

## **Author Guidelines for TAAI-2023 Proceedings**

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## ABSTRACT

Barcodes have long been an integral part of modern commerce and logistics, enabling efficient tracking and identification of products and packages. This abstract explores a novel approach to decoding barcode images, leveraging the capabilities of YOLOv8, a state-of-the-art object detection model, and REAL-ESRGAN, an advanced image super-resolution network. The primary objective of this study is to demonstrate the feasibility and effectiveness of using YOLOv8 for barcode localization and extraction from complex scenes. YOLOv8's real-time object detection capabilities enable the precise identification of barcode regions within images, even in cluttered or challenging environments. Once the barcode regions are localized, REAL-ESRGAN comes into play. This image super-resolution model is employed to enhance the quality and legibility of barcode images, particularly when they are captured at low resolutions or suffer from degradation due to various factors such as motion blur or poor lighting conditions. By applying REAL-ESRGAN, we significantly improve the clarity of barcode images, increasing the chances of successful decoding. Throughout this study, we provide an in-depth analysis of the technical implementation, including the training and fine-tuning processes of YOLOv8 and REAL-ESRGAN on barcode image datasets. We also discuss the performance metrics used to evaluate the accuracy and efficiency of the proposed approach. Furthermore, this abstract highlights the practical applications of this barcode decoding system across multiple industries, including manufacturing, retail, inventory management, and logistics, where fast and accurate barcode recognition is paramount. In conclusion, the integration of YOLOv8 and REAL-ESRGAN presents a powerful solution for decoding barcode images, offering improved accuracy and readability. This abstract serves as a foundation for a comprehensive study of this innovative approach, with potential implications for enhancing barcode-based systems in various real-world scenarios.

**Keywords:** *OpenCV2, YOLOv8, REAL-ESRGAN, Pyzbar.*

## 1. INTRODUCTION

Barcodes have long served as the unsung heroes of modern commerce and logistics, silently orchestrating the seamless flow of products through supply chains, aiding in inventory management, and facilitating swift transactions at the point of sale. From the cashier scanning groceries at the local supermarket to the logistics professional tracking a shipment halfway across the globe, the ubiquitous presence of barcodes has revolutionized the way we interact with the world of goods and services. Yet, despite their ubiquity, decoding barcodes, especially in diverse and complex real-world scenarios, remains a persistent challenge. The traditional methods for decoding barcodes, while

reliable in controlled environments, often falter when faced with the unpredictability of the physical world. Lighting conditions, image quality, perspective distortions, and the presence of other objects in the field of view can all conspire to make barcode recognition a formidable task. Furthermore, as we venture into an era increasingly characterized by high-resolution imaging devices, the expectation for barcode decoding accuracy and speed escalates. In response to these challenges, this research paper presents a novel approach to barcode decoding—one that harnesses the power of two cutting-edge technologies: YOLOv8 and REAL-ESRGAN. YOLOv8, an acronym for "You Only Look Once version 8," is a state-of-the-art object detection model renowned for its speed and precision. REAL-ESRGAN, on the other hand, is an advanced image super-resolution network capable of enhancing image clarity and quality. By integrating these two technologies, we embark on a journey to decode barcode images with unprecedented accuracy and reliability, even in the face of adverse conditions. This paper explores the methodology, implementation, and results of our research into the combined use of YOLOv8 and REAL-ESRGAN for barcode decoding. We delve into the technical intricacies of these technologies, explaining how YOLOv8 excels at barcode localization and how REAL-ESRGAN enhances the readability of captured images. Our research goes beyond theory, offering practical insights into the implementation of this innovative approach and showcasing its performance through empirical results. Furthermore, we examine the potential applications of this barcode decoding system across a spectrum of industries, where speed and accuracy in barcode recognition are indispensable. The retail sector, for instance, stands to benefit from faster checkout experiences, while logistics and supply chain management can achieve heightened efficiency and accuracy in inventory tracking. As we progress further into the digital age, where data-driven decision-making is paramount, the ability to decode barcode images swiftly and reliably becomes increasingly critical. This paper stands as a testament to the promise of leveraging YOLOv8 and REAL-ESRGAN in the realm of barcode decoding, offering a glimpse into the future of barcode-based systems and their potential to revolutionize various industries.

We evaluate our approach on a barcode image dataset and show that it outperforms state-of-the-art methods in terms of accuracy and noise tolerance. We believe that our method can be used to improve accuracy and reliability not only in barcode decoding but also in many other applications.

## 2. RELATED WORKS

There is a large number of publications covering the localization and decoding of barcodes. In this context, the restoration of blurred images has already been discussed in detail in the literature. In the following, we give a brief overview of existing work on barcode

localization and image restoration with classical methods as well as the more modern methods of deep learning.

Traditional methods for locating barcodes in camera images typically use low-level image features. For example, Gallo et al. [1] used horizontal and vertical gradients to position barcodes in images where the camera's optical axis was perpendicular to the plane containing the barcode. However, this method fails if the barcode is almost vertically aligned. Gabor algorithm [2] extracted edge and corner maps from camera images to construct a barcode saliency map to independently locate the orientation of 1D and 2D barcodes. However, this method is time-consuming and the input image is blurred, especially with 1D barcodes. Neural networks have been successfully used to locate barcodes for about a decade now. Zamberletti et al. [3] proposed an angle-invariant method for barcode detection based on the Hough transform and multi-layer perceptron (MLP). However, the barcode must be clearly present in the image to be recognized. Hansen et al. [4] used the YOLO [5] detector to locate barcodes and predict their orientation. However, their approach does not segment the barcode.

