QR Code Detection with Perspective Correction and Decoding in Real-World Conditions Using Deep Learning and Enhanced Image Processing

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Abstract: QR codes have become a vital tool across various industries, facilitating data storage and accessibility in compact, scannable formats. However, real-world environmental challenges, including lighting variability, perspective distortions, and physical obstructions, often impair traditional QR code readers such as the one included in OpenCV and ZBar, which require precise alignment and full code visibility. This study presents an adaptable QR code detection and decoding system, leveraging the YOLO deep learning model combined with advanced image processing techniques, to overcome these limitations. By incorporating edge detection, perspective transformation, and adaptive decoding, the proposed method achieves robust QR code detection and decoding across a range of challenging scenarios, including tilted angles, partial obstructions, and low lighting. Evaluation results demonstrate significant improvements over traditional readers, with enhanced accuracy and reliability in identifying and decoding QR codes under complex conditions. These findings support the system's application potential in sectors with high demands for dependable QR code decoding, such as logistics and automated inventory tracking. Future work will focus on optimizing processing speed, extending multi-code detection capabilities, and refining the method's performance across diverse environmental contexts.

1 INTRODUCTION

QR codes, or Quick Response codes, have become an indispensable tool in modern data storage and accessibility, offering a convenient way to encode information in a compact, scannable format. Industries ranging from retail and logistics to healthcare and event management have adopted QR codes due to their speed and reliability. However, QR code usage in uncontrolled environments often encounters real-world challenges such as variations in lighting (Li et al., 2022), perspective distortions (Karrach et al., 2020), and physical obstructions (Liu and Xu, 2020). Traditional QR code readers like OpenCV (bin Mahmod et al., 2023) and ZBar (Ferano et al., 2022), which rely on pattern matching and orientation-specific scanning, are often ineffective in these scenarios, as they require precise alignment and full pattern visibility. Therefore, enhancing the accuracy and robustness of QR code detection and decoding has become essential to expanding its practical applications.

This study seeks to develop an adaptable and accurate QR code detection and decoding system capable of overcoming the limitations of traditional methods. By leveraging deep learning, specifically the YOLO object detection model, combined with advanced image processing techniques, the study aims to create a solution that excels in challenging conditions. The objective is to demonstrate the effectiveness of this system in achieving reliable detection and decoding in complex environments, including scenarios where QR codes are tilted, in a far location, or subjected to poor lighting.

The study contributes to the field of computer vision by presenting a novel, multistep pipeline that combines object detection with image processing to enhance QR code decoding accuracy. The primary contributions are: (1) the integration of YOLO for robust QR code localization across various orientations

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and distortions; (2) the application of edge detection and perspective transformation for distortion correction; and (3) a comparative evaluation with existing QR code readers to highlight performance gains in accuracy and reliability. These contributions demonstrate the potential for improved QR code reading capabilities in fields where QR codes are widely used, such as supply chain management and automated inventory tracking.

2 LITERATURE REVIEW

2.1 QR Code Detection Techniques

Traditional QR code readers, such as OpenCV (bin Mahmod et al., 2023) and ZBar (Ferano et al., 2022), often exhibit limitations when faced with real-world complexities, including varying lighting conditions, perspective distortions and occlusions. These methods typically assume a good perspective on the code being scanned and rely on pattern recognition, which can result in decoding failures under suboptimal conditions (Barzazzi, 2023). Recent studies have investigated alternative approaches, such as histogram equalization (Su et al., 2023) and Generative Adversarial Network (GAN)-based image refinement (Dong et al., 2024; Zheng et al., 2023; Uehira and Unno, 2023), to enhance image quality and improve readability. While these methods address specific challenges, they often do not sufficiently accommodate situations involving significant angular distortions or partial obstructions.

2.2 Object Detection in Computer Vision

The You Only Look Once (YOLO) family of models has emerged as a widely adopted framework for object detection due to its ability to balance speed and accuracy (Kaur and Singh, 2023; Redmon et al., 2016). YOLO's application in object detection tasks has demonstrated effective handling of various visual conditions (Wang et al., 2023), making it a suitable candidate for detecting QR codes in complex settings. By integrating YOLO into the QR code detection process, this study aims to enhance detection reliability even in scenarios where traditional detection algorithms struggle due to partial occlusions or non-standard viewing angles.

