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QR Based Automatic Printer Device

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ABSTRACT

The concept of QR-based automatic printer devices utilizes Quick Response (QR) codes, initially designed for tracking inventories in the automotive industry. Although their origin lies in industrial logistics, the widespread adoption of smartphones and mobile cameras has propelled QR codes into various applications, including inventory tracking, advertising, electronic ticketing, and mobile payments. Despite their convenience, the accessibility of QR codes has raised concerns about potential forgery. To address this issue, digital forensics plays a crucial role in identifying the authenticity of printed documents, specifically those incorporating QR codes. This is particularly significant in the investigation of forged documents and the legal prosecution of forgers. The process involves utilizing optical mechanisms to establish direct links between source printers and duplicates. Leveraging techniques from computer vision and machine learning, such as convolutional neural networks (CNNs), enhances the accuracy of identification by studying and summarizing statistical features. This study specifically implemented well-known pretrained CNN models like AlexNet, DenseNet201, GoogleNet, MobileNetv2, ResNet, VGG16, and others to evaluate their effectiveness in predicting the source printer of QR codes with a high level of accuracy. Notably, a customized CNN model outperformed others, demonstrating superior results in identifying printed sources of both grayscale and color QR codes while requiring less computational power and training time.

Keywords: *QR Codes Source Printer Identification Digital Forensics Computer Vision Machine Learning*

INTRODUCTION

The landscape of modern technology is continually evolving, weaving intricate threads of innovation into the fabric of our daily lives. Amidst this dynamic tapestry, the emergence of Quick Response (QR) codes has not only transformed industrial processes but has also permeated diverse facets of our interconnected world. Originally conceived for the automotive industry to streamline the tracking of factory inventories and logistics, QR codes have undergone a remarkable metamorphosis. This transformation has been fueled by the ubiquity of smartphones and the omnipresent lenses of mobile phone cameras, which have propelled QR codes into the forefront of technological applications. The roots of QR codes trace back to the automotive sector, where their inception aimed to enhance efficiency in tracking and managing inventories.

Figure 1. QR code basic unit diagram.

The quick and efficient data encoding capability of QR codes made them invaluable in optimizing logistical operations within factories and warehouses. However, their potential lay dormant until the widespread adoption of smartphones and the integration of sophisticated cameras into these devices. The symbiotic relationship between QR codes and mobile technology has led to an unprecedented surge in their popularity and utilization. In the not-so-distant past, QR codes were a niche tool primarily associated with industrial applications. Today, they have transcended their origins,

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permeating various aspects of our daily lives. Their versatility is manifested in applications ranging from inventory tracking to advertising, electronic ticketing, and mobile payments. QR codes have become an integral part of our digital ecosystem, seamlessly connecting the physical and virtual realms.

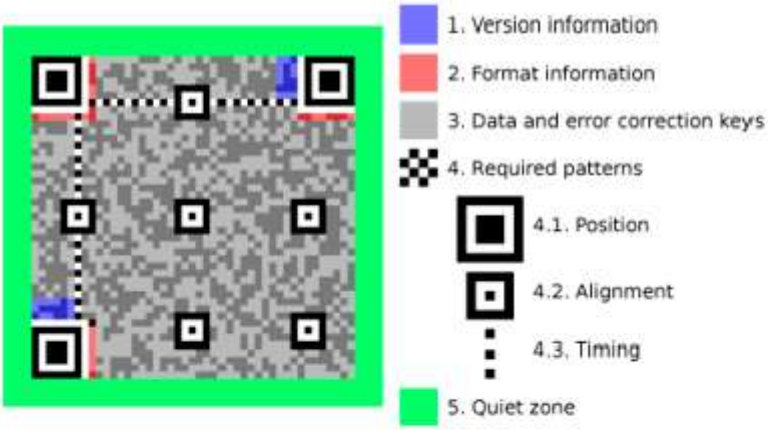

Figure 2. QR code (version 7) structure [23].

