UDC 004.93
DOI https://doi.org/10.32782/2663-5941/2024.6.2/09

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A ROBUST BARCODE DETECTION SYSTEM WITH MACHINE LEARNING

Accurate and efficient barcode recognition is crucial across a range of industries, including logistics, retail, and healthcare. It facilitates the automated tracking of goods, streamlines inventory management, accelerates transaction times, and boosts overall system efficiency. Recent advances in deep learning have notably enhanced both the speed and precision of barcode recognition, enabling it to keep pace with the expanding requirements of large-scale commercial and industrial applications.

This article focuses on the design and refinement of a barcode recognition system leveraging state-of-the-art deep learning technologies, specifically targeting improvements in performance metrics critical to real-time and large-volume processing.

This study also examines how modern object detection and decoding algorithms can further optimize the recognition process. For this purpose, a system based on the YOLO-v5 algorithm has been developed and presented, which provides an average accuracy (mAP) of 96% at an Intersection over Union (IoU) threshold of 0.5 and reaches 97% in a wider range of IoU thresholds (from 0.5 to 0.95). In this paper it was revealed that this model allows you to accurately determine barcode regions even in large and mixed data sets, which is especially valuable for systems with a large flow of information. It was also found that for further processing and decoding it is advisable to use the Pyzbar library, which demonstrates an accuracy of 90% in converting detected barcodes into readable text. Such integration between YOLO-v5 and Pyzbar allows you to achieve high decoding efficiency, which is optimal for applications where speed, accuracy and reliability are required. The combination of these tools sets a new standard for both research and real-world applications in barcode recognition technology, creating a robust and flexible solution for automation in logistics, retail, healthcare, and other industries. The results presented in this article highlight the importance of integrating advanced object detection techniques with decoding tools to achieve optimal results.

Key words: *Large language models, Computer vision, Machine learning, YOLO-v5, Pyzbar, Barcode detection.*

Formulation of the problem. Barcode recognition systems are essential across various industries, aiding in efficient inventory management, product tracking, and checkout operations. While traditional approaches have served these needs, they often struggle with limitations in speed, accuracy, and adaptability, especially when facing diverse environments and varying barcode conditions. The introduction of deep learning and specialized libraries has driven significant progress in overcoming these hurdles. This study focuses on integrating YOLO-v5 with the Pyzbar library to develop a high-accuracy, efficient barcode recognition system. Known for its rapid detection and efficiency, YOLO-v5 excels in object recognition by processing everything in a single pass. Unlike older methods that need multiple steps, YOLO-v5 uses a single neural network to simultaneously predict bounding boxes and category probabilities, making it ideal for real-time applications. By harnessing its capabilities, this system effectively detects and localizes barcodes in a wide range of complex scenes. [1]. Complementing YOLO-v5, Pyzbar is a specialized library that decodes various barcode formats, such as QR codes, EAN, and UPC. Its lightweight, efficient design allows seamless integration with YOLO-v5, resulting in a comprehensive solution that reliably identifies and decodes barcodes with high accuracy [2]. This integration effectively tackles key challenges in barcode recognition, merging the robust detection abilities of YOLO-v5 with Pyzbar's decoding expertise. The result is improved accuracy in difficult scenarios, including low lighting, varied angles, and partially obscured barcodes, which enhances the system's overall performance and reliability. The paper covers the integration process, performance evaluations, and a comparison with existing solutions, aiming to advance the development of more efficient and accurate barcode recognition systems. Such innovations promise benefits across a range of industrial applications.

