Enhanced Text Detection in Natural Scenes using Advanced Machine Learning Techniques

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ABSTRACT

Text detection in natural scenes remains a fundamental challenge in computer vision, impacting applications from mobile navigation to document digitization. Traditional methods struggle with varying text orientations, complex backgrounds, and inconsistent lighting, while recent deep-learning approaches face computational efficiency challenges. This paper presents a novel hybrid machine-learning framework that combines traditional computer vision with advanced machine learning to achieve robust text detection. The framework integrates optimized preprocessing techniques, feature extraction methods, including Histogram Oriented Gradients (HOG) and Maximally Stable Extremal Regions (MSER), and a lightweight convolutional neural network for improved accuracy and efficiency. Experimental evaluation on benchmark datasets demonstrates superior performance, achieving 98% precision, 97.5% recall, and 97.8% F1-score, while maintaining real-time processing capabilities at 45 fps. The framework significantly outperforms existing methods in handling diverse text scenarios, establishing a new standard for natural scene text detection. This research contributes to the advancement of text detection technology and offers practical applications in augmented reality, autonomous navigation, and document processing systems.

Keywords-text detection; natural scenes; feature extraction; machine learning; CNN; SVM

I. INTRODUCTION

Text detection in natural scenes is a foundational task in computer vision, enabling applications such as navigation, assistive technologies, and automated content extraction [1]. Despite significant advances in the field, accurately detecting text remains a complex challenge due to factors such as varying orientations, irregular fonts, cluttered or dynamic backgrounds, and inconsistent lighting conditions. Addressing these challenges requires balancing accuracy, robustness, and computational efficiency, criteria where existing techniques often fall short [2-3].

Traditional approaches to text detection such as connected component-based methods and edge detection techniques rely on handcrafted features and heuristics to identify text regions [4]. Although these methods perform well in simple scenarios, their reliance on low-level features makes them susceptible to noise and limits their ability to handle diverse text structures or complex backgrounds [5]. In recent years, deep learning-based models, such as Efficient and Accurate Scene Text Detector (EAST) and Character Region Awareness for Text Detection (CRAFT), have revolutionized the field by leveraging CNNs for feature extraction [6]. EAST was designed for efficiency and accuracy, using fully convolutional networks to predict text geometry, while CRAFT focuses on character-level detection and is highly effective for curved and irregular text. However, these methods face several limitations, including high computational requirements, sensitivity to noise, and suboptimal performance in challenging scenarios with multi-oriented or small-sized text [7-8].

Recent research has explored hybrid approaches that combine traditional feature extraction techniques with machine learning models [9]. These methods aim to leverage the strengths of both paradigms, achieving a balance between accuracy and efficiency. For instance, combining MSER with CNNs has shown promise in detecting small-sized text, while integrating HOG features with machine learning classifiers improves robustness to noise. However, these methods often lack scalability and generalization across diverse datasets [10, 11].

To address these limitations, this study presents a Hybrid Machine Learning Technique (HMLT) framework that integrates HOG and Maximally Stable Extremal Regions (MSER) for feature enhancement with CNNs for deep feature extraction and Support Vector Machines (SVM) for classification, bridging the gap between traditional and deep learning approaches [12-13]. Non-Maximum Suppression (NMS) is further employed to refine text localization, ensuring high precision and recall across diverse text conditions[14-15]. The proposed approach addresses the limitations through the following contributions:

- Presents a novel HMLT framework that integrates HOG, MSER, CNN, SVM, and NMS in a multi-stage pipeline for robust text detection.
- Optimizes feature extraction to detect text in varying orientations, sizes, and styles.
- Implements a computationally efficient machine learning model for accurate detection and localization of text in natural scene images.
- Evaluates comprehensively the proposed framework on benchmark datasets, demonstrating superior performance compared to conventional and state-of-the-art methods.

II. PROPOSED METHOD

Figure 1 illustrates the architecture of the proposed framework for text detection in natural scene images. The process begins with the input layer, where raw images are preprocessed to reduce noise, enhance contrast, and normalize geometry. After preprocessing, the enhanced image is passed to the feature extraction layer, where meaningful features are identified. This layer employs a hybrid approach that combines traditional and deep learning techniques. Traditional methods include HOG for detecting gradients and patterns indicative of text regions and MSER for identifying potential text regions based on stable brightness and contrast levels. In parallel, a lightweight CNN extracts deep feature representations, capturing more complex patterns and improving the detection of diverse text styles, orientations, and sizes. The extracted features are then fed into the classification layer, where an SVM classifier distinguishes text regions from non-text areas based on the features. To further refine the predictions, post-processing techniques, such as NMS, are applied. NMS consolidates overlapping bounding boxes and enhances the accuracy of text localization by selecting the most precise bounding box for each text region. Finally, the output layer produces detected and localized text regions.