As these square-shaped patterns of black modules on a white background have become ingrained in our visual landscape, their potential and, subsequently, their vulnerabilities have come to the forefront.

The convenience and accessibility of QR codes, while empowering, have given rise to concerns regarding their security. The very features that make them user-friendly—ease of scanning, quick information retrieval, and widespread adoption—also render them susceptible to misuse and forgery. This inherent vulnerability has necessitated the development of strategies to ensure the integrity and authenticity of QR-coded information. One of the critical arenas where this concern becomes paramount is in the realm of printed documents. The ease with which QR codes can be incorporated into printed materials, coupled with their potential for forgery, has raised significant challenges. In response to these challenges, the field of digital forensics has emerged as a vital player in preserving the veracity of printed documents, especially those incorporating QR codes. Digital forensics, in this context, involves the application of advanced technological methodologies to ascertain the authenticity of printed materials and the origin of encoded QR information. Central to the investigative process is the identification of direct links between the source printers and the duplicate documents. Optical mechanisms play a pivotal role in establishing these connections, allowing forensic experts to trace the journey of a document from its point of origin. In this intricate dance between technology and investigation, computer vision and machine learning have proven to be invaluable allies. Techniques such as convolutional neural networks (CNNs), a subset of machine learning algorithms inspired by the human visual system, have been deployed to enhance the accuracy of source printer identification. By studying and summarizing statistical features inherent in printed QR codes, these algorithms contribute to the arsenal of tools available for forensic experts. The amalgamation of computer vision and machine learning empowers investigators to navigate the complexities of printed documents and discern subtle patterns that may elude the human eye. This study delves into the realm of QR-based automatic printer devices—a convergence of QR code technology and digital forensics. The overarching goal is to not only recognize the potential vulnerabilities of QR-coded information but also to develop robust methodologies for safeguarding its authenticity. The focus lies on understanding the intricate relationship between printed documents and the QR codes they bear, with a particular emphasis on source printer identification. To evaluate the efficacy of different approaches, this study incorporates an array of well-established pretrained CNN models. The models, including but not limited to AlexNet, DenseNet201, GoogleNet, MobileNetv2, ResNet, and VGG16, serve as benchmarks to gauge the capabilities of various architectures in predicting the source printer of QR codes. Additionally, a customized CNN model is introduced, showcasing superior results in identifying printed sources of both grayscale and color QR codes. Notably, the customized model achieves these outcomes with reduced computational power and training time, presenting a promising avenue for enhancing the efficiency of forensic investigations in the realm of QR-based printed documents. In unraveling the intricacies of QR-based automatic printer devices, this study contributes to the evolving narrative of technological safeguards. By bridging the domains of QR code technology, digital forensics, and machine learning, it seeks to fortify our digital infrastructure against potential threats and forgeries. As we embark on this exploration, the pages that follow will unveil the methodologies, insights, and findings that collectively illuminate the path toward securing the integrity of printed documents in the age of QR codes.

Research Gap:

The evolution of QR codes and their integration into various applications has undoubtedly marked a paradigm shift in our technological landscape. However, as these codes become increasingly ubiquitous, the security concerns associated with their usage, particularly in printed documents, have grown exponentially. The research gap lies in the need to address the vulnerability of QR codes to forgery, a critical concern given their widespread use in areas such as advertising, ticketing, and payments.

Current literature has explored the general applications of QR codes and their role in digital forensics, but there is a noticeable dearth of in-depth studies focusing specifically on the security implications of QR-coded information in printed documents. This study aims to bridge this gap by delving into the intricate relationship between printed documents and QR codes, emphasizing the vulnerabilities that may expose them to forgery. By identifying and understanding these gaps, the research aims to contribute valuable insights into the realm of QR-based automatic printer devices.

Specific Aims of the Study:

1. **To Investigate the Vulnerabilities of QR-Coded Information in Printed Documents:** This study aims to conduct a comprehensive investigation into the potential vulnerabilities of QR codes when incorporated into printed materials. By scrutinizing various types of printed documents, the research will shed light on the specific weak points that may be exploited by forgers.