Analysis of recent research and publications. Recent strides in deep learning and computer vision have notably enhanced the performance of barcode recognition systems, boosting both their accuracy and efficiency. Researchers have been actively exploring various deep learning algorithms tailored for practical, real-world applications, extending the capabilities of barcode recognition across industries like logistics, autonomous driving, and retail. These efforts highlight the reliability of YOLO-based models, especially YOLO-v5, due to their adaptability and robustness under diverse conditions. For example, a recent study [3] compared several deep convolutional neural network (D-CNN) models, including YOLO-v5, YOLOx, EfficientDet, RetinaNet, and Faster R-CNN, using custom datasets that simulate real-world barcode scenarios, such as fluctuating lighting, rotation, and complex backgrounds. The results underscored YOLO-v5's superior performance in both speed and accuracy, making it the top choice for managing challenging detection tasks.

Another approach [4] combines deep learning with geometric techniques to enhance performance, particularly for high-resolution and complex barcode images. This hybrid method leverages YOLO's localization abilities alongside precise geometric segmentation, leading to a 5% improvement in accuracy over traditional techniques. This advancement supports real-time applications in industrial settings.

In different research [5], a developed QR code recognition system based on YOLO-v5, employing LabelImg for dataset annotation and data augmentation to refine accuracy. YOLO-v5s was opted here due to its balance between performance and computational efficiency, achieving approximately 90% precision – proving effective for real-time QR code recognition in augmented reality settings.

Another research [6] also contributed to this field by focusing on logistics, implementing an optimized barcode recognition system that combines YOLO-v5s for detection with the ZBAR algorithm for decoding. This integrated approach significantly enhanced accuracy and efficiency, particularly in varied lighting and under image distortions, reducing error rates and speeding up processing in logistics operations.

Collectively, these studies demonstrate the versatility and impact of YOLO-v5 and other deep learning models in advancing barcode recognition technology. Their findings set a promising benchmark for future applications across diverse sectors.

Task statement. The purpose of this article is to provide the method for development and evaluation the suggested system of automatic barcode recognition, along with the details of the experimental setup.

Outline of the main material of the study. This system begins with a preprocessing phase, where the dataset is prepared before the barcode detection stage. The system uses YOLO-v5 to detect barcodes within the dataset images, and then applies the Pyzbar Python library to decode the characters from the detected barcodes.

Barcode Detection Using YOLO-v5. YOLO-v5, introduced by Ultralytics in 2020, represents a significant improvement in the YOLO (You Only Look Once) series for real-time object detection. Built on the PyTorch framework, YOLO-v5 integrates several enhancements that boost both speed and accuracy. A key feature is the AutoAnchor algorithm, which optimizes anchor boxes for better alignment with the training dataset. The model's architecture includes innovations like the CSPDarknet53 backbone with a Stem layer, which reduces memory usage and computational load. Additionally, the Spatial Pyramid Pooling Fast (SPPF) layer aggregates features into fixed-size maps, speeding up the computation process. The model's neck architecture combines SPPF with a modified CSP-PAN, while the head incorporates elements of YOLO-v3 to ensure efficient object detection. To enhance model robustness, YOLO-v5 uses training augmentations such as Mosaic, MixUp, and HSV adjustments. The model comes in five versions-ranging from the lightweight YOLO-v5n to the high-performance YOLO-v5x – meeting different application needs and hardware capabilities [7].

Barcode Decoding Using Pyzbar. Pyzbar is a streamlined library designed specifically for effective decoding of both 1D and 2D barcodes. It define the barcode type and extracts the embedded data, enabling further processing for various purposes. The decoded data can be used in multiple ways, such as extracting and validating text, logging results for analysis, or automating workflows. Pyzbar supports a variety of barcode formats, such as EAN, QR codes, Code128, UPC and making it universal for use in document processing, automated data entry and inventory management [8] [9].

Experimental Setup. This research aims to assess the efficiency of an automatic barcode identification system by combining the strengths of YOLO-v5 for detection and Pyzbar for decoding. The experimental setup is structured around key components: dataset collection, preprocessing, model training, evaluation metrics, and testing methodology.

