IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, August 2026
Impact Factor: 8.2

Fake QR Detection using Machine Learning

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

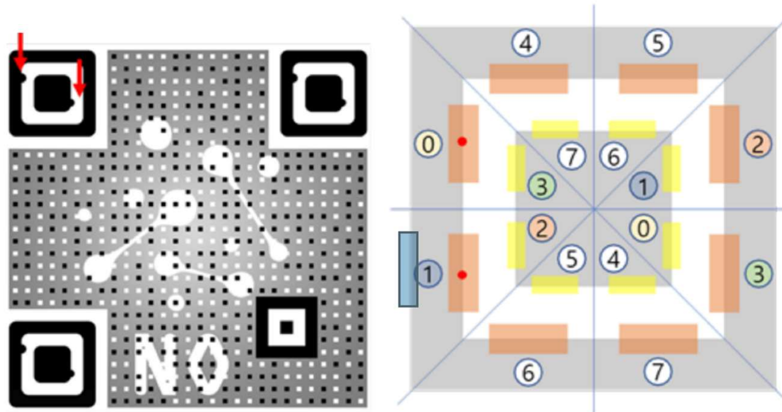
Abstract: *Quick Response (QR) codes have become an essential technology for rapid information encoding and data access across digital payments, authentication, healthcare, logistics, and smart services. However, reliable QR-code extraction and verification remain challenging under varying illumination, 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).

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, August 2026
Impact Factor: 8.2



(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. RELATED WORK

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. RESEARCH METHODOLOGY

The methodology addresses two major challenges: reliable QR extraction under real-world image degradation and accurate verification of genuine versus fake/manipulated QR patterns.

3.1 Input QR Image

The Input QR Image stage represents the initial phase of the proposed fake QR detection framework, in which a QR-code image is acquired from a mobile camera, digital image, scanned document, or other imaging device. The captured image may contain a genuine, fake, manipulated, or potentially degraded QR code. Since real-world QR images can be affected by illumination variations, motion blur, noise, rotation, perspective distortion, low resolution, shadows, reflections, and complex backgrounds, the input image may not always have ideal visual quality. These variations can influence subsequent QR localization, extraction, and verification processes. Therefore, the acquired RGB image is retained as the original input and forwarded to the preprocessing stage, where grayscale conversion, noise reduction, contrast enhancement, normalization, geometric correction, and adaptive binarization are performed.

3.2 QR Localization

The first processing stage will identify and localize the QR-code region from the input image. Conventional techniques such as contour detection, morphological operations, edge detection, and bounding-box analysis can be considered as baseline approaches. backgrounds.

3.3 Image Preprocessing

After localization, the extracted QR region will undergo preprocessing to improve its quality. The QR-code image preprocessing stage begins with the RGB image, which is first converted into a grayscale image to simplify the representation and reduce computational complexity while preserving important intensity information. The grayscale image is then subjected to noise reduction to minimize unwanted disturbances caused by sensor noise, printing imperfections, compression artifacts, or environmental interference. Subsequently, contrast enhancement is performed to improve the distinction between the dark QR modules and the surrounding background, particularly under uneven or low-light conditions.

3.4 QR Region Extraction

Following QR extraction, discriminative information will be obtained from the processed image. The research can investigate multiple feature categories:

- Structural features: finder patterns, alignment patterns, timing patterns, and module arrangements
- Geometrical features: shape, symmetry, aspect ratio, and spatial relationships

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, August 2026
Impact Factor: 8.2

- Feature fusion may subsequently be investigated to determine whether combining structural and deep visual characteristics improves fake QR detection.