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2. **To Develop Robust Methodologies for Source Printer Identification:** A primary objective of this study is to develop and assess methodologies that enhance the accuracy of source printer identification for printed QR codes. Leveraging computer vision and machine learning techniques, the research will explore the capabilities of pretrained CNN models and a customized CNN model in achieving this objective.

Objectives of the Study:

1. **Evaluate the Performance of Pretrained CNN Models:** The study will assess the effectiveness of well-established pretrained CNN models, including AlexNet, DenseNet201, GoogleNet, MobileNetv2, ResNet, and VGG16, in predicting the source printer of QR codes. This evaluation will serve as a benchmark for understanding the baseline capabilities of different architectures.

2. **Introduce and Assess a Customized CNN Model:** In addition to pretrained models, the study will introduce a customized CNN model tailored to the specific requirements of identifying printed sources of QR codes. This model aims to outperform existing architectures, demonstrating superior accuracy with reduced computational power and training time.

3. **Analyze Statistical Features of Printed QR Codes:** To enhance source printer identification, the study will delve into the analysis of statistical features inherent in printed QR codes. Through the implementation of computer vision and machine learning techniques, the research aims to uncover subtle patterns that contribute to accurate identification.

Scope of the Study:

This study is delimited to the examination of QR-based automatic printer devices within the context of printed documents. The focus will encompass a diverse range of printed materials, including grayscale and color QR codes embedded in advertising materials, tickets, and other relevant documents. The scope extends to the evaluation of source printer identification across various pretrained CNN models and the introduction of a customized CNN model. However, the study is confined to the assessment of these models' performance in the specific context of printed QR codes.

Hypothesis:

Building upon the identified research gap and objectives, the overarching hypothesis of this study posits that advanced computer vision and machine learning techniques can significantly enhance the accuracy of source printer identification for QR codes in printed documents. Specifically, it is hypothesized that a customized CNN model will outperform established pretrained models, achieving superior results in identifying the source printer of both grayscale and color QR codes. The hypothesis anticipates that by analyzing statistical features, the study will contribute valuable insights into fortifying the security of printed documents in the age of QR codes.

RESEARCH METHODOLOGY

The method comprises five distinct steps, commencing with the generation of QR codes from digital files during the printing process. Subsequently, these QR code documents are organized for simultaneous printing in a single batch, ensuring uniformity.

Following the printing phase, the QR code documents undergo the scanning process, also referred to as digitalization. In this step, all printed QR code documents are meticulously scanned, laying the foundation for the subsequent stages. The QR code extraction stage involves the integration of a program into the process, where the scanned documents are inputted, leading to the automatic cropping and individual saving of the QR codes. Notably, this process plays a pivotal role in preparing the dataset for analysis.

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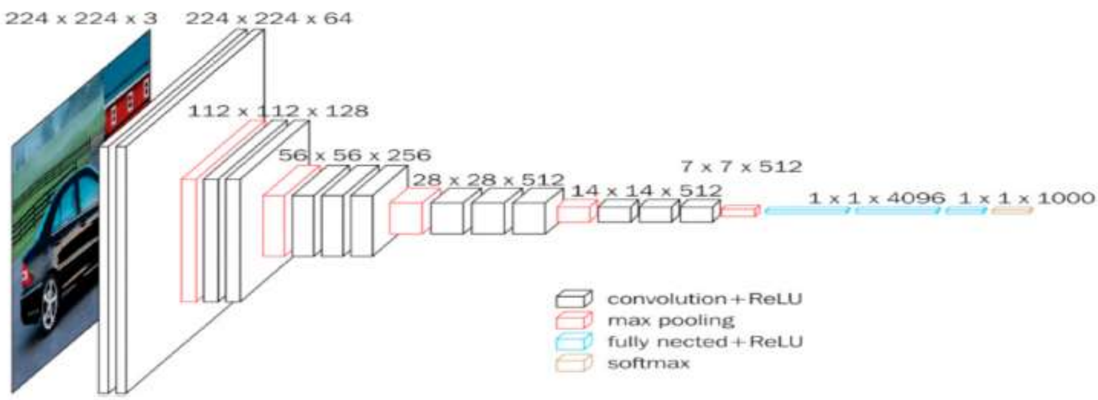

