Adverse Condition Number Plate Detection

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Abstract

The "Adverse Condition Number Plate Detection" project addresses the challenge of detecting vehicle license plates in difficult environmental conditions such as fog, rain, snow, strong sunlight, and low light. Utilizing a hybrid approach that combines image enhancement, deep learning-based weather classification, and object detection models like YOLOv12, the system significantly improves plate visibility and recognition accuracy. OCR methods like PaddleOCR are integrated to extract plate numbers even in poor visibility. This end-to-end pipeline is designed for smart surveillance, traffic enforcement, and stolen vehicle detection in real-world environments.

Introduction

In real-world scenarios, number plate recognition systems often struggle in adverse conditions, such as rain, fog, snow, or poor lighting. These environmental variables result in occlusion, glare, and distortion, reducing detection reliability. This project proposes a robust real-time number plate detection system capable of operating under such challenging weather and visibility conditions. It utilizes advanced computer vision and deep learning techniques, aiming to aid traffic enforcement, security checkpoints, and stolen vehicle recovery systems.

Methodology

Image Classification for Weather Conditions

A custom CNN is trained to classify images into five classes:

- Snowy
- Sunny
- Rainy
- Foggy/Hazy
- Low Light

This classification step helps in applying specific enhancement techniques for the identified condition.

Model Used: MobileNet

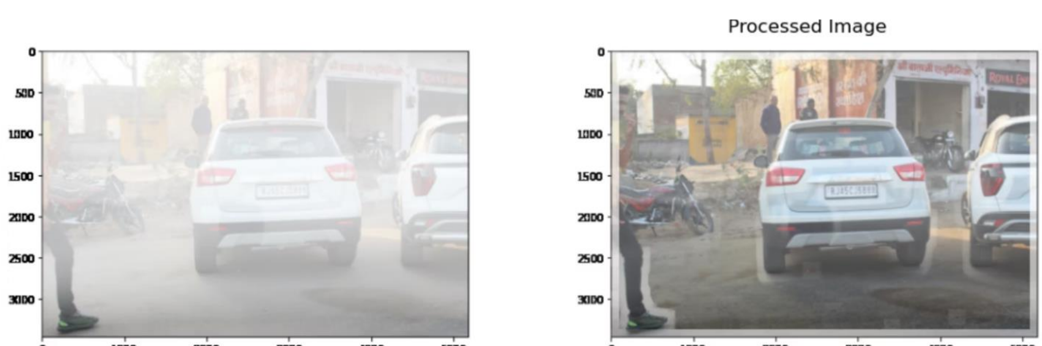
- Uses depthwise separable convolutions to reduce computation and model size.
- Lightweight and fast, ideal for mobile and embedded devices.
- Employs pointwise convolutions (1×1 conv) after depthwise layers for channel-wise mixing.
- Uses global average pooling before the final classification layer.
- Combined loss:
- $L\_total = L\_classification + \lambda \times L\_regression$

Image Enhancement Techniques

Low Light: Histogram equalization on the luminance channel in YUV space.

Rain Removal: Bilateral filtering, morphological operations, CLAHE, and sharpening.

Fog Removal: Dark Channel Prior (DCP) method with atmospheric light estimation.



Sunny Conditions: CLAHE applied to LAB color space for glare and reflection handling.

Snow Removal: Bilateral filtering, morphological operations, denoising, and sharpening.

License Plate Detection – YOLOv12

- **Backbone:** Modified CSP (Cross Stage Partial) network with SiLU activations and residual optimizations for efficient feature extraction.
- **Neck**: PANet (Path Aggregation Network) for multi-scale fusion, enhancing detection of small/license plates.
- **Head:** Anchor-free detection (center-based) with distribution-aware localization (e.g., DFL) for precise bounding boxes.
- **Loss Function:** Hybrid of:
  - Focal Loss (classification),
  - CIoU/EIoU Loss (localization),
  - Objectness BCE Loss (confidence scoring).

