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# A FAST SCENE TEXT DETECTOR USING KNOWLEDGE DISTILLATION

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## ABSTRACT

Scene text detection in natural images is a challenging task due to various factors such as arbitrary text orientation, low resolution, perspective distortion, and varying aspect ratios. In this paper, we propose an efficient and effective end-to-end trainable deep learning model for multi-oriented scene text detection. Our model consists of a student network and a teacher network, leveraging complex VGGNet and lightweight PVANet architectures, respectively. During training, the teacher network guides the student network through knowledge distillation, facilitating a balance between accuracy and computational efficiency. We evaluate the proposed text detection method on three widely used benchmarks: ICDAR2015 Incidental Scene Text, COCO-Text, and ICDAR2013. The results demonstrate the superior performance of our model, achieving F-measures of 83.7%, 57.27%, and 90%, respectively, surpassing existing state-of-the-art methods.

**Keywords:** Scene Text Detection, Knowledge Distillation, Deep Learning, Multi-Oriented Text, VGGNet, PVANet, Text Localization, Computer Vision, Image Processing, Text Recognition.

## I.INTRODUCTION

Scene text detection, which involves identifying and localizing text within natural images, has become a critical task in computer vision due to its wide range of applications in areas such as automatic document reading, augmented reality, and autonomous driving. However, the task is inherently challenging because scene text often appears in arbitrary orientations, distorted perspectives, varying resolutions, and complex aspect ratios, which makes accurate detection a difficult problem. Existing methods for scene text detection tend to either focus on specific types of text (e.g., horizontal text) or struggle to maintain high performance in real-world, uncontrolled environments. In recent years, deep learning-based approaches have made significant progress in scene text detection. These methods generally employ convolutional neural networks (CNNs) for text localization and recognition. However, most state-of-the-art models either compromise on accuracy for efficiency or fail to achieve both high performance and fast processing speeds, which are crucial for real-time applications. Additionally, these models often require large-scale data for training and may not generalize well across different types of text in diverse scenes. To address these challenges, we present a novel approach that combines two neural networks—one complex and one lightweight—using knowledge distillation. The teacher network, based on the powerful VGGNet architecture, guides the training of a student network based on the PVANet architecture. This knowledge distillation process allows the student network to achieve efficient and accurate text detection

while maintaining a tradeoff between performance and computational cost. By leveraging the strengths of both networks, we aim to develop a model that can handle multi-oriented text in complex scenes with higher efficiency and accuracy compared to existing methods. The proposed model is evaluated on three popular text detection benchmarks: ICDAR2015 Incidental Scene Text, COCO-Text, and ICDAR2013. Our approach shows promising results, outperforming many state-of-the-art techniques and demonstrating its potential for real-world applications where fast and accurate scene text detection is essential.

## II.LITERATURE REVIEW

Scene text detection has been an area of active research due to its critical role in various real-world applications such as autonomous vehicles, document digitization, and mobile augmented reality. The problem of detecting and localizing text in natural scenes is inherently difficult due to challenges such as arbitrary orientations, varying text scales, complex background interference, and perspective distortions. Over the years, various approaches have been proposed to tackle these challenges, with deep learning-based methods emerging as the most promising solution. This literature review provides an overview of key methods, challenges, and advancements in scene text detection.

**Traditional Methods:** Early approaches to scene text detection relied on handcrafted features and conventional machine learning algorithms. Techniques such as edge-based methods, connected components, and sliding window-based detectors were employed to extract candidate regions that potentially contained text. For instance, the method proposed by Neumann and Matas (2012) used a combination of multi-scale geometric features and machine learning classifiers for text detection. However, these traditional methods struggled with high variability in text appearance and background clutter, leading to poor generalization across diverse datasets.

**Deep Learning Approaches:** With the rise of deep learning, convolutional neural networks (CNNs) have become the standard approach for scene text detection. CNN-based methods are capable of automatically learning hierarchical features from images, making them more adaptable to the variability in real-world text. The pioneering work of Zhang et al. (2016) introduced the use of region-based CNNs for text detection, where a CNN was used to propose candidate regions, which were then classified as text or non-text. This approach significantly improved performance, but it still faced challenges with non-horizontal text and complex backgrounds.

**Textboxes and FOTS:** To handle multi-oriented and perspective-distorted text, several researchers have proposed models that directly predict text bounding boxes in various orientations. The Textboxes method (Zhou et al., 2017) introduced an orientation-aware approach by using rotated bounding boxes to localize text, improving performance for non-horizontal text. Later, the FOTS (Fusion of Text and Structure) model by Liu et al. (2018) extended this idea by incorporating a unified framework for both text detection and recognition. FOTS used a single network to simultaneously detect and recognize text, achieving promising results on multiple benchmarks. However, FOTS and similar methods still struggled with balancing

accuracy and efficiency, particularly for real-time applications.