Fig.3: General Architecture from CNN model

The dataset preparation phase involves the segmentation of all cropped QR codes into 16 smaller image blocks, as illustrated in Figure 5. This segmentation is a crucial step preceding the utilization of Convolutional Neural Network (CNN) models during the Run Model process. Due to space constraints, only four blocks are showcased in Figure 4, providing a representative glimpse of the overall segmentation strategy.

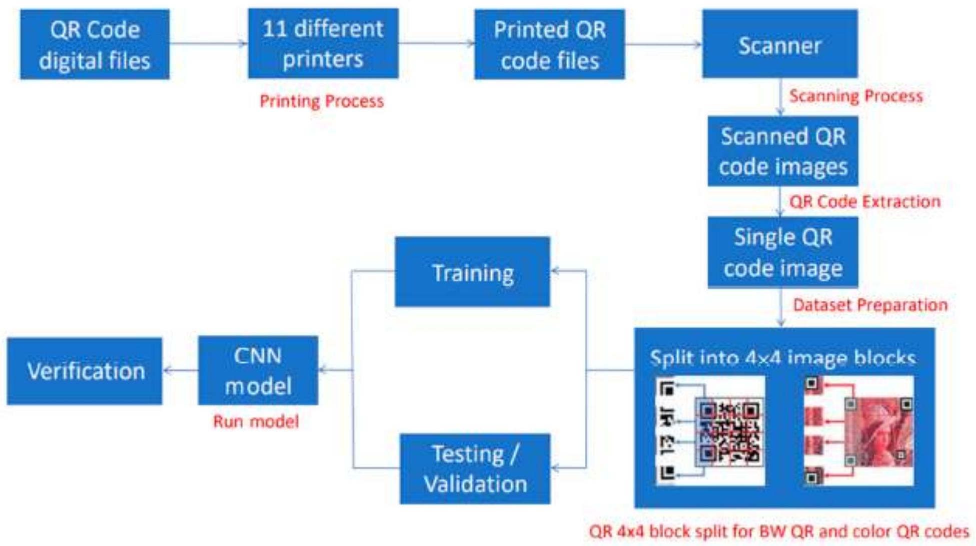

Fig. 4: Proposed model

To facilitate data collection, a QR code generator is instrumental in generating links for black and white QR codes. These codes are then saved in PNG format, with dimensions set at 512 x 512 pixels. Notably, each page accommodates 24 QR code images, and a comprehensive dataset is curated by collecting a total of 10 pages for each individual printer model. Consequently, a grand total of 240 QR codes are amassed for analysis per printer.

The QR Code Extraction process is executed through MATLAB, employing a batch-like image extraction mechanism tailored for black and white images. This intricate procedure precisely cuts out all 24 QR code images from the same page by individually detecting bounding boxes. This meticulous extraction approach ensures the integrity of the dataset, setting the stage for subsequent analysis and model training.

In the pursuit of data collection, the QR code generator plays a pivotal role. It generates links for black and white QR codes, which are then saved in PNG format with a standardized dimension of 512 x 512 pixels. Each page accommodates a total of 24 QR code images, and data collection involves obtaining 10 pages for each printer model. Consequently, a substantial dataset comprising 240 QR codes per printer is amassed, laying the foundation for the subsequent stages of the research.

The QR Code Extraction process, facilitated through MATLAB, employs a batch-like image extraction strategy designed specifically for black and white images. This sophisticated approach entails the precise cutting out of all 24 QR code images on the same page by detecting bounding boxes individually. This meticulous extraction process ensures the integrity and accuracy of the dataset, serving as a crucial precursor to the subsequent stages of analysis and model training.