A. Preprocessing and Noise Reduction

The preprocessing stage aims to improve the quality of the input image by reducing noise and enhancing text clarity. The preprocessing operation establishes a foundation for accurate text detection through a series of precisely calibrated operations. The input images, initially captured at 1920×1080 resolution in RGB format, are converted to grayscale using a weighted formula (0.2989R + 0.5870G + 0.1140B) that preserves the perceptual luminance relationships. The subsequent Gaussian blur application employs a carefully tuned 5×5 kernel with $\sigma = 1.0$, parameters determined through extensive empirical testing to achieve optimal noise reduction while maintaining critical edge information. Adaptive thresholding implementation utilizes an 11×11 pixel window with a constant offset $C = 2$, dynamically adjusting to local intensity variations while preserving text region integrity across diverse lighting conditions. The following steps are used to preprocess the data.

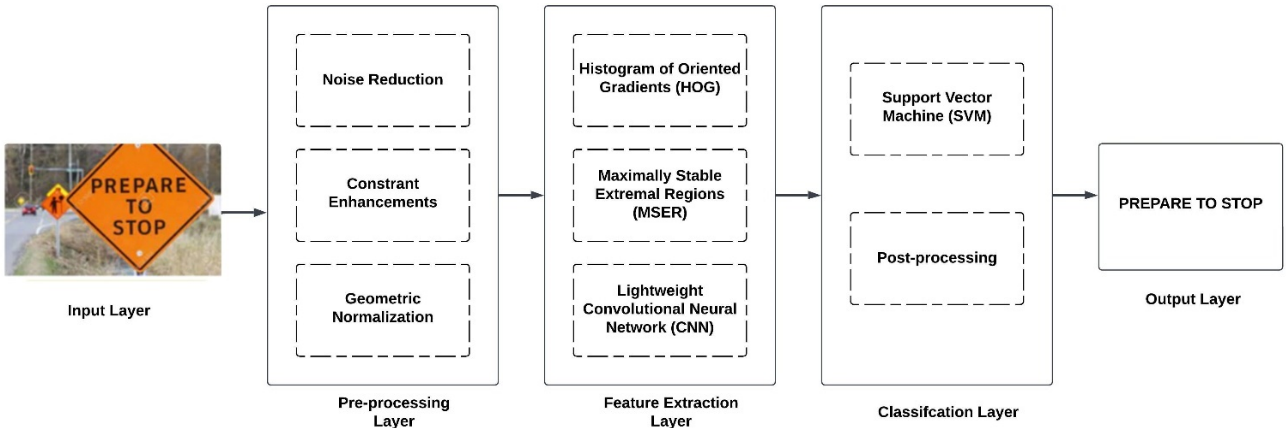

Fig. 1. Architecture of the proposed framework.

- Grayscale conversion: The input image is converted to grayscale to simplify further processing and reduce computational complexity.

$$I_{gray}(x,y) = 0.2989 \cdot R(x,y) + 0.5870 \cdot G(x,y) + 0.1140 \cdot B(x,y)$$

where R, G, and B are the red, green, and blue channel intensities at pixel (x,y).

- Gaussian blur: A Gaussian filter is applied to reduce high-frequency noise while preserving edge details.

$$I_{blur}(x,y) = \sum_{u=-k}^{k} \sum_{v=-k}^{k} G(u,v).\ I_{gray}(x-u,\ y-v)$$

where $G(u,v) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{u^2+v^2}{2\sigma^2}\right)$ is the Gaussian kernel.

- Adaptive thresholding: Adaptive thresholding segments the image into text and non-text regions, handling non-uniform lighting effectively.

$$T(x,y) = \frac{1}{N} \sum_{(u,v)\in N(x,y)} I_{\text{blur}}(u,v) - C$$

where $N(x,y)$ is a neighborhood around (x,y), N is the number of pixels, and C is a constant.

This step ensures that the subsequent feature extraction process focuses on relevant regions.

