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Fake QR Detection using Machine Learning: A Review

Sevy Singh[1] and Prof. (Dr.) Neelam Shrivastava[2]
[1]M.Tech Scholar, Department of Computer Engineering & Technology,
[2]Professor, Department of Computer Engineering & Technology,
HRIT University, Ghaziabad

Abstract: *Quick Response (QR) codes have become an essential technology for rapid information encoding and data access across digital payments, authentication, healthcare, logistics, and smart services. However, reliable QR-code extraction and verification remain challenging under varying illumination, complex backgrounds, image noise, geometric distortion, and counterfeit or manipulated patterns. This paper proposes an integrated framework combining adaptive QR-code extraction with lightweight deep-learning-based verification. The extraction methodology employs an enhanced adaptive thresholding strategy that dynamically adjusts the window size according to local image characteristics. Statistical weighting and post-thresholding refinement are further incorporated to improve QR-code region discrimination, remove unwanted regions, and preserve structural information. For authenticity verification, ShuffleNetV2 is employed as a lightweight deep learning architecture that provides an effective balance between classification accuracy and computational efficiency. The model is trained on a dataset comprising 28,523 images across 24 QR-code pattern classes, incorporating variations in illumination, noise, and background conditions. Experimental results demonstrate that the proposed framework achieves a processing time of approximately 0.08 seconds, supporting its suitability for real-time applications. Furthermore, ShuffleNetV2 achieves a validation accuracy of 99.99% under the evaluated conditions for distinguishing genuine and counterfeit QR-code patterns. The findings demonstrate that combining adaptive image processing with lightweight deep learning can improve QR-code extraction and verification. The proposed framework offers a robust and computationally efficient solution for real-time QR-code security and authentication applications.*

Keywords: Quick Response (QR) Codes; QR-Code Extraction; Adaptive Thresholding; Deep Learning; QR-Code Verification.

I. INTRODUCTION

Quick Response (QR) codes, two-dimensional barcodes, have become an indispensable component of the contemporary digital ecosystem. Their ability to store substantial data and offer rapid scanning makes them pivotal in sectors ranging from payments to ticketing and marketing. As Industrial Internet of Things (IoT) and deep learning technologies advance [1–3], QR codes serve as cost-effective reading labels, especially in high-demand settings such as COVID- 19 testing centers and logistics hubs. However, despite their widespread utility, they are not without challenges. Motion blur, uneven lighting, and issues in dynamic environments, particularly where mobile robots operate, underscore the complexities of QR code recognition in our technologically advanced age (Figs. 1).

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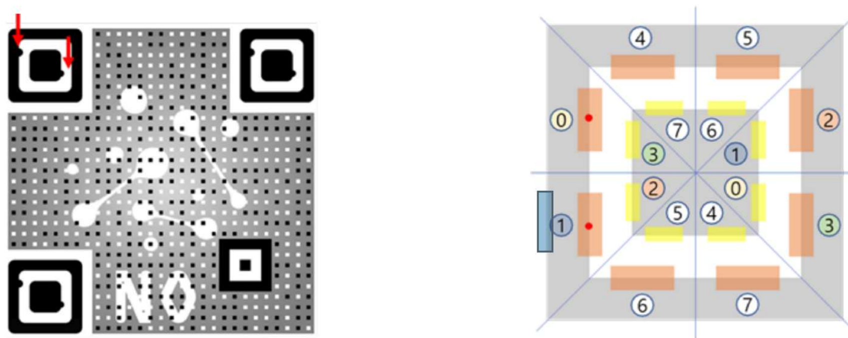

(a) (b)

Fig. 1 Sample of an authentic QR code illustrating its intricate pattern design components. Each segment represents the structural elements integral to its uniqueness and readability

Historically, the journey of QR code recognition has been marked by continuous evolution. Initial recognition methods leaned heavily on image-processing techniques, which, while groundbreaking in their time, faced significant challenges. Uneven illumination, highlight spots, and complex backgrounds often degraded QR code readability. Techniques like Otsu's thresholding were effective for images with simple backgrounds but faltered under varying conditions [4]. Blanger and Hirata enhanced QR code recognition in natural scenes using a modified Single Shot Detector that incorporates subpart annotations [5]. While effective for individual QR code identification, their approach was less suited for batch processing in dense environments.