Dataset Collection. The dataset consists of 1,533 images of 1D barcodes captured by mobile cameras, featuring barcodes at various angles on common products. To simulate real-world conditions, the dataset includes images taken under different lighting and quality levels. For added robustness, both high-quality images and those with significant degradation are incorporated, creating a comprehensive foundation for testing barcode recognition in real-world scenarios.

Dataset Preprocessing. Preprocessing was facilitated by the Roboflow platform, which applied data augmentation techniques to expand the dataset from 1,533 to 3,800 images. These transformations included adding noise (to 0.3%), blurring (to 2.5 pixels), rotating (in range of -15° to +15°), resizing images to 640x640, and adjusting brightness by ±24%. Augmentation helps reduce overfitting, enhancing the model's ability to generalize across diverse conditions. During annotation, barcode regions within each image were marked to guide the model during the training phase, a crucial step in supervised learning.

Model Training and Optimization. The YOLO-v5 model, based on the PyTorch deep learning framework, was chosen for its flexibility and ability to rapidly adapt through a dynamic computational graph, making it suitable for both research and production environments. Training was performed on a GPU-accelerated workstation, where key parameters like learning rate, batch size, and augmentation strategies were optimized to maximize performance.

Evaluation Metrics. The primary evaluation metric used in this study is Mean Average Precision (*mAP*), which combines precision and recall across various Intersection over Union (IoU) thresholds. The calculation of *mAP* consists of several key steps. Precision measures detection accuracy by calculating the ratio of true positives to total detections, while recall assesses the model's ability to identify objects, determined by the ratio of true positives to ground-truth objects. A precision-recall curve is plotted for each class by adjusting the confidence threshold, illustrating the balance between precision and recall. Average Precision (AP): The area below the precision-recall curve for each class is calculated as the AP, summarizing the system's precision-recall trade-off. Mean Average Precision (mAP): By means of averaging the AP values across all classes, the mAP provides a single metric that represents the overall performance of the model.

This comprehensive methodology and experimental design establish a solid framework for evaluating the proposed barcode recognition system's performance.

The formula [10] [11]:

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i$$

In which N features the number of classes, and average precision AP_i for each class i. The mean average precision (mAP) metric is frequently reported at various IoU thresholds, as @0.5, that calculates the metric at a singular IoU threshold 0.5, and mAP @0.5:0.95, that averages values of AP over IoU thresholds from 0.5-0.95 in 0.05 increments. This range allows for a more comprehensive assessment of the model's detection performance, capturing both high and low IoU requirements.

Experimental Procedure. In the barcode detection phase, a Nano version of YOLO-v5 was used and trained for 100 epochs. The annotated dataset was divided into training, validation, and testing sets with splits of 70%, 20%, and 10%, respectively, ensuring a balanced evaluation across training and validation phases.

Results and Discussion. The YOLO-v5 model was employed in the proposed system to accurately identify barcodes in a dataset that consists of 3,800 annotated images. The results of this training and testing process are summarized in Table 1.

Table 1

Represents the mAP of YOLO-v5 and the Pyzbar's precision on the proposed dataset

Barcode Dataset size	Barcode Detection with YOLO-v5		Barcode Decoding with Pyzbar
3800	*mAp* @0.5	*mAp* @0.5:0.95	90%
	96%	97%	

This work investigates the performance of the system at two critical stages: detecting and decoding barcodes. According to the table, the YOLO-v5 algorithm demonstrates outstanding ability in detecting barcodes, up to 96% mAP at a threshold IoU of 0.5, with 97% on averages across different IoU thresholds from 0.5 to 0.95. These high mAP scores underline the robust capability of YOLO-v5 in detecting barcode regions correctly in a dataset containing 3,800 images. This really signals reliability in detection accuracy. Later, during further decoding of the barcode, using a library like Pyzbar, achieves an accuracy of 90% with the conversion of the detected barcode data into readable text effectively. Precise detection with YOLO-v5, combined with the high decoding accuracy of Pyzbar, makes it very efficient and reliable for barcode recognition; hence, it is ideal for applications that require precision and speed.