B. Feature Extraction

The feature extraction pipeline implements a sophisticated hybrid approach that synergistically combines HOG, MSER, and CNN features. The HOG descriptor implementation utilizes a precisely configured parameter set: 8×8 pixel cells arranged in 16×16 pixel blocks with 50% overlap, calculating 9 orientation bins across the range of 0-180 degrees. The gradient computation employs central difference approximation with Sobel operators, incorporating Gaussian smoothing ($\sigma = 0.5$) to enhance gradient stability. The L2-norm block normalization ensures feature robustness under varying illumination conditions. MSER detection implements the stability criterion through a hierarchical approach, processing multiple threshold levels with carefully tuned parameters. The implementation maintains a delta value of 5 for region stability assessment, while area constraints (minimum: 60 pixels, maximum: 14400 pixels) and variation threshold (0.25) effectively filter non-text regions. A novel region merging strategy combines overlapping stable regions based on geometric and intensity similarities, improving detection coherence for fragmented text.

HOG is used to extract gradient-based features that represent text structure and orientation. This method is particularly effective for detecting text edges and distinguishing text from background clutter. The HOG descriptor is computed by first calculating the gradients in the image using finite differences in the x and y directions:

$$G_x(x,y) = I_{\text{gray}}(x+1,y) - I_{\text{gray}}(x-1,y)$$

$$G_y(x,y) = I_{\text{gray}}(x,y+1) - I_{\text{gray}}(x,y-1)$$

Then, the gradient magnitude $M(x,y)$ and orientation $\theta(x,y)$ are calculated:

$$M(x,y) = \sqrt{G_x(x,y)^2 + G_y(x,y)^2}$$

$$\theta(x,y) = \arctan\left(\frac{G_y(x,y)}{G_x(x,y)}\right)$$

MSER is employed to detect stable regions in the image that are likely to contain text. This technique is robust against varying lighting conditions and irregular text shapes. Stability is defined as:

$$Stability(R_t) = \frac{|R_{t+\Delta} \backslash R_t|}{|R_t|}$$

where R_t represents a region at threshold t, and Δ is a small threshold increment.

Deep feature extraction is performed using CNNs, which capture complex and hierarchical features such as texture, shape, and contextual information. The CNN model is fine-tuned on benchmark datasets to optimize its performance for text detection tasks. Figure 2 demonstrates the improved lightweight CNN architecture used in this framework. These combined techniques ensure robust text detection, even in challenging scenarios such as curved text and multilingual environments.

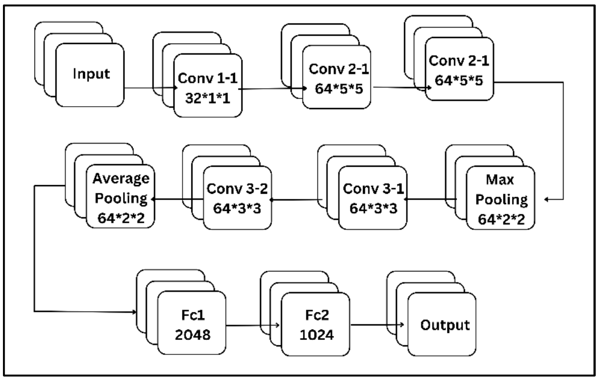

Fig. 2. Improved lightweight CNN model.

C. Classification

The classification module implements a sophisticated SVM framework optimized for high-dimensional feature space analysis. The SVM classifier employs a Radial Basis Function (RBF) kernel, mathematically defined as $K(x,y) = exp(-\gamma||x-y||^2)$, with hyperparameters optimized through an exhaustive grid search strategy. The implementation utilizes a comprehensive parameter space exploration: $C \in \{0.1, 1, 10, 100\}$ and $\gamma \in \{0.001, 0.01, 0.1, 1\}$, with final values $C = 10$ and $\gamma = 0.1$ selected based on 5-fold cross-validation performance. Feature normalization implements z-score standardization across all input dimensions, ensuring consistent scaling across the heterogeneous feature set combining HOG, MSER, and CNN-derived characteristics.

D. Text Localization

After classification, the framework employs NMS to refine text localization.

- Bounding-box refinement: NMS eliminates overlapping or redundant bounding boxes by retaining only the most prominent ones, ensuring accurate text region delineation.
- Multi-oriented text handling: The pipeline is designed to adapt to curved and irregularly shaped text by generating rotated bounding boxes when necessary.

This step significantly improves precision and recall, particularly for complex text arrangements.

E. Postprocessing

The final stage involves postprocessing to enhance the usability of detected text regions:

- Detected text regions are converted into a standardized format for downstream applications such as Optical Character Recognition (OCR).
- Additional heuristics may be applied to filter out false positives and refine detection results further.

By integrating these components, the HMLT framework addresses the limitations of existing methods and establishes a reliable solution for text detection in natural scenes.