Jiang et al. addressed this limitation with their app, which specifically improves handling densely arranged QR codes through an adaptive code detection mechanism and a novel image refocus technique but struggled with code detection in extremely small or closely spaced scenarios [6]. He and Yang improved upon previous methods by implementing an adaptive binarization method that dynamically adjusts to lighting conditions, enhancing QR code image processing under uneven illumination [7]. However, their method's complexity increases computational demands due to the necessity for adaptive window sizing and threshold calculations. Zhang et al. further advanced this field by developing a region based network capable of finely localizing and classifying multi-class barcodes in complex environments [8]. Their approach, which integrates multi-scale spatial pyramid pooling and quadrilateral bounding box regression, effectively handles small-scale barcodes and distortions but introduces complexity in terms of computational overhead. Dong et al. improved previous works by introducing a generative adversarial network combined with an attention mechanism to recognize motion-blurred QR codes, significantly improving processing time and recognition accuracy [9]. As the field progressed, there was a shift towards more advanced strategies, such as morphological processing, which, despite being computationally intensive, aimed to tackle more intricate backgrounds. However, many of these methods had a narrow focus, often limited to specific QR code scenarios, which proved inadequate in diverse environments.

II. QR CODE EXTRACTION

QR codes, initially designed for tracking automotive parts, have expanded to various applications, from mobile payments to augmented reality. This diversification has increased the demand for advanced extraction techniques [18]. Traditional extraction methods relied heavily on image processing strategies such as thresholding, morphological operations, and edge-based contour detection. However, these methods often faltered in diverse imaging scenarios, especially with challenges such as variable lighting, complex backgrounds, and varying orientations.

Several methodologies have been introduced to address these limitations. Ohbuchi et al. utilized the intrinsic Digital Signal Processor (DSP) of the QR code for location discernment [19]. Although effective in certain scenarios, this method struggles with QR codes that have damaged or obscured DSPs. Hu et al. differentiated texture differences between QR codes and backgrounds [20]. The performance of their proposed method is degraded by complex or noisy backgrounds. Dubská et al. [21] and Gabriel [22] used the Hough transform and parallel line detection, respectively.

These methods, while innovative, were susceptible to errors in images with multiple parallel or perpendicular lines not related to QR codes. The methods in [23] and those of Tingting Huang [24] relied on dilation, erosion, and morphological operators. However, they often had limited detection rates, especially in cluttered environments. Tzu-Han Chou et al. [25] used convolutional neural networks, showcasing the potential of deep learning. However, these methods required substantial computational resources and extensive training data. The method by Hou et al. [26] was optimized for simple image data but could struggle with more complex or degraded QR codes. Ostkamp et al. [27], M. Ahn et al. [28], Y. Kato et al. [29], Liu Y. [30], CH Chu [31], and Qichao Chen [32] focused on improving image quality. While these methods improved readability, they did not always guarantee accurate extraction. The method by Luiz Belussi and Nina S. T. Hirata [33] achieved a commendable detection rate but could not be universally effective in all scenarios.
These gaps in existing methodologies highlight the need for a comprehensive and adaptive extraction strategy, which led to our proposed method. Our approach aims to integrate the strengths of previous techniques while addressing their limitations, offering a balanced solution for QR code extraction.

III. QR CODE VERIFICATION

A number of IPAs were compared by Qader et al. (2003) [19]. These included the Canny, Sobel,
The widespread adoption of QR codes in areas such as digital payments and personal data sharing underscored a pressing challenge: the need for robust verification of the authenticity of QR codes. Initial verification strategies, which focused primarily on basic structural checks of QR codes, quickly became obsolete as forgery techniques evolved, leaving a significant gap in the security landscape.
Xie and Tan [34] developed an anti-counterfeiting system that emphasized QR code copy detection. While their approach enhanced the estimation of QR pattern locations in images, it primarily addressed product counterfeits and was not effective for more sophisticated forgeries. The method in [35] utilized the decentralized nature of blockchain combined with smart contracts. Although promising, the complexity and scalability of blockchain solutions can sometimes be a limitation, especially in real-time verification scenarios. Tran and Hong [36] leveraged RFID techniques, focusing on tag authentication. However, the dependency of
RFID on specialized hardware can be a constraint. Similarly, the holography method [37], although innovative, requires specialized equipment and might not be feasible for all applications. Yiu's approach [38], rooted in Near-Field Communications (NFC), provided product origin tracking.
Although NFC offers a layer of security, its range limitation and hardware dependency can be restrictive in various scenarios. Krishna and Dugar [39] encrypted the information within QR codes, offering server-side verification. Their method, however, authenticated a QR code only once, which might not be suitable for all use cases. Similarly, Wan et al. [40] combined visual secret sharing with QR codes.
Although innovative, reliance on secret visual data might pose challenges in environments with variable lighting or image quality.
In [43], the authors used a variation of the Hough Transform to detect the QR Code blocks. In [44], the authors used a contour tracking approach to locate the codes under variations of light and perspective, although their experiments showed a performance degradation when too extreme rotations were applied. Although effective, both of these methods seem to focus on images with well-behaved acquisition properties.