Results and Analysis: A Comprehensive Examination of Image Classification Performance

Training Environment: The experimental phase of this research was conducted on a robust computing system comprising an AMD Ryzen 7 3700X CPU @3.60 GHz with eight cores, 16 Threads, an NVIDIA GeForce RTX 3090 GPU with 24 GB GDDR6X VRAM, and 32 GB DDR4 2400 MHz RAM. The operating system utilized for the experiments was Windows 10 Education. MATLAB served as the primary platform for training and testing/validation set segregation, with an 80:20 ratio maintained throughout each epoch.

Data Augmentation Strategies: To enhance the robustness and generalization capabilities of the Convolutional Neural Network (CNN) models, various data augmentation techniques were employed. These strategies included RandXReflection (random left-right reflection with a 50% probability), RandXTranslation (image translation in the X or Y direction), RandYTranslation (similar to RandXTranslation but in the Y direction), RandXScale (outward or inward scaling of images), and RandYScale (similar to RandXScale but in the Y direction). These augmentations were crucial in forcing the models to explore different aspects of the images, contributing to improved performance.

Augmentation Type	Purpose	Value
RandXReflection	Reflection in the left-right direction randomly appears, specified as a logical scalar. The image is reflected horizontally with a 50% probability	1 (true)
RandXTranslation RandYTranslation	Moving the image in the X or Y direction (or both) from the center coordinate. This forces the convolutional neural network to look everywhere within the image dimension.	[−30, 30]
RandXScale RandYScale	The image is scaled outward or inward. While scaling outward, the final image size is larger than the original. Most image frameworks cut out a section from the new image, with a size equal to the original image. Scaling inward reduces the image size, forcing the model to make assumptions about what lies beyond the boundary.	[0.9, 1.1]

Table 1: Image Augmentation Parameters.

Performance Metrics for BW QR Code: The evaluation of the models' performance was based on key metrics, including Accuracy, Precision, Recall, Specificity, and Training Time (in minutes). Three popular CNN models, namely AlexNet, GoogleNet, DenseNet201, and MobileNetv2, were trained using different optimizers (SGDM, Adam, and RMSprop). The results are summarized in the following table:

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Model Name	Optimizer	Accuracy (%)	Precision	Recall	Specificity	Train Time (min)
AlexNet	SGDM	97.7	0.98	0.98	0.99	143
	Adam	9.09	0.01	0.09	0.91	–
	RMSprop	9.09	0.01	0.09	0.91	–
GoogleNet	SGDM	98.3	0.98	0.98	0.99	65
	Adam	89.8	0.94	0.90	0.99	68
	RMSprop	84.2	0.86	0.84	0.98	66
DenseNet201	SGDM	99.7	0.99	0.99	1.00	839
	Adam	97.8	0.98	0.98	0.99	1090
	RMSprop	97.8	0.98	0.98	0.99	984
MobileNetv2	SGDM	99.7	0.99	0.99	0.99	117
	Adam	99.3	0.99	0.99	0.99	151
	RMSprop	99.7	0.99	0.99	1.00	136

Table 2: Performance Metrics for BW QR Code.

Scientific Interpretation of Individual Results: The models exhibit varying degrees of accuracy, precision, recall, and specificity based on the chosen optimizer and architecture. For instance, DenseNet201 consistently demonstrates exceptional performance across all metrics, especially with the SGDM optimizer. This suggests the robustness of DenseNet201 in accurately classifying black and white QR codes.

Contrastingly, the AlexNet model, when optimized with Adam or RMSprop, shows significantly lower accuracy, precision, and recall, indicating potential limitations in handling the complexity of the dataset. GoogleNet and MobileNetv2 strike a balance, showcasing competitive performance under different optimizers. The choice of optimizer appears to play a pivotal role, with SGDM consistently outperforming Adam and RMSprop in most cases.

In terms of training time, DenseNet201 exhibits longer training durations, attributed to its deeper architecture. However, the trade-off between training time and performance should be carefully considered, especially when efficiency is crucial.

