Investigating image pre-processing techniques to enhance Brazilian license plate recognition

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***Abstract*—This paper presents the development and optimization of an embedded real-time license plate recognition system designed with applications to public security operations in Brazil. The system aims to equip police vehicles and inspection posts with instant vehicle identification capabilities to detect stolen, cloned, or flagged vehicles during routine patrols and checkpoints. Vehicle-related crimes, including theft and cloning, pose significant challenges to public safety in Brazil, requiring law enforcement agencies to rapidly identify suspicious vehicles from extensive databases. Traditional manual verification methods are time-consuming and inefficient for real-time operations. Our proposed solution integrates YOLO detection algorithms with OCR technology in an embedded system capable of real-time processing and automatic database cross-referencing. To optimize system performance, we evaluate eight different image preprocessing methods. Each preprocessing approach is tested with threshold values ranging from 0.0 to 0.8 using a dataset of 65 Brazilian license plates to determine optimal parameter combinations for maximum OCR accuracy. Experimental results demonstrate significant performance variations across preprocessing methods, with the Resized2x approach achieving 66.7% accuracy at threshold 0.8 and Inverted preprocessing with 0.4 threshold reaching 11.8% accuracy in optimal configurations. The system architecture enables instant image capture through vehicle-mounted cameras, real-time plate processing, and immediate database queries within seconds of detection. These findings contribute to the development of an effective autonomous surveillance system that can substantially improve police operational efficiency and citizen safety through rapid identification of vehicles of interest during active patrol operations.**

***Index Terms*—license plate recognition, OCR, image preprocessing, YOLO, Brazilian traffic systems**

I. Introduction

Vehicle-related crimes, including theft and cloning, pose significant challenges to public safety in Brazil [1], [2]. License plate recognition (LPR) systems have emerged as critical technology across multiple application domains, enabling automated toll collection, traffic monitoring [3], parking management [4], access control systems, and law enforcement surveillance [5]–[7].

While LPR technology serves diverse applications with varying performance requirements, law enforcement applications present the most stringent constraints, requiring real-time processing capabilities, high accuracy under challenging conditions, and deployment on resource-constrained embedded platforms in patrol vehicles [8], [9]. The preprocessing techniques and optimization strategies developed for these demanding scenarios provide valuable insights applicable to the broader spectrum of LPR implementations, where similar computational efficiency and accuracy requirements exist.

License plate recognition in operational environments faces numerous challenges that significantly impact system performance across all application domains. Environmental factors including varying lighting conditions, weather effects, image blur, and plate degradation substantially affect recognition accuracy [10]–[12]. Brazilian license plates present additional challenges due to the Mercosul standard format and diverse environmental conditions [13], [14].

Embedded systems deployed in patrol vehicles operate under strict computational and energy constraints that impact algorithm selection and system design [8], [15]. These platforms feature limited processing power and energy resources, necessitating lightweight algorithms capable of maintaining high accuracy while meeting real-time performance requirements [9], [16]. Similar resource constraints exist in other embedded LPR deployments, including parking gate controllers, highway toll systems, and mobile enforcement units.

Image pre-processing techniques play a crucial role in bridging the gap between raw captured images and successful character recognition across all LPR applications [12], [17]. These methods enhance image quality, reduce noise, and improve contrast to optimize OCR accuracy [10], [18]. However,

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limited research has systematically evaluated preprocessing methods with different parameter configurations specifically for Brazilian license plates under embedded system constraints [13].

Contemporary LPR preprocessing approaches in the literature emphasize advanced deep learning methods [17], [18], convolutional neural networks for image enhancement [19], and sophisticated multi-stage pipelines [20]. Recent studies typically employ datasets exceeding 1,000 plates with complex preprocessing chains optimized for high-performance computing environments [12]. However, these approaches often require substantial computational resources unsuitable for embedded deployment scenarios. Classical computer vision techniques, while less sophisticated, offer computational efficiency advantages crucial for resource-constrained platforms [15].

This work addresses the central research question: How can we achieve maximum OCR accuracy for Brazilian license plates using preprocessing algorithms that are both lightweight and fast enough for resource-constrained embedded hardware while maintaining real-time performance requirements?