IV. COMPARISON OF EXISTING TECHNIQUES

The comparison indicates that earlier QR-authentication approaches generally fall into three categories: traditional image-processing methods, watermarking/Siamese-based authentication, and deep-learning-based classification. Traditional approaches such as GrabCut, image splicing, SIFT, and OCR can provide interpretable processing stages, but their multi-step nature increases complexity and their reported accuracy is comparatively low at 85.25%. Siamese-network-based approaches provide stronger authenticity verification, with the referenced method reporting 98% accuracy, but their computational requirements can restrict real-time deployment. The source specifically identifies increased computational complexity as a limitation of Siamese and dual-network approaches. Deep-learning approaches such as AlexNet and ResNet18 substantially improve classification performance, with reported accuracies of 95.04% and 99.96%,

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respectively. However, the need for computationally efficient deployment motivates investigation of lightweight architectures.

Author Name	Technique	Outcomes	Advantages	Disadvantages
Cu Vinh Loc et al.	Digital watermarking + Siamese Neural Network	High QR authenticity-verification accuracy	Provides strong protection against QR-code tampering; watermark-based authentication improves security	High computational complexity; Siamese architecture requires considerable processing resources.
Loc et al.	Deep-learning-based data hiding + DNN + Siamese Network	Provides tamper-proof QR verification via embedded security features	Embeds a secret security feature into the QR code; strong protection against tampering	Dual-network architecture increases computational and resource requirements.
Hantono et al.	Multi-feature secure 2D grayscale code + spatial/frequency-domain analysis + grayscale watermarking	Improved counterfeit detection and image-quality assessment	Uses both spatial and frequency information; effective for counterfeit detection	Higher processing complexity; approach is based on specialized secure grayscale codes rather than general QR-code scenarios.
Siamese Network	Siamese Neural Network	98% accuracy; dataset size: 5,000	Effective similarity/authenticity verification; comparatively high classification performance	Computationally more expensive and less suitable for highly constrained real-time applications.
Combined	GrabCut + Image Splicing + SIFT + Optical Character Recognition (OCR)	85.25% accuracy	Combines segmentation, image-splicing analysis, local features, and OCR for QR validation	Multi-stage processing increases complexity; comparatively lower accuracy; dependent on several hand-engineered processing steps.
AlexNet	AlexNet-based Deep Learning Classification	95.04% accuracy; dataset size: 2,640	Learns image features automatically; better performance than the combined conventional approach	Larger computational requirements than lightweight architectures; lower accuracy than ResNet18 and the proposed approach.
ResNet18	Residual Convolutional Neural Network	99.96% accuracy; dataset size: 2,640	Very high classification accuracy; residual connections facilitate effective deep feature learning	More computationally demanding than lightweight models; relatively small dataset compared with the proposed study.

V. CONCLUSION

The literature review indicates that QR code detection, extraction, restoration, and verification have received considerable attention due to their widespread use in digital payments, product authentication, healthcare, logistics, and information sharing. Early QR code extraction methods primarily relied on traditional image-processing techniques, including thresholding, morphological operations, contour detection, Hough transform, line detection, and texture analysis. Although these methods can perform effectively under controlled conditions, their accuracy often decreases in the presence of complex backgrounds, uneven illumination, noise, blur, perspective distortion, rotation, and multiple QR codes. Deep learning approaches, including CNN, YOLO, Faster R-CNN, RetinaNet, and MobileNetV2, have demonstrated improved detection capabilities and greater robustness; however, they may require substantial training data, computational resources, and hardware acceleration.

Several studies have also investigated QR code restoration and image-quality enhancement using super-resolution, segmentation, and deep restoration techniques to improve readability under blur and distortion. For QR verification and anti-counterfeiting, researchers have explored blockchain, RFID, holography, NFC, encryption, visual secret sharing, and database-based authentication. These approaches provide additional security but may suffer from hardware dependency, scalability, implementation complexity, or vulnerability to QR-code copying.

Recent research highlights the increasing threat of malicious QR codes and *quishing*, particularly through manipulated URLs and phishing websites. URL-based machine-learning methods and image-level QR feature analysis have shown promising results, while hybrid approaches combining visual and URL characteristics offer broader security coverage. Overall, the literature reveals a need for an adaptive, computationally efficient, and robust QR-code extraction and fake/genuine verification framework capable of handling degraded images, complex environments, and evolving QR-based security threats.

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