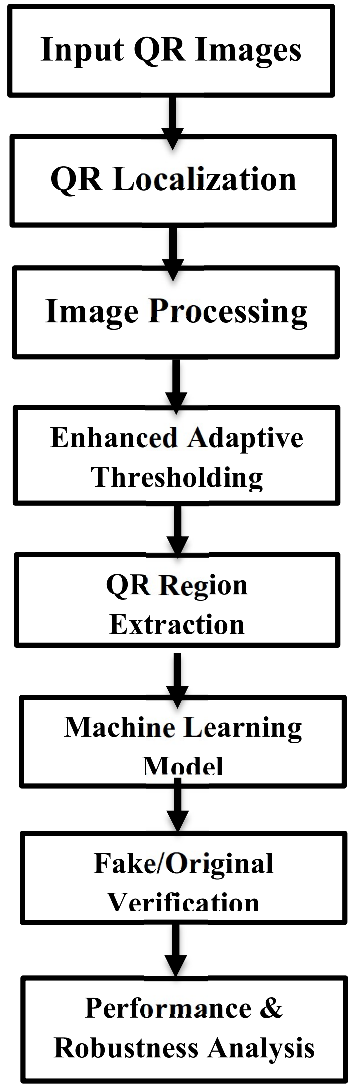


Fig 2 Proposed Research Methodology

3.5 Lightweight Deep Learning Model (ShuffleNetV2)

The extracted QR representation will be supplied to a classification network for authenticity verification. Several architectures may initially be evaluated, such as ResNet, MobileNet, EfficientNet, DenseNet, and ShuffleNetV2.

3.6 Fake/Genuine Verification

The Fake/Genuine Verification stage is the final and most critical component of the proposed QR-code detection framework, where the extracted and preprocessed QR-code image is analyzed to determine whether it represents a genuine or fake QR code. After QR localization, preprocessing, adaptive binarization, and feature extraction, the resulting QR image is provided as input to a lightweight deep-learning-based classification model.

DOI: 10.48175/568

3.7 Performance & Robustness Analysis

The proposed model will be evaluated under controlled degradation conditions, including noise, blur, illumination variation, perspective distortion, and printed artifacts. This stage is important because a model that performs well only on clean images may not be suitable for practical deployment.

IV. DEEP LEARNING BASED QR CODE VERIFICATION SYSTEM

The classification of QR codes faces resource-intensive processing, background interference, and the critical need for high accuracy. To address these challenges, a solution has been developed that involves the use of the lightweight ShuffleNet v2 network, enhanced through transfer learning and optimized activation functions. This novel approach offers an end-to-end QR verification/classification model that strikes a balance between efficiency and accuracy, as depicted in Fig. 3.

It starts by forming a foundational feature extraction network using the ShuffleNet v2 framework, which serves as the backbone. To enhance the model's initial state for training, the weights of this backbone network are initialized through transfer learning. This strategic step fine-tunes the model's starting point, bolstering the prominence of valuable features and downplaying less pertinent ones.

ShuffleNet v2

The evolution of convolutional neural network (CNN) architectures has ushered in remarkable breakthroughs, redefining the landscape of efficiency and accuracy. This chapter presents ShuffleNet v2 [19], an evolutionary advance beyond its precursor, ShuffleNet v1, introduced by MEGVII. Guided by four design principles and propelled by the innovative channel shuffle mechanism, ShuffleNet v2 represents a significant change in CNN design. It outshines its predecessors in accuracy while upholding computational efficiency.

Rooted in the ethos of efficiency and performance, ShuffleNet v2 introduces the concept of channel shuffle, ingeniously overcoming the limitations posed by grouped convolution. Grouped convolution, pioneered by Krizhevsky et al. [20] and Zhang et al. [21], economizes computational resources by focusing convolution kernels on specific channel groups. However, this efficiency compromises intergroup information exchange, hindering feature expressiveness.

Inter-channel shuffle, proposed by Shuffle Net [22], is a simple yet transformative stratagem that disrupts the output features of previously grouped convolutions in the channel dimension.

Four distinctive characteristics served as the foundation for ShuffleNet v2's design and development, resulting in the cell structure seen in Fig. 4. This framework depends on DW convolution, which stands for depthwise convolution, and channel separation, a method that divides input features into discrete parts [23].