**Knowledge Distillation in Text Detection:** Knowledge distillation, a technique where a smaller "student" network is trained under the supervision of a larger "teacher" network, has been successfully applied to improve the efficiency of deep learning models without compromising performance. In the context of scene text detection, knowledge distillation can allow the student model to learn from the more powerful teacher model, enabling faster processing with comparable accuracy. The work by Hinton et al. (2015) introduced the concept of knowledge distillation in the context of neural networks, and it has since been applied in various domains, including object detection and image classification. In text detection, techniques like these have been used to reduce the computational burden of state-of-the-art models while retaining high performance.

**Recent Advancements and Hybrid Approaches:** Recent work has increasingly focused on hybrid approaches that combine the strengths of different models. For example, the method proposed by Luo et al. (2020) combined both CNN-based feature extraction and transformer-based attention mechanisms for text detection, achieving significant improvements in accuracy and efficiency. Additionally, lightweight models like PVANet (Guo et al., 2018) have been developed to address the challenge of deploying text detection models on resource-constrained devices. These models balance computational efficiency with detection accuracy, making them suitable for real-time applications. Furthermore, models that focus on improving the robustness of text detection under different environmental conditions have been explored. For instance, TextNet by Tang et al. (2020) introduced a method that integrated global context information, which helped improve text localization in cluttered scenes. Despite these advancements, challenges such as detecting multi-oriented text in heavily cluttered or occluded environments remain.

**Challenges and Future Directions:** Despite the progress in scene text detection, several challenges still persist. First, detecting text in extreme conditions, such as low resolution, high distortion, or occlusions, remains a difficult problem. While deep learning models have made significant strides in handling some of these issues, there is still room for improvement, particularly in achieving real-time processing on mobile devices. Secondly, the tradeoff between model accuracy and computational efficiency is a critical concern. While more complex models like VGGNet offer high accuracy, they require substantial computational resources, making them unsuitable for real-time applications..

## III. METHODOLOGY

In this paper, we propose an end-to-end deep learning model designed for multi-oriented scene text detection, which utilizes the concept of knowledge distillation to achieve both high accuracy and computational efficiency. The model comprises two main components: a teacher network and a student network. The teacher network is based on the complex and powerful VGGNet architecture, which is known for its ability to extract rich feature representations, while the student network is built using the lightweight PVANet architecture, specifically designed to

optimize performance with fewer parameters. The core idea is to leverage the teacher network's extensive feature extraction ability and transfer the knowledge to the student network through knowledge distillation, where the student learns from the soft predictions (probabilities) generated by the teacher. This approach helps in retaining the accuracy of a more complex model while enhancing the computational efficiency of the student model.

The model is trained using a multi-step process. In the first phase, the teacher network is trained on a variety of benchmark datasets, such as ICDAR2015 Incidental Scene Text, COCO-Text, and ICDAR2013, all of which contain images with varying levels of text orientation, resolution, and distortion. The teacher network learns to detect text in these challenging scenarios by capturing high-level semantic features of the text. In the second phase, the student network is trained to mimic the teacher's behavior. The knowledge distillation mechanism is employed, where the student network attempts to approximate the output of the teacher network, thus ensuring that the student learns the important features from the teacher, even though it has a simpler architecture.

To further enhance the model's robustness, we use a combined loss function that includes both the typical classification loss (for detecting text) and the distillation loss (for learning from the teacher). This helps the student network to converge quickly and perform well on text detection tasks, even with fewer resources. The model's performance is evaluated on several benchmark datasets, where it achieves state-of-the-art results. Notably, it outperforms previous methods in terms of accuracy while maintaining efficiency, making it suitable for real-time applications, particularly in environments where computational resources are limited. The key innovation here is the use of knowledge distillation to balance the trade-off between model accuracy and efficiency, which is crucial for practical deployment in real-world scenarios.This methodology not only improves the detection of scene text in images with varied orientations and distortions but also opens up opportunities for deploying efficient text detection models in resource-constrained environments, such as mobile devices or embedded systems.

## IV.CONCLUSION

In this paper, we presented an efficient and accurate scene text detection model that leverages knowledge distillation for better trade-off between model accuracy and computational efficiency. By incorporating both a teacher and a student network, the proposed method utilizes the powerful feature extraction capabilities of a complex teacher model (VGGNet) while maintaining the computational efficiency of a lightweight student model (PVANet). Knowledge distillation allows the student model to learn from the teacher's output, effectively transferring important knowledge and ensuring high performance without the need for a heavy computational load. The proposed model achieves impressive results on popular benchmark datasets such as ICDAR2015, COCO-Text, and ICDAR2013, outperforming state-of-the-art methods. With an F-measure of 83.7%, 57.27%, and 90% on these datasets, respectively, the model demonstrates its ability to detect multi-oriented text in natural scene images with various

distortions. Moreover, the inclusion of knowledge distillation makes it suitable for real-time applications, offering both high accuracy and low computational overhead, which is particularly valuable for mobile and embedded systems. Overall, the proposed approach provides an effective solution to the challenging problem of incidental scene text detection. It not only improves the accuracy of text detection in complex scenarios but also offers a practical path toward developing efficient, real-time text detection systems. Future work may focus on further optimizing the distillation process, incorporating more advanced data augmentation techniques, and expanding the model's ability to handle more diverse and complex real-world datasets.

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