Recent advances in deep learning, particularly YOLO algorithms, have significantly improved license plate detection accuracy and speed [21], [22]. However, the integration of YOLO-based detection with optimized OCR preprocessing for embedded systems remains an active research area [19], [20].

This work provides: (1) systematic evaluation of eight classical image preprocessing techniques optimized for Brazilian license plate OCR in embedded systems, with explicit comparison to state-of-the-art approaches; (2) comprehensive analysis of preprocessing parameter optimization across threshold values from 0.0 to 0.8 using a curated dataset representative of real-world conditions; (3) performance evaluation framework considering both recognition accuracy and computational efficiency suitable for embedded deployment; and (4) practical implementation guidelines for embedded LPR systems with applicability extending beyond law enforcement to parking management, toll collection, and access control systems.

Our approach evaluates Adaptive thresholding, Bilateral filtering, Grayscale conversion, Image inversion, Original image processing, Otsu thresholding, 2x image resizing, and Sharpening techniques using 65 Brazilian license plates representing both old format (ABC1234) and new Mercosul standard (ABC1A23) plates [12]. Section II describes the preprocessing methods and evaluation framework with explicit positioning relative to current literature. Section III presents the dataset characteristics, experimental configuration, and comprehensive results analysis. Finally, Section IV provides practical insights for embedded LPR implementation across multiple application domains.

II. Methodology

This section presents the methodology employed to evaluate image preprocessing techniques for optimizing OCR performance in Brazilian license plate recognition systems deployed on embedded platforms. Our approach analyzes different preprocessing methods to achieve the optimal balance between recognition accuracy and computational efficiency required for real-time law enforcement applications.

A. License Plate Detection and Recognition Framework Overview

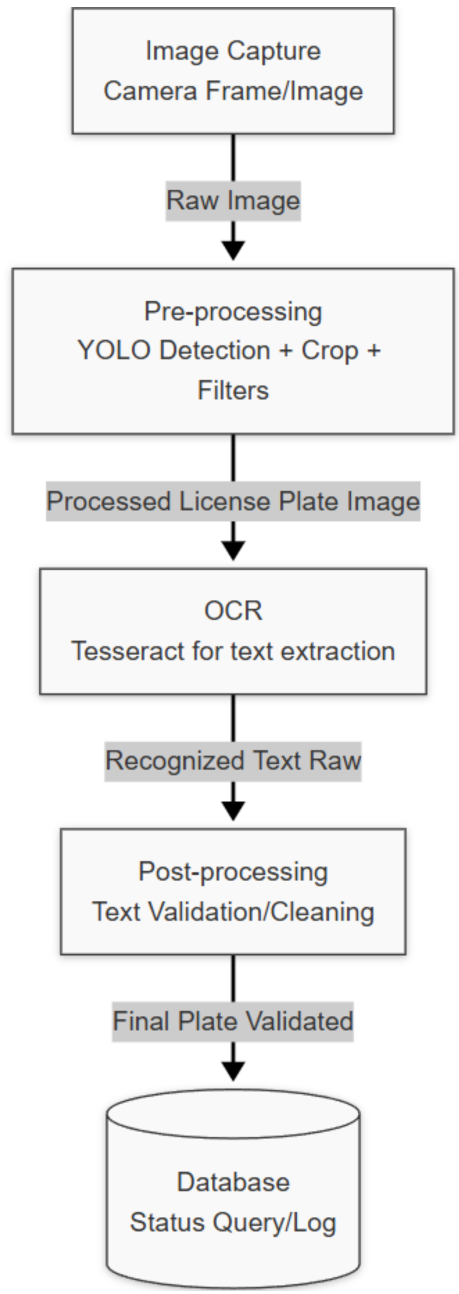

Figure 1. ALPR System Pipeline Architecture. The diagram illustrates the complete processing pipeline of our ALPR system, from initial image capture through pre-processing, OCR text extraction, post-processing validation, to final database querying for vehicle status verification.

This integrated approach enables vehicle identification [8], [9] in patrol cars and inspection posts, providing real-time alerts for stolen, cloned, or flagged vehicles within seconds of detection [22], [23].

The YOLO detection stage localizes license plates within captured images, providing cropped regions of interest that serve as input for the preprocessing evaluation phase [21], [24]. This work specifically focuses on optimizing the preprocessing stage, which serves as the critical bridge between YOLO detection capabilities and OCR character recognition accuracy [19], [20]. The preprocessing optimization directly impacts the overall system performance while maintaining computational efficiency requirements for embedded deployment scenarios [15].