YOLOv12 is chosen for its enhanced attention mechanisms, real-time speed, and improved accuracy over YOLOv11,YOLOv10 especially in distorted or low-quality images.

Text Recognition – PaddleOCR

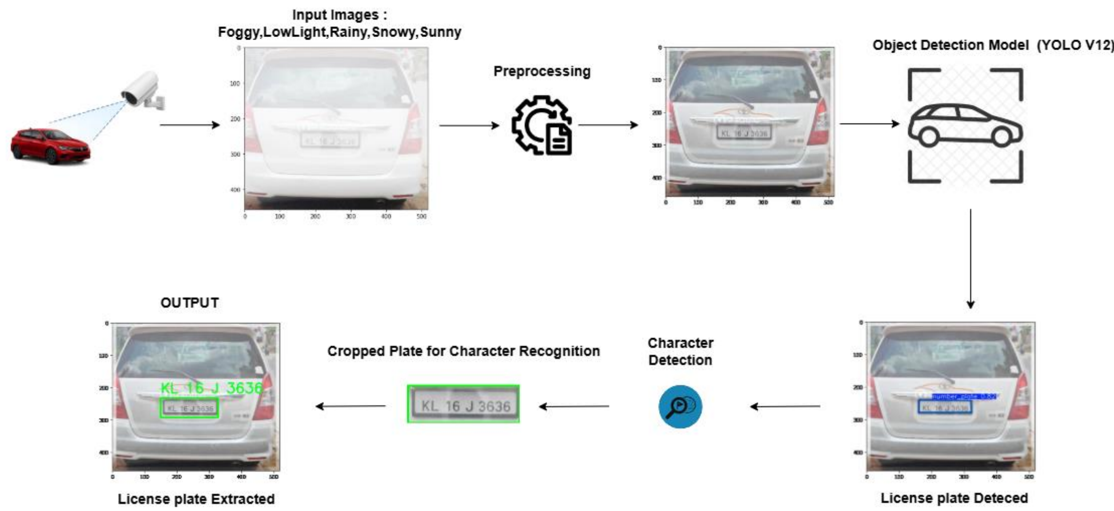
- For number plate character extraction, PaddleOCR proves to be the most effective OCR tool among the three evaluated. Unlike Tesseract, which often fails on real-world plates without extensive preprocessing, and EasyOCR, which struggles with tilted or low-quality images, PaddleOCR consistently delivers high accuracy. It leverages advanced text detection methods like DBNet and deep learning-based recognition models, making it robust against common issues such as blur, rotation, and noise. Additionally, it supports GPU acceleration and fine-tuning, making it suitable for large-scale or real-time applications. These features make PaddleOCR the most reliable and accurate choice for license plate recognition in challenging environments

- PaddleOCR offers:

  - Better accuracy in low-light and distorted images.

- End-to-end detection and recognition.
- Deep learning-based recognition suited for real-world use.

System Diagram



Conclusion

This project introduces a robust and adaptive solution for license plate recognition under **adverse environmental conditions**, focusing on challenges such as **low light, glare from sunlight. snowfall, rain, and fog**. Unlike traditional approaches that primarily address generic weather effects, our system leverages **condition-aware image preprocessing** tailored for each adverse scenario, significantly enhancing the clarity of plates before detection and recognition.

We integrate a custom pipeline that combines **YOLOv12** for real-time license plate detection and **PaddleOCR** for high-accuracy character recognition. The synergy of deep learning-based detection with targeted enhancement techniques allows our model to maintain strong performance across a wide range of complex visual conditions.

Experimental evaluations show **high precision and recall** across diverse test cases, confirming the system's potential in real-world applications. This approach is particularly suited for regions like **Pakistan**, where vehicles frequently operate under unpredictable and harsh visual environments.