2.3 Image Processing for Enhanced Decoding

Advanced image processing techniques, such as edge detection (Su et al., 2021; Orujov et al., 2020) and perspective trnsformation(Hou et al., 2020; Muthalagu et al., 2020), are increasingly applied to address image distortions and improve decoding accuracy. Edge detection facilitates the identification of key corner points (Su et al., 2021), essential for aligning and correcting the QR code image through perspective transformation (Muthalagu et al., 2020). Studies indicate that combining multiple image processing steps, including grayscale conversion (Selva Mary and Manoj Kumar, 2020) and adaptive thresholding (Liao et al., 2020; Xing et al., 2021; Guo et al., 2022), can significantly improve the decoding success rate, especially under challenging lighting conditions. The present study leverages these methods to create a multi-stage pipeline, ensuring robustness in QR code decoding.

3 METHODOLOGY

3.1 Data Collection and Preprocessing

A comprehensive dataset was constructed to represent real-world challenges in QR code detection. It included 1,338 images with QR codes presented under various orientations, distances, and lighting conditions. The dataset was downloaded (N.D, 2022) and manually annotated with bounding boxes around each QR code, facilitating accurate model training and evaluation. To ensure consistency, the dataset was divided into training (87%), validation (8%), and testing (5%) sets and was managed within the Roboflow platform. This setup enabled controlled annotation and versioning, supporting reproducible results across model iterations.

3.2 YOLO Detection Model

YOLOv5-640 was chosen for its advanced object detection capabilities, which are well-suited for detecting objects in diverse environments. Training was conducted on the annotated dataset through Roboflow's platform, resulting in high-performance metrics: mean Average Precision (mAP) of 99.1%, precision of 99.3%, and recall of 99.1%. Post-training, the YOLO model was employed to identify and crop QR code regions from images, as shown in Fig. 1, serving as the foundation for further image processing steps. The cloud-based inference provided by Roboflow facilitated scalable and efficient testing, especially in varied lighting and distortion scenarios. In addition, the system is executed locally to compare the results with the cloud-based system.

Figure 1: QR code detection with the YOLO model.

3.3 Edge Detection and Perspective Correction

After detecting the QR code region, edge detection was applied using the Canny edge detector with optimized threshold values to maximize accuracy in corner identification. The optimized threshold values were chosen through hyperparameter tuning. Different thresholds were tested and the most QR codes detected among a chosen subset of the dataset were chosen. Sample images are shown in Fig. 2. Detecting the four corner points allowed for perspective transformation, a technique that corrects image distortions and aligns the QR code for accurate decoding. OpenCV's perspective transformation tool was used to achieve alignment, ensuring the QR code's orientation was corrected for optimal readability. To account for minor inaccuracies in corner detection, an additional padding variable was introduced, which provided robustness by accommodating slight deviations that could impact decoding accuracy.

3.4 Decoding

Following perspective correction, the decoding phase applied various scaling factors and image processing techniques, including grayscale conversion, color inversion, and sharpening filters. These processing

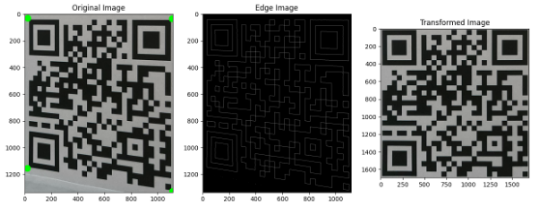

Figure 2: Perspective transformation of QR code after Edge Detection.

techniques are shown in Fig. 3. Then each image version processed was analyzed using OpenCV's QR decoding library, maximizing the probability of successful decoding under a variety of conditions. This multiscale approach allowed the solution to handle different levels of image quality and complexity, enhancing robustness against challenges like low contrast and partial obstructions.

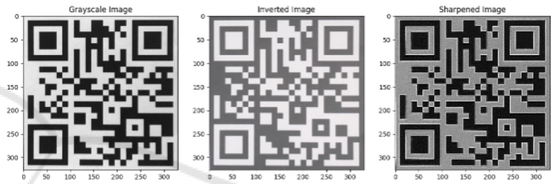

Figure 3: Applied image processing techniques on a QR code.

3.5 Evaluation

The performance of the proposed approach was assessed through several key evaluation metrics.