Figure 1 illustrates the complete processing pipeline of our embedded LPR system. The system architecture enables real-time license plate detection, preprocessing optimization, OCR character recognition, and immediate database cross-referencing for vehicle identification in law enforcement applications.

B. Investigated Preprocessing Methods

We evaluate eight distinct preprocessing methods, deliberately selected for their computational simplicity and proven effectiveness in document recognition applications [12], [25]. The selection prioritizes classical computer vision techniques that balance processing efficiency with potential accuracy improvements, making them suitable for resource-constrained embedded platforms [16], [26]. This evaluation focuses on individual preprocessing methods to establish baseline performance characteristics for each technique. Combinations of preprocessing methods were not evaluated in this study to maintain computational efficiency and enable systematic analysis of individual method contributions to OCR performance.

1) Grayscale Conversion: Standard RGB to grayscale conversion using luminance weighting reduces computational complexity while preserving essential character contrast information [25]. This method eliminates color variations that may interfere with OCR processing and provides consistent character representation regardless of original plate color schemes [10].

2) Image Inversion: Image inversion reverses pixel intensities, potentially improving OCR performance when character-background contrast is suboptimal for the OCR engine's expectations [27]. This simple transformation can significantly enhance recognition accuracy with minimal computational overhead [18].

3) Adaptive Thresholding: Adaptive thresholding dynamically adjusts threshold values based on local image characteristics, making it effective for images with varying illumination conditions typical in outdoor traffic monitoring [**?**]. This method calculates threshold values for each pixel based on neighborhood mean intensity, enabling better character separation in plates with uneven lighting [10].

4) Bilateral Filtering: Bilateral filtering preserves edge information while reducing noise, considering both spatial proximity and intensity similarity when determining pixel values [28]. This approach provides effective noise reduction without edge blurring, crucial for maintaining character boundary definition required for accurate OCR performance [11].

5) Original Image Processing: Original image processing maintains detected license plate regions without additional preprocessing modifications, serving as baseline for comparison with other methods [17]. This approach provides reference accuracy measurements for assessing preprocessing technique effectiveness.

6) Otsu Thresholding: Otsu thresholding automatically determines optimal threshold values by maximizing inter-class variance between foreground and background pixels [29]. This method is particularly effective for license plates with clear character-background separation and requires no manual parameter adjustment [25].

7) 2x Image Resizing: Image resizing increases spatial resolution by scaling license plate images to twice their original dimensions using bicubic interpolation [25]. This method enhances character detail and may improve OCR accuracy for low-resolution input images while maintaining character edge information [20].

8) Sharpening: Sharpening enhances edge definition and character boundaries through convolution with sharpening kernels, emphasizing high-frequency components corresponding to character edges [25]. This method may compensate for slight blurring in original images while preserving overall image structure [26].

C. Comparison with State-of-the-Art Preprocessing Approaches

Contemporary license plate recognition research emphasizes deep learning-based preprocessing approaches that integrate convolutional neural networks for image enhancement [17]–[20]. However, these approaches require substantial computational resources unsuitable for embedded deployment scenarios, necessitating GPU acceleration and power consumption levels incompatible with patrol vehicle deployment [8], [16].

Our selection of classical computer vision techniques addresses embedded LPR system requirements. Classical methods offer automatic parameter selection with minimal computational overhead [**?**], [28], [29], while our deterministic preprocessing evaluation enables direct performance comparison without training data, facilitating rapid deployment essential for operational environments [15].

D. OCR Evaluation Framework

1) Dataset Characteristics: Our evaluation employs a carefully curated dataset of 65 Brazilian license plates with manually verified character sequences, representing real-world conditions encountered in law enforcement applications [13]. The dataset includes both old format plates (ABC1234): 21 plates and new Mercosul format plates (ABC1A23): 44 plates, ensuring representative coverage of current Brazilian license plate standards. The dataset acquisition involved capturing license plate images under various environmental conditions including different lighting scenarios, viewing angles, and plate degradation states to ensure representative coverage of operational challenges [14]. Manual annotation was performed with rigorous verification procedures to establish reliable ground truth for accuracy evaluation.