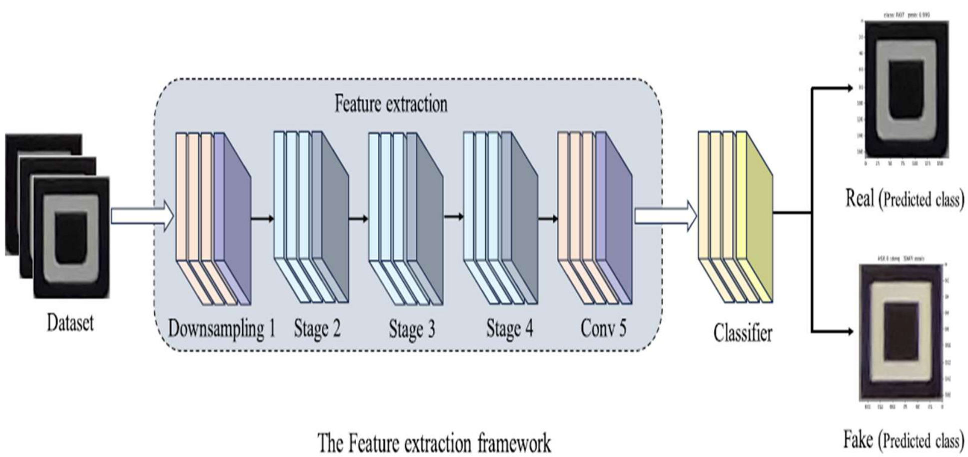
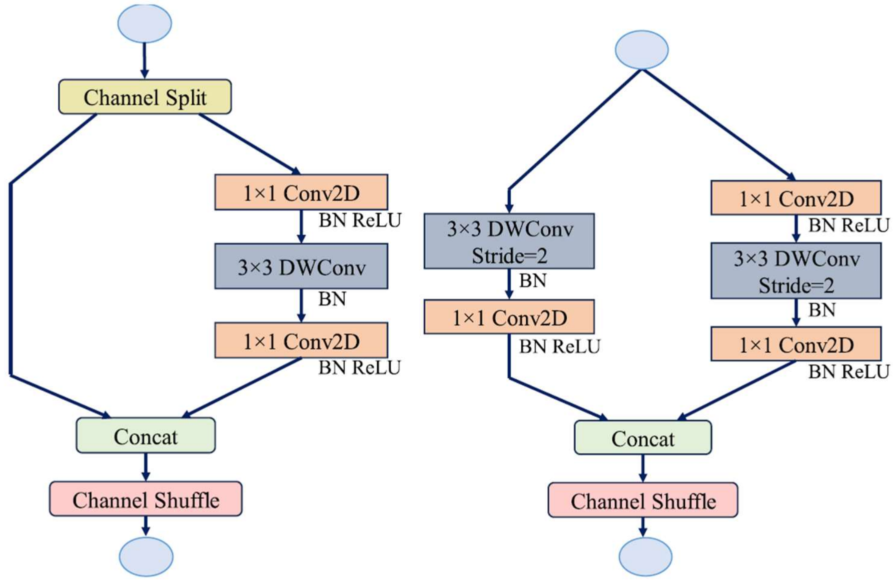


Fig. 3 End-to-end QR classification using the optimized Shuffle Net v2 network, highlighting a balance between efficiency and accuracy

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, August 2026
Impact Factor: 8.2



(b)

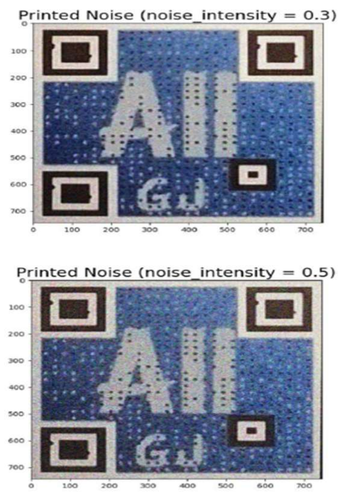
Fig. 4 Shuffle Net v2 cell structure, showcases its design based on channel separation and depth wise convolution These components are expertly put together to form the fundamental building block of ShuffleNet v2, each meticulously aligned with four guiding principles that underpin its design stance.

V. RESULT ANALYSIS

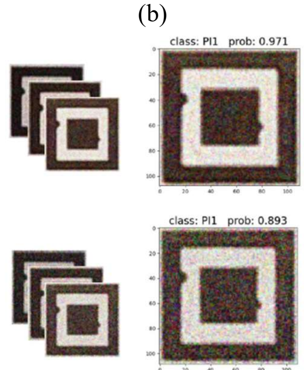
The proposed model was tested against various lighting conditions commonly encountered in real-life scenarios involving QR code images. Despite these variations, the model consistently predicted the correct patterns, demonstrating its robustness and reliability under different lighting conditions Lastly, we evaluated our proposed QR code authentication model against Printed Noise, a common real-world scenario involving QR code images. In Fig. 5, you can see the model's predictions on images with Printed Noise intentionally introduced. In Fig. 5(c), the proposed model correctly predicted every image, with an accuracy rate ranging from 89.3% to 98.4%.

