests in simulated urban environments to evaluate the model's real-world applicability.The test used photos of non motorized lanes in the city and photos of work scenes of construction workers. The performance metrics, including precision, recall, and F1-score, were calculated to quantify the model's efficacy. These indicators facilitate a comprehensive reflection of the training results, and the evaluation results of these indicators all reach around 90%.

3.4. Performance metric

In evaluating the effectiveness of our model in detecting helmet usage among urban cyclists, we focused on several key metrics, each providing unique insights into the accuracy and reliability of the model. The mean average precision (mAP) was calculated across a range of Intersection over Union (IoU) thresholds, from 0.5 to 0.95. This can comprehensively evaluate the detection accuracy of the model at different levels of strictness.A higher IoU threshold indicates a stricter criterion for correct detection, offering a rigorous assessment of the model's precision in detecting helmets.

Additionally, we analyzed the model's precision and recall. Precision, the proportion of true positive detections in all positive detections, is crucial for minimizing false positives.Reducing false alarms can provide better services for people and reduce the identification of people who are not wearing helmets as wearing them. Conversely, recall assesses the model's ability to identify all actual instances of helmet usage, ensuring no helmet-wearing cyclist is overlooked. Not missing any riders without helmets can help reduce the occurrence of accidents. By evaluating both precision and recall at various thresholds, we gained insights into the trade-off between accurate helmet detection and minimizing false detections.

The F1 score, as the harmonic mean of precision and recall, provided a comprehensive metric of the model's overall accuracy. F1 score balances accuracy and comprehensiveness, providing a comprehensive performance metric. This metric was especially useful for presenting a straightforward assessment of the model's effectiveness to stakeholders who prefer a simple, yet informative evaluation over more complex statistical analyses.

Together, these metrics offered a multifaceted evaluation of our model, ensuring its suitability for practical application in urban cycling environments where accuracy, reliability, and comprehensive detection are crucial.The urban cycling environment is complex, and the accuracy, reliability, and comprehensive detection ability of the model are conducive to providing more safety guarantees for cyclists.

4. Experiment result

Table 1. AutoML performance.

	mAP	*Precision*	*Recall*	*F1-Score*
EasyDL	91.3%	87.8%	90.0%	89.0%

In the evaluation of our AutoML model, specifically using EasyDL, the performance metrics indicated a high level of accuracy and reliability in detecting helmet usage among urban cyclists. As summarized in Table 1, the model achieved a mAP of 91.3%, reflecting its strong capability in accurately identifying helmeted cyclists across a range of IoU thresholds. This high mAP score suggests that the model was highly effective in distinguishing correctly between images of cyclists with and without helmets.

The precision of the model, which measures the accuracy of positive predictions, was recorded at 87.8%. This indicates that when the model predicted the presence of a helmet, it was correct 87.8% of

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the time. This high precision rate is significant in reducing the likelihood of false positives, where a cyclist without a helmet might be incorrectly identified as wearing one.

Furthermore, the model demonstrated a recall of 90.0%. This metric assesses the model's ability to correctly identify all relevant instances of helmet usage. A recall rate of 90.0% implies that the model successfully detected 90% of the actual helmet-wearing instances in the dataset, thus ensuring that few helmeted cyclists were missed.

The F1-Score, which is the harmonic mean of precision and recall, was calculated to be 89.0%. This score is indicative of a well-balanced model that maintains a strong equilibrium between precision and recall. An F1-Score of 89.0% underscores the model's overall accuracy and reliability in the context of helmet detection, signifying its practical applicability in urban cycling safety monitoring.

In summary, the AutoML model, implemented through EasyDL, demonstrated excellent performance in helmet detection tasks, as evidenced by its high scores across all key metrics: mAP, precision, recall, and F1-Score.These results demonstrate the effectiveness of this model in urban cycling safety monitoring.

5. Conclusion

Our study, utilizing the EasyDL AutoML model, has demonstrated significant strides in enhancing helmet detection accuracy in urban cycling environments. The high performance metrics - a mAP of 91.3%, precision of 87.8%, recall of 90.0%, and an F1-Score of 89.0% - underscore the model's effectiveness in accurately identifying helmet usage among cyclists. These results not only highlight the model's technical capabilities but also its potential to significantly contribute to urban cycling safety.

The integration of automated machine learning into safety monitoring tools presents a novel approach to addressing the challenges of helmet compliance in urban areas. By providing real-time, accurate detection of helmet usage, our model can aid in the enforcement of safety regulations and serve as a deterrent against non-compliance. Furthermore, the insights gained from the model's data can be instrumental in shaping future urban cycling policies and safety campaigns.

Moreover, the accessibility and ease of use of EasyDL make this technology particularly valuable for widespread adoption. It opens up possibilities for local authorities, urban planners, and safety advocates to utilize advanced machine learning tools without the necessity for extensive technical expertise.

In conclusion, our research illustrates the vast potential of AutoML tools in enhancing public safety measures. As urban cycling continues to grow in popularity, the deployment of such technologies will be crucial in ensuring a safer cycling environment. We advocate for the continued exploration and adoption of automated machine learning solutions in urban safety initiatives, paving the way for smarter, safer cities.

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