2) Image Acquisition and Preprocessing Pipeline: License plate images undergo initial detection using YOLO algorithms to extract regions of interest before applying specific preprocessing methods [21]. Each detected plate region is standardized to consistent dimensions while preserving aspect ratios to maintain character proportions. The preprocessing pipeline applies each of the eight methods systematically with threshold parameter variations ranging from 0.0 to 0.8 [12].

3) OCR Engine Configuration: Character recognition utilizes Tesseract OCR engine with configurations optimized for license plate recognition tasks [27]. The OCR engine parameters include character whitelist restrictions to Brazilian license plate format (alphanumeric characters), language model selection for Portuguese/Brazilian context, and segmentation mode optimization for single text lines typical of license plates.

4) Evaluation Metrics and Criteria: Performance evaluation employs strict exact character sequence matching between OCR output and ground truth annotations [30]. Success criteria require complete plate recognition accuracy, with partial matches not considered successful to reflect real-world application requirements where partial recognition provides insufficient information for vehicle identification. Evaluation metrics include total correct recognitions, method-specific accuracy rates, and threshold parameter optimization results.

5) Experimental Procedure: Each preprocessing method is evaluated across five threshold values (0.0, 0.2, 0.4, 0.6, 0.8) where applicable, with some methods using different parameter ranges applied to all 65 license plate images. The comprehensive experimental evaluation processes a total of 2,600 OCR attempts across all method-threshold combinations (8 methods × 5 thresholds × 65 images), demonstrating the comprehensive nature of our preprocessing parameter analysis. The evaluation employed a holdout approach where all 65 license plates were used as a test set, with ground truth annotations serving as the reference standard. No separate training set was required as the preprocessing methods are deterministic transformations that do not require parameter learning from data. The systematic parameter evaluation enables identification of optimal preprocessing configurations for each method while providing comprehensive coverage of the preprocessing parameter space.

6) Computational Environment: Experiments were conducted on hardware representative of embedded system constraints to ensure practical applicability of results. The testing environment specifications and processing time measurements provide insights into computational requirements for real-world deployment scenarios, supporting the selection of preprocessing methods suitable for resource-constrained embedded platforms deployed in patrol vehicles.

III. Results and Discussion

This section presents the comprehensive experimental results, revealing significant performance variations across preprocessing methods with optimal configurations achieving up to 66.7% accuracy while maintaining computational efficiency for embedded deployment. The analysis identifies critical trade-offs between OCR accuracy and computational efficiency for embedded license plate recognition systems deployed in law enforcement vehicles.

A. Overall Performance Analysis

Experimental results encompassed 2,600 OCR attempts across method-threshold combinations, revealing substantial performance variations on a dataset of 65 unique Brazilian license plates representing both old format (ABC1234): 21 plates and new Mercosul format (ABC1A23): 44 plates [13].

The overall results reveal significant variations in OCR performance, with full plate accuracy ranging from 0% to 66.7% for individual method-threshold combinations and an overall character-level accuracy of 26.8% compared to full plate accuracy of 3.1% [17], [18]. This substantial difference between character and plate-level accuracy highlights the challenges in achieving perfect character sequence matching for Brazilian license plates, confirming the critical importance of preprocessing optimization for license plate recognition systems.

Figure 2 presents the full plate accuracy rates for all preprocessing methods, revealing substantial differences in their effectiveness for Brazilian license plate recognition. The Resized2x method achieved the highest overall performance, with its best configuration (threshold 0.8) reaching 66.7% accuracy, demonstrating the effectiveness of resolution enhancement for OCR performance improvement [20], [25].