(a)

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, August 2026
Impact Factor: 8.2



(b)



(c)

Fig. 5 Model predictions on QR code images with introduced Printed Noise, displaying accuracy rates between 89.3% and 98.4%.

This evaluation highlights the proposed QR code authentication model's robustness in handling common real-world scenarios involving printed noise. Despite the introduced noise, the model consistently predicted the correct patterns, demonstrating its effectiveness and reliability for QR code classification

We evaluate the performance of our proposed method against several existing methodologies in the field of QR code validation. We compare our approach with the Siamese network [25], Combined (Grab Cut + Image Splicing + SIFT + Optical Character Recognition) [26], AlexNet, and ResNet18 [27] based on their dataset sizes and achieved accuracies, as shown in Table 5.

Table 1 Comparison of several QR Code Validation Methodologies, highlighting the dataset sizes and accuracy levels attained by Siamese network, Grab Cut + Image Splicing + SIFT + Optical Character Recognition), AlexNet, ResNet18, and our proposed approach

Method	Dataset Size	Accuracy
Siamese network [25]	5000	98%
Combined (GrabCut+Image Splicing+SIFT+Optical Character Recognition) [26]	5000	85.25%
AlexNet [27]	2640	95.04%

IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429

Volume 6, Issue 1, August 2026

Impact Factor: 8.2

ResNet18 [27]	2640	99.96%
Ours	28523	99.99%

Our method achieves an excellent accuracy of 99.99% with a dataset size of 28,523, surpassing existing methodologies. While the Siamese network demonstrates promising results at 98% accuracy, our approach significantly outperforms it. Despite the Combined method's integration of various techniques, it achieves an average accuracy of 85.25%, highlighting the effectiveness of our proposed method. Furthermore, compared to traditional deep learning architectures like AlexNet and ResNet18, our method demonstrates superior accuracy, emphasizing its practical applicability. These results affirm the effectiveness and robustness of our proposed methodology.

VI. CONCLUSION

This study presented an integrated framework for QR-code recognition and verification under challenging imaging conditions, particularly in the presence of noise, illumination variations, complex backgrounds, and other environmental factors. The proposed two-stage methodology combines enhanced adaptive thresholding for reliable QR-code extraction with a lightweight deep-learning-based verification approach. Experimental results demonstrate the effectiveness of the framework, achieving a processing time of approximately 0.08 seconds and a validation accuracy of 99.99% under the evaluated constrained conditions. Furthermore, the proposed framework demonstrated prediction accuracy ranging from 90.04% to 99.00% across complex and varied imaging environments, indicating its robustness and practical applicability. The deep-learning-based verification model effectively distinguishes genuine QR codes from counterfeit patterns, while the enhanced extraction process improves the quality and reliability of QR-code regions before verification. The integration of adaptive image processing and deep learning provides improvements in both processing efficiency and recognition performance compared with conventional approaches. Despite these promising results, the proposed framework has certain limitations. Its performance across different hardware platforms, energy consumption, and large-scale real-world deployments has not yet been comprehensively investigated. Moreover, the continuous evolution of QR-code forgery techniques necessitates periodic model refinement and adaptation. Future research will therefore focus on hardware-level validation, energy-efficient implementation, larger and more diverse datasets, and adaptive learning strategies to enhance robustness against emerging counterfeit techniques. Overall, the proposed framework provides a promising foundation for secure, accurate, and real-time QR-code authentication.