- **Detection Accuracy** - Assessed by comparing the YOLO-detected QR code regions with ground truth annotations, measuring the system's ability to accurately identify QR codes under varied conditions.
- **Decoding Success Rate** - The proportion of QR codes successfully decoded after detection, reflecting the solution's robustness across different environmental conditions.
- **Distance Tolerance** - Determined by testing the maximum distance at which accurate QR code detection and decoding could be achieved, providing insight into the effective range of the solution.
- **Angle Tolerance** - Evaluated by positioning QR codes at increasing angles until decoding failure, measuring the maximum angular distortion the system could accommodate.
- **Mean Read Time** - Average processing time from detection to de-coding, providing insight into the trade-off between processing speed and accuracy. Although the proposed method prioritizes accuracy, the mean read time metric offers a compar-

ison against traditional readers like OpenCV and ZBar.

4 RESULTS AND DISCUSSION

4.1 Accuracy and Robustness

The proposed solution was evaluated against other QR code readers, specifically the one included in OpenCV and ZBar, on a dataset encompassing various conditions. Results indicate that the solution demonstrates significantly higher decoding accuracy and robustness, consistently outperforming the baseline methods in identifying and decoding QR codes under non-ideal conditions. This robustness is evident across a range of angles, distances, showcasing the adaptability of the proposed approach.

4.2 Distance and Angle Tolerance Testing

Extensive tests were conducted to determine the maximum readable distance and angle tolerance as shown in Fig. 5. The proposed solution maintains decoding accuracy at distances significantly greater than those achieved by OpenCV and ZBar as shown in Fig. 4. Additionally, it maintains decoding functionality at an angular distortion tolerance of up to 80 degrees, surpassing the limits of ZBar (70 degrees) and OpenCV (52 degrees) as noted in Table 1. These findings confirm the method's effectiveness for applications where QR codes are often viewed from challenging angles or distances.

Table 1: QR Code Decoding Maximum Angle of Distortion Comparison.

QR Reader	Maximum Angle of Distortion
OpenCV	52 degrees
ZBar	70 degrees
Ours	**80 degrees**

4.3 Decoding Efficiency and Processing Speed

While the proposed method demonstrated superior decoding accuracy, it exhibited a higher mean read time, as shown in Table 2, averaging 439 milliseconds for the cloud-based system and 92 milliseconds for the local-based system, compared to 36 milliseconds for OpenCV and 46 milliseconds for ZBar. This increased processing time reflects a trade-off designed to prioritize accuracy, making the method particularly suited for applications where reliability is more critical than speed, such as inventory management in warehouses. When comparing the cloud-based and local-based implementations of the proposed system, the local implementation performs better, reducing the processing time by more than 300 milliseconds. This behavior is expected for both systems. Although the proposed approach, when run locally, is slower than conventional readers, the processing time remains within an acceptable range.

Table 2: QR Code Reader Performance Comparison.

QR Reader	Total successfully decoded QR codes	Mean Read Time
OpenCV	214	36 ms.
ZBar	352	46 ms.
Ours (cloud-based)	**459**	**439 ms.**
Ours (local-based)	**459**	**92 ms.**

4.4 Comparative Performance Analysis

In comparative testing, also shown in Table 2, the solution successfully decoded 459 QR codes, compared to 352 by ZBar and 214 by OpenCV. This 30% improvement over conventional readers underscores the utility of the proposed approach for applications with complex environmental variables, validating its effectiveness for real-world scenarios where traditional QR code readers may falter due to environmental inconsistencies.

5 CONCLUSIONS

The study demonstrates that integrating YOLO, edge detection, and perspective transformation significantly enhances QR code detection and decoding in challenging conditions. The solution's superior performance over traditional readers confirms its potential for reliable QR code reading in complex applications.

The robustness of the proposed approach makes it particularly suited for industries such as logistics, warehousing, and automated systems that require dependable QR code decoding. Its ability to handle angular distortions, and varying lighting conditions renders it versatile in diverse real-world settings.