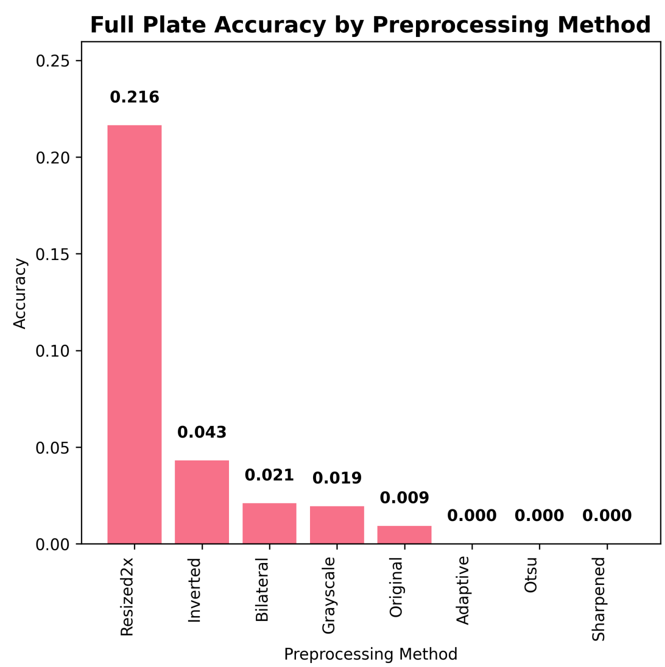

Figure 2. Full plate accuracy comparison across different preprocessing methods.

Figure 3 illustrates the critical impact of confidence thresholding on system performance. Threshold application improved average accuracy by 121.7%, from 2.0% without thresholding to 4.3% with confidence thresholds, though this improvement was not statistically significant (p = 0.5865) [30]. This finding suggests that while confidence thresholding provides practical benefits, the improvement variability indicates the need for more sophisticated filtering approaches.

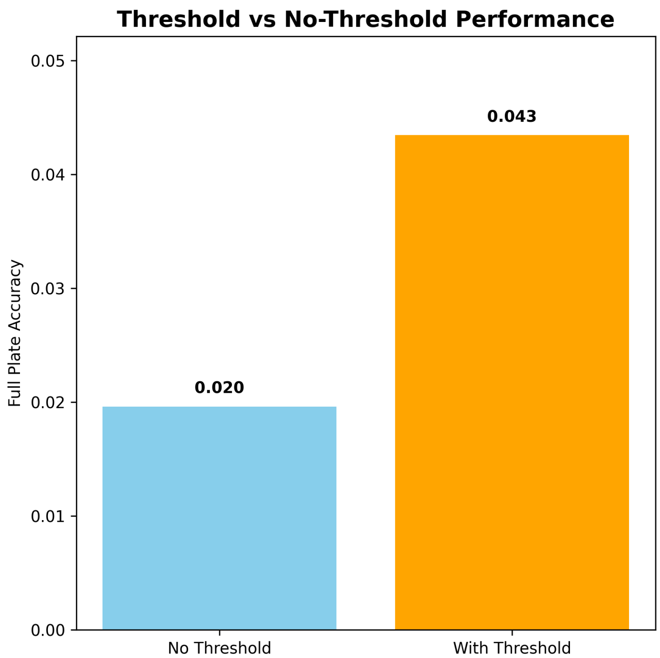

Figure 3. Performance comparison between no-threshold and threshold-based filtering.

B. Method-by-Method Performance Analysis and Computational Trade-offs

1) Resized2x Method: Superior Performance, High Computational Cost: The Resized2x method demonstrated superior performance across multiple threshold configurations, achieving the top five performing combinations in our evaluation [25]. The optimal configuration (threshold 0.8) reached 66.7% full plate accuracy, representing a dramatic improvement over baseline approaches. However, this method requires 4x memory allocation and substantial processing time for bicubic interpolation, making it potentially unsuitable for resource-constrained embedded systems [15], [16].

Figure 4 provides a comprehensive view of all method-threshold combinations, clearly showing Resized2x's dominance across higher threshold values. The computational overhead includes increased memory usage, processing latency, and power consumption that may exceed available resources in patrol vehicle deployments [9].

2) Inverted Method: Balanced Performance for Embedded Systems: The Inverted method achieved competitive performance with its best configuration (threshold 0.4) reaching 11.8% full plate accuracy, ranking third overall while requiring virtually zero computational overhead [18]. Image inversion requires only simple arithmetic operations (pixel = 255 - pixel), making it extremely efficient for real-time processing requirements [10]. The effectiveness across different threshold values demonstrates robustness suitable for embedded deployment scenarios.