REFERENCES

1. Liu H, Zhang C, Deng Y, Xie B, Liu T, Li YF (2023) Transifc: invariant cues-aware feature concentration learning for efficient fine-grained bird image classification. IEEE Trans Multimed
2. Liu H, Liu T, Zhang Z, Sangaiah AK, Yang B, Li Y (2022) Arhpe: Asymmetric relation-aware representation learning for head pose estimation in industrial human-computer interaction. IEEE Trans Industr Inf 18(10):7107–7117
3. Liu H, Fang S, Zhang Z, Li D, Lin K, Wang J (2021) Mfdnet: Collaborative poses perception and matrix fisher distribution for head pose estimation. IEEE Trans Multimedia 24:2449–2460
4. Otsu N et al (1975) A threshold selection method from gray-level histograms. Automatica 11(285–296):23–27
5. Blanger L, Hirata NS (2019) An evaluation of deep learning techniques for qr code detection. In: 2019 IEEE international conference on image processing (ICIP), IEEE, pp 1625–1629
6. Jiang B, Ji Y, Tian X, Wang X (2019) Batch reading densely arranged qr codes. In: IEEE INFOCOM 2019-IEEE conference on computer communications, IEEE, pp 1216–1224
7. He Y, Yang Y (2019) An improved sauvola approach on QR code image binarization. In: 2019 IEEE 11th international conference on advanced infocomm technology (ICAIT), IEEE, pp 6–10 (2019)
8. Zhang J, Min X, Jia J, Zhu Z, Wang J, Zhai G (2021) Fine localization and distortion resistant detection of multi-class barcode in complex environments. Multimed Tools Appl 80:16153–16172

9. Dong H, Liu H, Li M, Ren F, Xie F (2024) An algorithm for the recognition of motion-blurred qr codes based on generative adversarial networks and attention mechanisms. Int J Compu Intell Syst 17(1):1–17
10. Liu H,Nie H, Zhang Z, LiYF (2021) Anisotropic angle distribution learning for head pose estimation and attention understanding in human-computer interaction. Neurocomputing 433:310–322
11. Liu H, Zhang C, Deng Y, Liu T, Zhang Z, LiY-F (2023) Orientation cues-aware facial relationship representation for head pose estimation via transformer. IEEE Trans Image Process 32:6289–6302
12. Liu T, Yang B, Liu H, Ju J, Tang J, Subramanian S, Zhang Z (2022) Gmdl: Toward precise head pose estimation via gaussian mixed distribution learning for students' attention understanding. Infrared Phys Technol 122
13. Yan Y, Zou Z, Xie H, Gao Y, Zheng L (2020) An iot-based anti-counterfeiting system using visual features on qr code. IEEE Internet Things J 8(8):6789–6799
14. Ismail S, Alkawaz MH, Kumar AE (2021) Quick response code validation and phishing detection tool. In: 2021 IEEE 11th IEEE symposium on computer applications & industrial electronics (ISCAIE), IEEE, pp 261–266
15. Vinh Loc C, Xuan Viet T, Hoang Viet T, Hoang Thao L, Hoang Viet N (2023) Deep learning based-approach for quick response code verification. Appl Intell 53(19):22700–22714
16. Loc CV, De TC, Burie JC, Ogier JM (2023) An approach for tamper-proof qr code using deep learning based-data hiding. In: Asian conference on intelligent information and database systems, Springer, pp 129–141
17. Hantono BS, Alfarozi SAI, Pratama AR, Rizqi AAA, Mustika IW, Riasetiawan M, Asih AMS (2023) Enhancing counterfeit detection with multi-features on secure 2d grayscale codes. Comput 12(9):183
18. Minh D,Wang HX, LiYF,Nguyen TN (2022) Explainable artificial intelligence: a comprehensive review. Artif Intell Rev 1–66
19. Ohbuchi E, Hanaizumi H, Hock LA (2004) Barcode readers using the camera device in mobile phones. In: 2004 international conference on cyberworlds, IEEE, pp 260–265
20. Hu H, Xu W, Huang Q (2009) A 2d barcode extraction method based on texture direction analysis. In: 2009 5th international conference on image and graphics, IEEE, pp 759–762
21. Dubská M, Herout A, Havel J (2016) Real-time precise detection of regular grids and matrix codes. J Real-Time Image Proc 11:193–200
22. Klimek G, Vamossy (2013) Qr code detection using parallel lines. In: 2013 IEEE 14th international symposium on computational intelligence and informatics (CINTI), IEEE, pp 477–481
23. Wu B, Zhong S (2012) A distortion rectification method for distorted qr code images based on self-adapting structural element. In: 2012 8th international conference on wireless communications, networking and mobile computing, IEEE, pp 1–6
24. HuiyingD, Tingting H(2015) Transmission line extraction method based on hough transform. In: The 27th chinese control and decision conference (CCDC), IEEE, pp 4892–4895
25. Chou TH, Ho CS, Kuo YF (2015) Qr code detection using convolutional neural networks. In: 2015 international conference on advanced robotics and intelligent systems (ARIS), IEEE, pp 1–5
26. Hou AL,Yuan F,YingG(2011) Qr code image detection using run length coding. In: Proceedings of 2011 international conference on computer science and network technology, vol 4. IEEE, pp 2130–2134
27. Ostkamp M, Luzar S, Bauer G (2014) Qr codes on curved media facades: Two approaches for inverse distortion based on raytracing and image warping. In: 2014 international conference on computer graphics theory and applications (GRAPP), IEEE, pp 1–6
28. AhnM, Hong S, Lee S (2015) A research on the qr code recognition improvement using the cloud-based pre-generated image matching scheme. In: 2015 international conference on information networking (ICOIN), IEEE, pp 356–357
29. Kato Y, Deguchi D, Takahashi T, Ide I, Murase H (2011) Low resolution qr-code recognition by applying super-resolution using the property of qr-codes. In: 2011 international conference on document analysis and recognition, IEEE, pp 992–996
30. Liu Y, Yang J, Liu M (2008) Recognition of qr code with mobile phones. In: 2008 chinese control and decision conference, IEEE, pp 203–206