To enhance the effectiveness and versatility of QR code detection, it is recommended to implement support for detecting multiple QR codes within a single

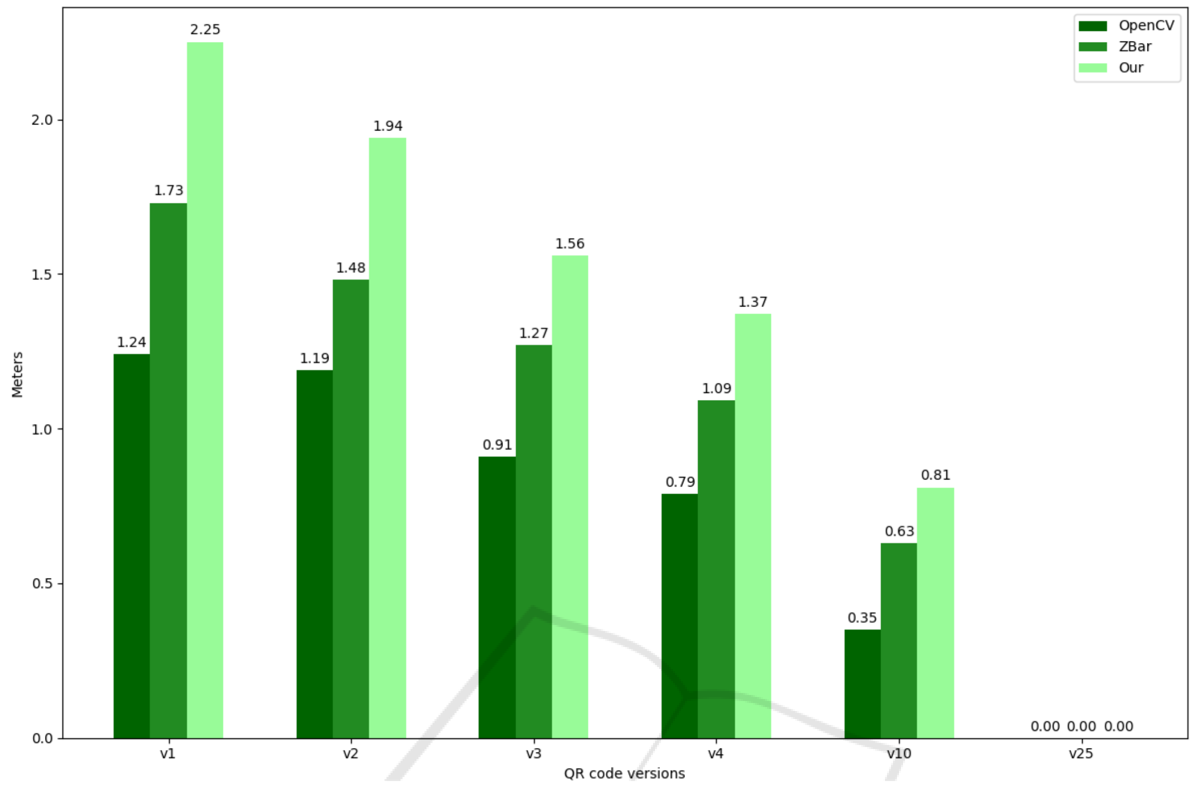

Figure 4: Code Decoding Maximum Distance Comparison.

Figure 5: Testing samples: (a) live video, (b) sourced dataset, (c) synthetic.

image. This capability would enable the solution to operate efficiently in environments where numerous QR codes are present simultaneously, thereby broadening its range of applications.

Transitioning from the Roboflow API to a locally trained object detection model is advisable, as this approach would allow for greater control over the training process and minimize dependency on external services. Such a transition could lead to enhanced efficiency and customization, ensuring that the model is specifically tailored to particular needs and use cases.

It is also essential to develop a model that ensures the bounding box precisely encloses each QR code, or alternatively, to implement a method that determines optimal padding for each detection. This improvement would increase the accuracy of QR code isolation, thereby minimizing decoding errors and enhancing reliability.

Optimizing the process of identifying corner coordinates, particularly around edge detection, is also crucial. Implementing code that adjusts to various thresholds for hysteresis in edge detection would likely improve the accuracy of QR code boundary identification, especially in complex image contexts.

Further, the integration of advanced image processing techniques could substantially improve QR code decoding. By exploring methods such as adaptive thresholding, noise reduction, and contrast enhancement, the readability of QR codes under challenging conditions may be significantly enhanced, thus increasing the robustness of the solution.

In addition, optimizing the read time of the solution could enhance its practical utility. Techniques such as parallel processing, algorithmic enhancements, or hardware acceleration may reduce read times without compromising accuracy. Conducting tests across a broader variety of QR code types and environmental conditions would provide valuable insights into performance, ensuring the solution remains reliable and effective across diverse scenarios.

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