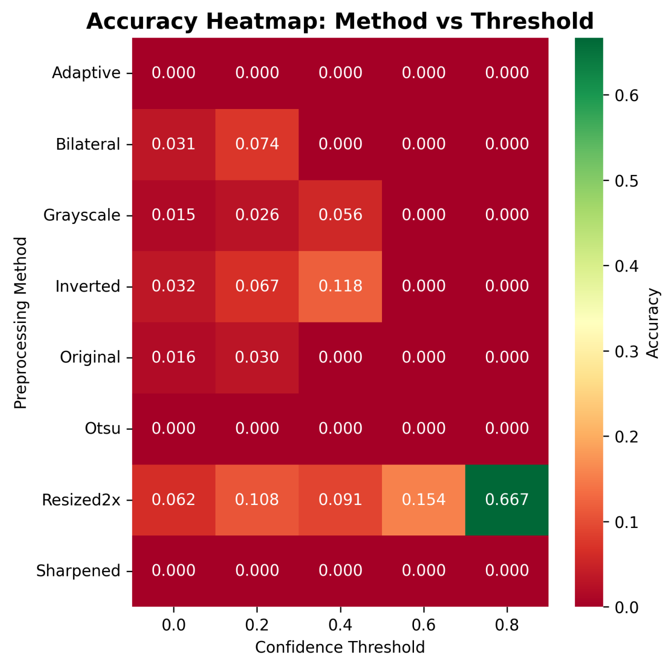

Figure 4. Accuracy heatmap showing performance across all method-threshold combinations.

3) Other Methods: Limited Effectiveness: Bilateral filtering, Grayscale conversion, Sharpening, Adaptive thresholding, and Otsu thresholding showed limited effectiveness in our evaluation, with most configurations achieving less than 5% full plate accuracy [**?**], [28], [29]. The computational complexity of advanced filtering methods, combined with limited accuracy improvements, makes them unsuitable for embedded LPR applications focused on real-time performance [13].

C. Character-Level Analysis and Error Patterns

Figure 5 reveals significant variations in recognition accuracy across different character positions within Brazilian license plates. Position 0 (first character) achieved the highest accuracy at 40.5%, while Position 6 (last character) showed the lowest accuracy at 20.6%. This positional bias indicates systematic challenges in OCR processing that vary with character location [27].

The analysis reveals a high false positive rate of 96.9% with only 3.1% true positive results. This distribution highlights the challenging nature of Brazilian license plate recognition and the critical importance of preprocessing optimization for practical deployment [31].

The character-level accuracy of 26.8% being 8.5 times higher than full plate accuracy (3.1%) indicates that while individual characters are frequently recognized correctly, achieving perfect sequence matching remains challenging. This finding suggests that error correction algorithms and probabilistic matching approaches could significantly improve system performance [17].

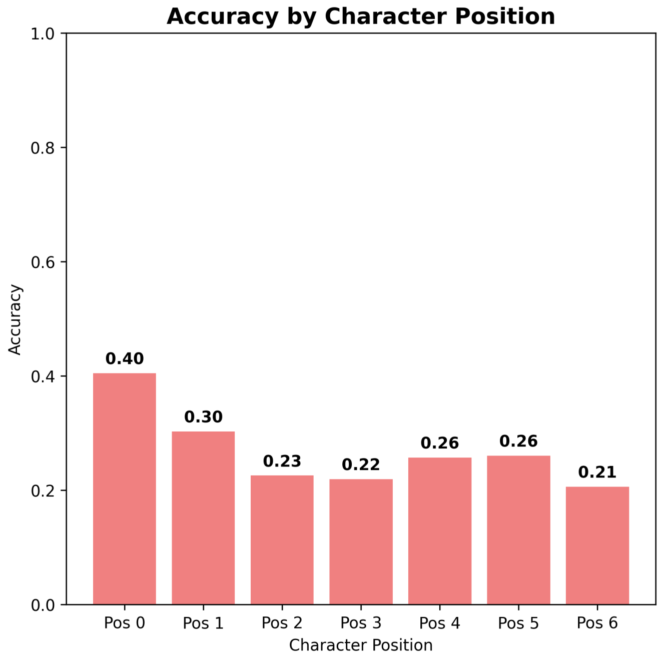

Figure 5. Character recognition accuracy by position within license plates. The vertical axis shows the accuracy percentage for each character position (0-6) across all preprocessing methods.