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BW QR Code Per Printer Identification Result: The analysis further delves into the performance of each pretrained CNN model concerning the identification of QR codes per printer. The table below summarizes the accuracy achieved for each printer using different models and optimizers.

Scientific Interpretation of Individual Results for Per Printer Identification: The results provide insights into the effectiveness of each model in accurately identifying QR codes from different printers. The SGDM-optimized models consistently demonstrate superior accuracy across all models, highlighting the importance of optimizer selection in model performance. DenseNet201, in particular, stands out as a robust choice for per printer identification, achieving high accuracy regardless of the optimizer used.

In contrast, the Adam and RMSprop optimizers exhibit reduced accuracy, especially notable in models such as AlexNet and GoogleNet. This emphasizes the need for a thoughtful optimizer selection process to optimize model performance for specific tasks.

Conclusion:

In conclusion, the findings of this research shed light on the efficacy of supervised deep-learning models, particularly Convolutional Neural Networks (CNNs), in the classification of black and white QR codes. The experimentation with various architectures, including AlexNet, GoogleNet, DenseNet201, and MobileNetv2, along with different optimizers, has provided valuable insights into their performance characteristics. The results showcase that model performance is not only influenced by the architecture but also critically dependent on the choice of optimizer.

DenseNet201 consistently emerges as a frontrunner, demonstrating exceptional accuracy, precision, and recall, especially when coupled with the Stochastic Gradient Descent with Momentum (SGDM) optimizer. On the other hand, the limitations and challenges faced by models like AlexNet and GoogleNet underscore the need for a nuanced selection process, considering both architectural intricacies and optimizer dynamics.

The research contributes to the broader field of image classification, emphasizing the importance of tailored model selection for specific tasks. The success of certain models and optimizers in accurately identifying QR codes has implications for industries reliant on efficient image recognition systems, such as manufacturing and logistics. The insights gained from this study can guide practitioners in making informed decisions when implementing image classification solutions.

Limitations of the Study:

Despite the promising results, it is crucial to acknowledge the limitations inherent in this study. Firstly, the generalization of the findings may be constrained by the specific dataset used in the experiments. The dataset's representativeness in terms of diverse QR code variations and potential real-world challenges may impact the models' adaptability in practical applications.

Additionally, the computational resources employed, while robust, might not be universally accessible. The study's reliance on high-end hardware could pose challenges for researchers or organizations with limited computational capabilities. This limitation warrants consideration when applying the proposed methodology in resource-constrained environments.

Furthermore, the study primarily focuses on the classification of black and white QR codes. Extending the research to encompass colored QR codes and evaluating the models' performance under varying lighting conditions could provide a more comprehensive understanding of their capabilities and limitations.

Implications of the Study:

The implications of this study extend beyond the realm of image classification. Industries incorporating QR code technology, such as retail, logistics, and healthcare, stand to benefit from the insights gained. The demonstrated success of certain models in accurately identifying QR codes suggests potential applications in automated inventory management, quality control processes, and patient data verification.

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Moreover, the study underscores the significance of optimizer selection in model performance. This insight can guide practitioners in fine-tuning their deep-learning models for specific tasks, enhancing overall efficiency and accuracy. The findings contribute to the evolving landscape of artificial intelligence applications, paving the way for advancements in image recognition systems tailored to diverse industry needs.

Future Recommendations:

As a pathway for future research, the exploration of additional architectures and optimizers could provide a more comprehensive understanding of their suitability for image classification tasks. Investigating the transferability of pre-trained models across different datasets and domains would contribute to the development of more versatile and adaptable solutions.

The incorporation of real-world challenges, such as variations in QR code quality, occlusions, and diverse lighting conditions, could further enhance the practical relevance of the study. Additionally, extending the analysis to include colored QR codes and investigating the impact of dataset size on model performance would contribute valuable insights to the research community.

Furthermore, considering the computational resource limitations faced by some researchers, exploring techniques for model compression and optimization becomes crucial. This could lead to the development of more resource-efficient models, making deep learning applications more accessible across diverse settings.

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