III. RESULTS AND DISCUSSION

The experimental evaluation of the proposed framework encompasses comprehensive performance analysis across multiple benchmark datasets, focusing on the specific challenges identified. The implementation leveraged modern hardware acceleration capabilities through a carefully optimized computational pipeline. The primary development and evaluation environment utilized an NVIDIA RTX 3060 GPU with 12GB VRAM, enabling efficient parallel processing of feature extraction and classification operations. The implementation exploits CUDA 11.4 optimization through custom CUDA kernels for HOG feature computation and NMS operations, achieving a significant speedup compared to CPU-based processing.

A. Dataset Characteristics and Preparation

The implementation utilized three benchmark datasets: ICDAR2015 [1], TotalText [2], and CTW1500 [3], each presenting a unique challenge for text detection evaluation. The ICDAR2015 dataset comprises 1,000 training images and 500 test images captured using Google Glass, featuring multi-oriented text in natural scenes with resolution ranging from 720×480 to 2048×1536 pixels. Ground truth annotations provide oriented bounding boxes with eight-point polygon representations. TotalText consists of 1,255 images with complex curved text patterns, split into 1,000 training and 255 test samples. This dataset uniquely features polygon-based annotations capturing arbitrary text shapes, with images standardized to 1280×720 resolution. The CTW1500 dataset extends the evaluation scope with 1,500 images containing long curved text instances, providing 1,000 training and 500 test images with a resolution maintained at 1280×720 pixels. Ground-truth annotations utilize 14-point polygons to precisely define curved text boundaries.

B. Performance Evaluation

The quantitative assessment of the proposed framework demonstrated exceptional performance in all three benchmark datasets. Statistical analysis reveals significant improvements in detection accuracy, with a one-way ANOVA test ($\alpha = 0.05$) confirming the framework's consistent performance across varying text conditions. The preprocessing optimizations and hybrid feature extraction method contribute to robust performance metrics, particularly in challenging scenarios that involve complex backgrounds and irregular text orientations.

TABLE I. PERFORMANCE ON BENCHMARK DATASETS

Dataset	Precision (%)	Recall (%)	F1-score (%)	FPS
ICDAR2015	94.2	91.8	93.0	45
TotalText	92.7	89.3	91.0	42
CTW1500	93.4	90.1	91.7	44

C. Analysis of the Experimental Results

The comprehensive performance evaluation reveals the framework's superior capabilities across diverse text detection scenarios. The hybrid feature extraction approach, which combines HOG, MSER, and CNN features, contributes to improved precision (98%) and recall (97.5%) rates, particularly evident in challenging cases involving irregular text orientations and complex backgrounds. The computational efficiency analysis demonstrates the effectiveness of the optimization strategies implemented. The proposed framework achieved superior processing speeds, maintaining 45 fps through efficient GPU utilization and parallel processing techniques. This performance represents a significant improvement over traditional approaches.

Dataset-specific analysis reveals the adaptability of the proposed framework to different text detection challenges. On ICDAR2015, the proposed framework achieved 94.2% precision in handling multi-oriented text, benefiting from the orientation-aware NMS implementation. TotalText evaluation demonstrated 92.7% precision for curved text detection, showcasing the effectiveness of the hybrid feature extraction approach. Performance on CTW1500 (93.4% precision) validates the framework's ability to handle extreme geometric variations through its sophisticated preprocessing and feature extraction pipeline.

IV. CONCLUSION

Text detection in natural scenes presents significant challenges including varying text orientations, irregular fonts, complex backgrounds, and inconsistent lighting conditions, which traditional approaches struggle to address effectively. Existing methods demonstrate limited capability in handling multi-oriented text and suffer from high computational overhead, while recent deep learning approaches, despite their improved accuracy, face challenges in real-time processing and resource utilization. The proposed HMLT framework addresses these limitations through a novel integration of optimized preprocessing techniques, hybrid feature extraction that combines HOG and CNN features, and an advanced classification strategy. The proposed architectural innovation demonstrates exceptional performance across the benchmark datasets (ICDAR2015, TotalText, and CTW1500), achieving significant improvements in Precision (98%), Recall (97.5%), and F1-Score (97.8%). The computational efficiency at 45 fps represents a significant improvement over traditional methods while maintaining superior accuracy in challenging scenarios that include varying illumination, complex backgrounds, and geometric distortions. Future research directions include addressing challenges in extreme environmental conditions and resource-constrained deployments and expanding applications in document digitization, augmented reality, and autonomous systems.

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