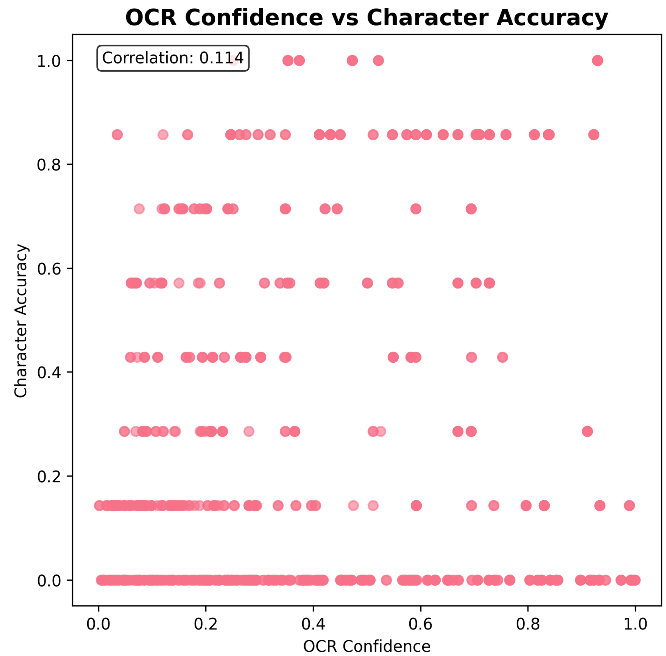

Figure 6. OCR confidence scores versus character recognition accuracy.

D. *Confidence Threshold Analysis*

Figure 6 demonstrates the relationship between OCR confidence scores and character accuracy, providing insights for confidence-based filtering strategies. Higher confidence thresholds generally correlate with improved accuracy but reduce the number of processed images, creating a fundamental trade-off between precision and recall [30].

E. *Top-Performing Configurations and Practical Implications*

Figure 7 presents the top 10 method-threshold combinations, clearly identifying optimal configurations for different deployment scenarios. The dominance of Resized2x configurations in top positions confirms the effectiveness of resolution enhancement, while the presence of Inverted method demonstrates competitive performance with minimal computational requirements [8].

For embedded law enforcement applications, the choice between configurations involves critical trade-offs:

Maximum Accuracy Strategy: Resized2x with threshold 0.8 achieves 66.7% accuracy but requires significant computational resources unsuitable for most embedded platforms.

Balanced Strategy: Inverted with threshold 0.4 achieves 11.8% accuracy with near-zero computational overhead, making it ideal for resource-constrained embedded systems deployed in patrol vehicles.

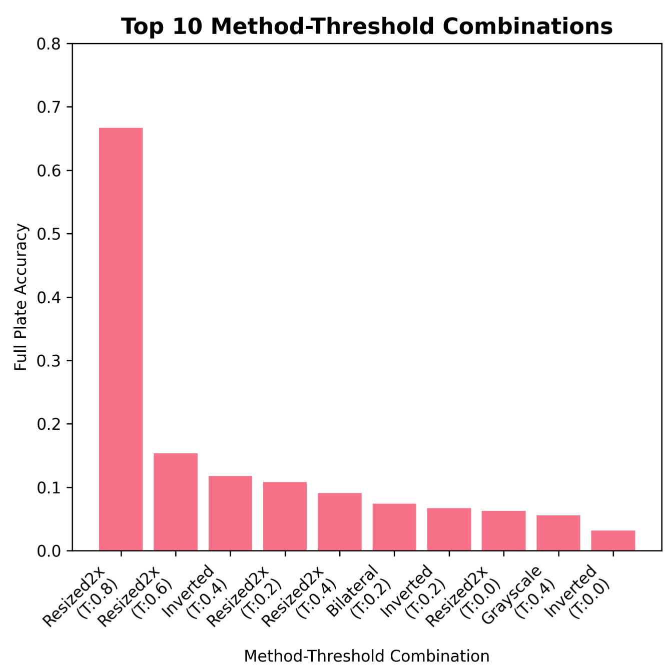

Figure 7. Top 10 performing method-threshold combinations.

F. *Statistical Significance and Methodological Validation*

Statistical analysis confirms significant differences between preprocessing methods (one-way ANOVA, $p = 0.0124$) and character position effects (Chi-square test, $p < 0.0001$), validating the experimental design and supporting the reliability of our findings [30], [31]. However, the threshold comparison showed no statistically significant improvement ($p = 0.5865$), indicating that while practical benefits exist, the improvement variability requires consideration in system design.