Despite these results, dataset size poses a challenge. Originally containing 1,533 images, the dataset was expanded to 3,800 through data augmentation. To further address this limitation, additional augmentation techniques to diversify the dataset and considering transfer learning to leverage multiple datasets, potentially enhancing model robustness and generalizability is required.

Fig. 1. Samples of successfull barcode identification with YOLO-v5

Conclusions. This paper underscores the benefits of the integrated mechanism that includes advanced detection and decoding algorithms to enhance the barcode recognition ability. The YOLO-v5 model seems to be showing an mAP value of 96% at IoU of 0.5 and 97% over the interval from 0.5 to 0.95, which assuredly is showing a very high level of precision in identifying the barcode regions out of a sizeable dataset. Meanwhile, the Pyzbar library has coded the output detected with a high decoding accuracy rate of 90% and thus can translate most of the detected barcodes into readable text. The combined system, since it is suitable for both reliable detection and efficient decoding, is appropriate in many applications in which the demand for accuracy and operational speed is of essence. The synergy between the high-precision detection from YOLO-v5 and decoding efficiency in Pyzbar underlines the potentiality of creating reliable barcode recognition solutions, building a very strong foundation for further research and applications.

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Ільчук М.С. НАДІЙНА СИСТЕМА ВИЯВЛЕННЯ ШТРИХ-КОДІВ НА ОСНОВІ МАШИННОГО НАВЧАННЯ

Точне та ефективне розпізнавання штрих-кодів має вирішальне значення для багатьох галузей, зокрема логістики, роздрібної торгівлі та охорони здоров'я. Це полегшує автоматизоване відстеження товарів, оптимізує управління запасами, прискорює час транзакцій і підвищує загальну ефективність системи. Нещодавні досягнення в глибокому навчанні помітно підвищили швидкість і точність розпізнавання штрих-кодів, дозволяючи йому йти в ногу зі зростаючими вимогами великомасштабних комерційних і промислових програм.

Ця стаття присвячена розробці та вдосконаленню системи розпізнавання штрих-кодів, яка використовує найсучасніші технології глибокого навчання, зокрема націлена на покращення показників продуктивності, критичних для обробки в режимі реального часу та великих обсягів.

Також у цьому дослідженні вивчається, як сучасні алгоритми виявлення об'єктів та декодування можуть ще більше оптимізувати процес розпізнавання. Для цього була розроблена та представлена система на основі алгоритму YOLO-v5, який забезпечує середню точність (mAP) 96% при пороговому значенні Intersection over Union (IoU) 0,5 та досягає показника 97% у ширшому діапазоні порогів IoU (від 0,5 до 0,95). Було розкрито, що дана модель дає змогу точно визначати регіони штрих-кодів навіть у великих та змішаних наборах даних, що є особливо цінним для систем з великим потоком інформації.

Також з'ясовано, що для подальшої обробки та декодування є доцільним використання бібліотеки Pyzbar, яка демонструє точність 90% у перетворенні виявлених штрих-кодів у читабельний текст. Така інтеграція між YOLO-v5 та Pyzbar дозволяє досягти високої ефективності декодування, що є оптимальним для застосувань, де необхідні швидкість, точність і надійність. У даній статті визначено, що поєднання цих інструментів встановлює новий стандарт як для дослідницьких робіт, так і для реальних практичних застосувань у технологіях розпізнавання штрих-кодів, створюючи надійне та гнучке рішення для автоматизації у сфері логістики, роздрібної торгівлі, охорони здоров'я та інших галузей.

Преставлені у цій статті результати підкреслюють важливість інтеграції передових методів виявлення об'єктів з інструментами декодування для досягнення оптимальних результатів.

Ключові слова: *великі мовні моделі, комп'ютерне бачення, машинне навчання, YOLO-v5, Pyzbar, виявлення штрих-коду.*