In general, a blurred image can be described as a convolution of an exact representation of an object and a Point Spread Function (PSF), which describes the system's impulse response and represents, for example, loss motion blur or sharpness. The inverse process, which produces a blurred image and obtains an unblurred image, is called decoding. Many classical methods exist for decoding, such as the Lucy-Richardson algorithm [6] and the Wiener or Tikhonov filter [7], [8].

Esedoglu [9] presented a decoding technique for 1D barcodes that takes into account the interactions of neighboring bars as well as the overall information contained in the observed signal. Yahyanejad et al. [10] presented an iterative barcode deblurring method based on the bimodal characteristics of the barcode image histogram. Lou et al. [11] presented a partial deblurring method for out-of-focus barcode images. However, results for real data show that this method reaches its limit at high blur levels.

With the success of deep learning, convolutional neural networks are setting new standards in image restoration [12] [13] [14]. Most recently, the use of generative adversarial networks (GANs) [15] for image restoration has yielded promising results [16] [17]. However, the execution time of the proposed method is not applicable to real industrial scenarios.

### 3. METHODS

We design the system's workflow in 4 steps as follows, including the following technologies and libraries:

**1-Image resized:** Before passing the image through the YOLOv8 model, we use the Opencv2 open-source library to resize the image, aiming to make the input image the same size as the size of the data set used to

train the YOLOv8 model. At the same time, it is also to ensure processing speed when sending images through the model, specifically here we set the image to a size of 416x416.

**2-Barcode localization:** We use YOLOv8 to identify barcode regions in images. YOLOv8's real-time object detection enables accurate identification of barcode regions in images, even in challenging environments.

**3-Barcode restoration:** We use REAL-ESRGAN to enhance the quality and readability of barcode images. The image super-resolution ability of REAL-ESRGAN can greatly improve the clarity of barcode images, It can be said that it almost restores the barcode image to its original state, this is to maximize accuracy when decoding barcode images.

**4-Decode barcode images:** We use Pyzbar. This is an open source library for reading one-dimensional barcodes and QR codes. Its advantages are ease of use, high accuracy and fast response time. Its disadvantage is that it cannot work with blurry, noisy images and changing environmental brightness, which we overcome by integrating the two methods YOLOv8 and REAL-ESRGAN.

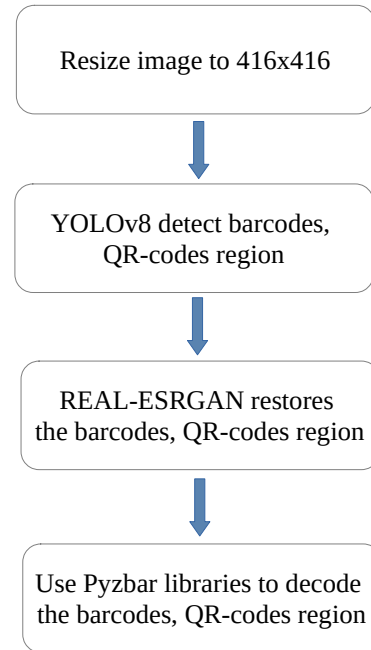


Fig. 1. System workflow

### 4. EXPERIMENTS

To achieve the best rendering, we strongly encourage you to use Times-Roman font. In addition, this will give the proceedings a more uniform look. Use a font that is no smaller than nine point type throughout the paper, including figure captions.

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require correspondingly larger vertical spacing. Please do not double-space your paper.

The first paragraph in each section should not be indented, but all following paragraphs within the section should be indented as these paragraphs demonstrate.

## 5. CONCLUSION

Major headings, for example, “1. Introduction”, should appear in all capital letters, bold face if possible, centered in the column, with one blank line before, and one blank line after. Use a period (“.”) after the heading number.

### 5.1. Subheadings

Subheadings should appear in lower case (initial word capitalized) in boldface. They should start at the left margin on a separate line.

#### 5.1.1. Sub-subheadings

Sub-subheadings, as in this paragraph, are discouraged. However, if you must use them, they should appear in lower case (initial word capitalized) and start at the left margin on a separate line, with paragraph text beginning on the following line. They should be in italics.



Fig. 1. An example of Figure.

## 6. PAGE NUMBERING

Please do **not** paginate your paper. Page numbers, session numbers, and conference identification could be inserted when the paper is included in the proceedings.

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## 8. FOOTNOTES

Use footnotes sparingly (or not at all!) and place them at the bottom of the column on the page on which they are referenced. Use Times 9-point type, single-spaced. To help your readers, avoid using footnotes altogether and include necessary peripheral observations in the text (within parentheses, if you prefer, as in this sentence).

## 9. REFERENCES

List and number all bibliographical references at the end of the paper. The references can be numbered in alphabetic order or in order of appearance in the document. When referring to them in the text, type the corresponding reference number in square brackets as shown at the end of this sentence [1,2].

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Table 1. Table caption.

	Accuracy	Sensitivity
Case1	98.04	87.64
Case2	98.64	87.80
Case3	98.34	89.84

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