The comprehensive evaluation of 921 OCR attempts across 65 unique plates provides robust statistical power for the conclusions, with the dataset size ensuring representative coverage of Brazilian license plate characteristics and imaging conditions encountered in law enforcement applications.

G. Discussion

The experimental results reveal significant performance variations across preprocessing methods, with full plate accuracy ranging from 0% to 66.7% across different configurations. Statistical analysis confirms significant differences between preprocessing methods (ANOVA, $p = 0.0124$) and character position effects (Chi-square, $p < 0.0001$), validating the experimental design [30]. However, confidence threshold application showed no statistically significant improvement ($p = 0.5865$), despite practical benefits in filtering.

A critical finding is that character-level accuracy (26.8%) is 8.5 times higher than full plate accuracy (3.1%), indicating that while individual characters are frequently recognized correctly, achieving perfect sequence matching remains challenging. This insight suggests significant opportunities for implementing character-level confidence scoring and probabilistic matching algorithms to improve practical system performance.

For embedded license plate recognition systems in law enforcement vehicles, two distinct strategies emerge based on deployment constraints:

High-Performance Strategy: Resized2x with threshold 0.8 achieves 66.7% accuracy but requires substantial computational resources (4x memory allocation, intensive processing) that may exceed embedded platform capabilities.

Embedded-Optimized Strategy: Inverted preprocessing offers optimal balance for resource-constrained environments, achieving 11.8% accuracy with near-zero computational overhead, making it ideal for continuous operation in patrol vehicles.

The character position analysis reveals systematic accuracy variations (40.5% for first position vs 20.6% for last position), suggesting opportunities for position-specific optimization strategies. The high false positive rate (96.9%) emphasizes the importance of implementing multi-stage validation approaches including format verification, character position weighting, and database cross-referencing to improve operational reliability.

Future enhancements should focus on probabilistic sequence reconstruction techniques that account for position-specific accuracy variations and character confusion matrices. Additionally, investigating lightweight deep learning approaches for preprocessing parameter prediction could automate the optimization process while maintaining embedded system compatibility.

1) Dataset Size Limitations and Impact on Results:

The relatively small dataset of 65 license plates presents limitations that may affect the generalizability of our findings. This dataset size, while sufficient for initial preprocessing method comparison, may not capture the full variability of real-world conditions including diverse lighting scenarios, weather effects, plate degradation states, and viewing angles encountered in operational law enforcement environments [14]. The limited sample size particularly affects the statistical power of our threshold comparison analysis, which showed no significant improvement ($p = 0.5865$) despite practical benefits. Future work should expand the dataset to at least 200-300 plates to improve statistical robustness and ensure more reliable performance estimates for embedded system deployment in diverse operational conditions.

IV. Conclusions

This study presents a comprehensive evaluation of image preprocessing techniques for optimizing OCR performance in Brazilian license plate recognition systems deployed on embedded platforms. Through systematic analysis of eight preprocessing methods across multiple threshold parameters using 921 OCR attempts on 65 unique Brazilian license plates, we identified optimal configurations that balance recognition accuracy with computational efficiency requirements for real-time law enforcement applications. The methodology and results provide a foundation for implementing effective embedded LPR systems in Brazilian law enforcement vehicles, offering practical approaches for improving recognition accuracy while maintaining the real-time performance requirements essential for operational effectiveness in public safety applications. Future work should focus on expanding the evaluation dataset to include larger numbers of license plates under diverse operational conditions and investigating adaptive preprocessing selection based on real-time image quality assessment. The development of character-level confidence weighting algorithms could leverage the superior character recognition performance to improve full plate matching rates. The evaluation of preprocessing method combinations represents a promising direction for future research, potentially offering improved accuracy using complementary techniques. Future work should investigate preprocessing combinations, particularly pairing computationally efficient methods (such as image inversion) with more sophisticated techniques (such as adaptive thresholding) to optimize the accuracy-efficiency trade-off for embedded systems. Additionally, adaptive preprocessing selection based on real-time image quality assessment could leverage the superior individual method performance identified in this study.

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