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, August 2026
Impact Factor: 8.2

31. Chu CH, Yang DN, Chen MS (20017) Image stablization for 2d barcode in handheld devices. In: Proceedings of the 15th ACM international conference on multimedia, pp 697–706
32. Chen Q, DuY, Lin R, TianY(2012) Fast qr code image process and detection. In: Internet of things: International workshop, IOT 2012, Changsha, China, August 17-19, 2012. Proceedings, Springer, pp 305–312
33. Belussi L, Hirata N (2011) Fast qr code detection in arbitrarily acquired images. In: 2011 24th SIBGRAPI conference on graphics, patterns and images, IEEE, pp 281–288
34. Xie S, Tan HZ (2021) An anti-counterfeiting architecture for traceability system based on modified two-level quick response codes. Electron 10(3):320
35. Bala Krishna M, Dugar A (2016) Product authentication using qr codes: a mobile application to combat counterfeiting. Wireless Pers Commun 90:381–398
36. Wan S, Lu Y, Yan X, Liu L (2017) A novel visual secret sharing scheme based on qr codes. Int J Digit Crime Forensic (IJDCF) 9(3):38–48
37. Denso Wave, "QR Code Standardization," ISO/IEC 18004:2015, International Organization for Standardization, 2015.
38. S. Liu and P. Zhao, "A Review of QR Code Security: Attacks and Defenses," *IEEE Internet Computing*, vol. 25, no. 6, pp. 63-71, Nov.-Dec. 2021.
39. G. Klimek and Z. Vamossy, "QR code detection using parallel lines," in International Symposium on Computational Intelligence and Informatics (CINTI), 2013.
40. H. Qi, X. Lu, and L. Lu, "A localization algorithm for distorted or rotated QR code," in International Conference on Computing, Communication and Networking Technologies (ICCCNT), 2014.
41. L. F. F. Belussi and N. S. T. Hirata, "Fast component based QR code detection in arbitrarily acquired images," Journal of Mathematical Imaging and Vision, vol. 45, no. 3, 2013.
42. L. Tong, X. Gu, and F. Dai, "QR code detection based on local features," in International Conference on Internet Multimedia Computing and Service, 2014, ICIMCS '14.
43. I. Szentandrási, A. Herout, and M. Dubská, "Fast detection and recognition of QR codes in high-resolution images," in 28th Spring Conference on Computer Graphics, 2013.
44. T. Grósz, P. Bodnár, L. Tóth, and L. Nyúl, "QR code localization using deep neural networks," in International Workshop on Machine Learning for Signal Processing (MLSP). IEEE, 2014.
45. T. Chou, C. Ho, and Y. Kuo, "QR code detection using convolutional neural networks," in International Conference on Advanced Robotics and Intelligent Systems (ARIS). IEEE, 2015.

DOI: 10.48175/568