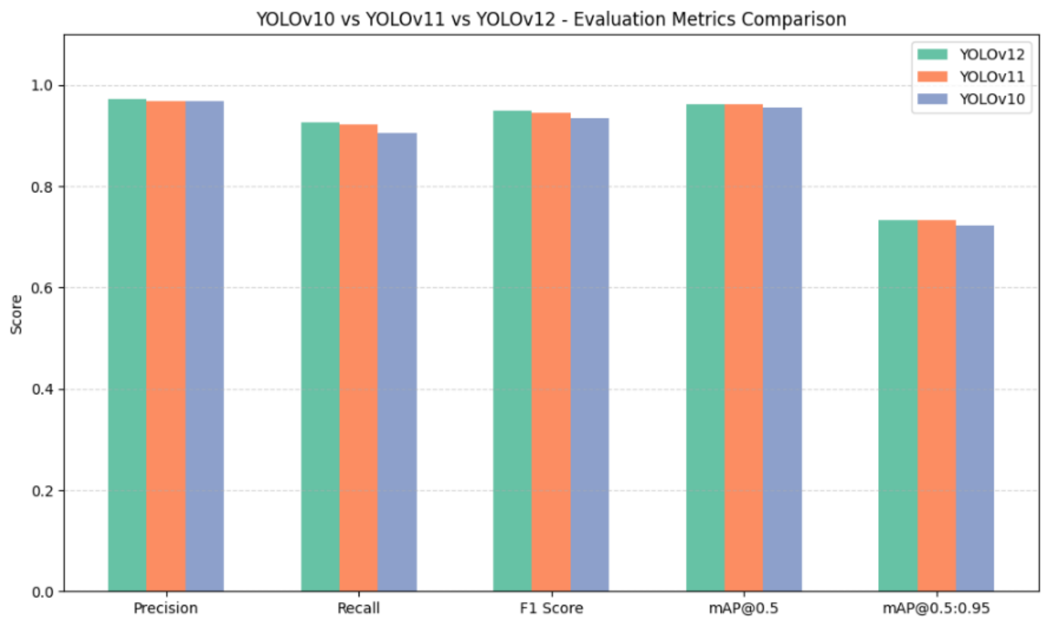
While the current implementation excels in static image recognition, future work will aim to incorporate **real-time video processing**, **support for multilingual plates**. and **optimization for edge deployment**, paving the way for a fully scalable, intelligent traffic monitoring and surveillance solution aligned with smart city initiatives.

Results

Testing and Results

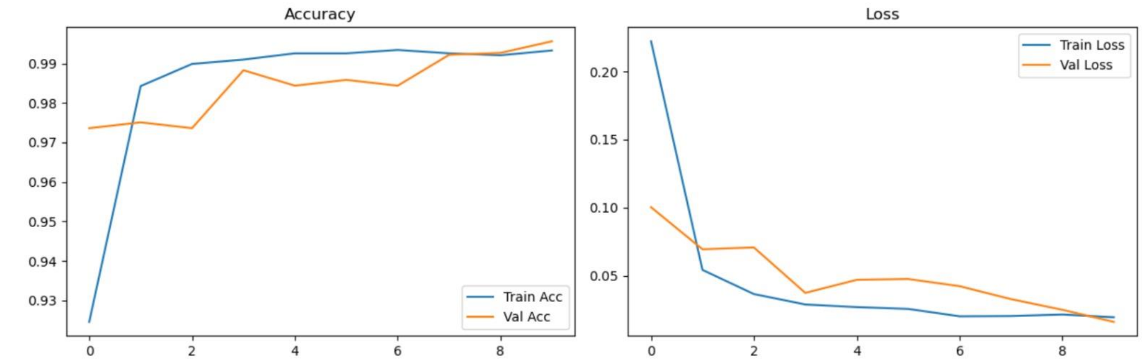
Each step was independently tested for performance:

- **Classification Accuracy**: 0.9956% Validation Accuracy and Validation Loss:0.160 for weather condition classification(MobileNet).
- **Image Enhancement**: Visibly improves clarity (qualitative results).
- **YOLOv12:** Achieved strong performance on a weather-diverse dataset with **Precision:** 0.9736 **Recall:** 0.9275 **F1 Score:** 0.9500 **mAP@0.5:** 0.9622
- **PaddleOCR**: Improved recognition rates by 20% over Tesseract and Easy OCR. **Accuracy:** 0.8462

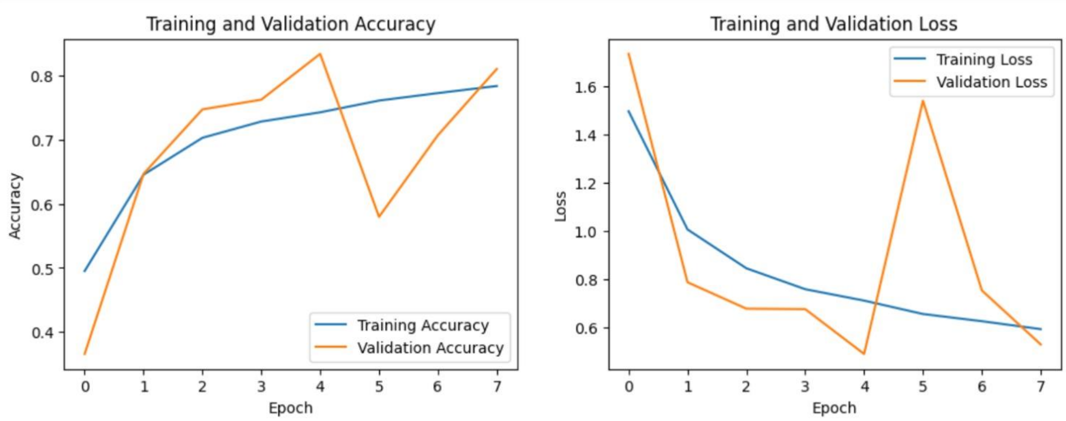


Model	Precision	Recall	F1 Score	mAp @0.5	mAP @0.5:0.95
YOLOV12	0.9736	0.9275	0.9500	0.9622	0.7322
YOLOV11	0.9689	0.9221	0.9450	0.9621	0.7339
YOLOV10	0.9679	0.9047	0.9353	0.9565	0.7238

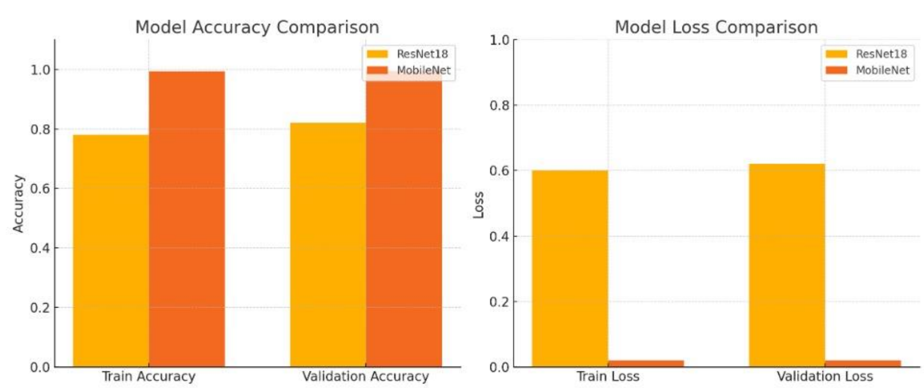
MobileNET



ResNet-18



Comparison between ResNet-50 and MobileNet



OCR Comparison :

Literature Review

1. Introduction to Generative Models and Image Processing

Generative models, particularly Generative Adversarial Networks (GANs), have revolutionized tasks such as **image synthesis**, **super-resolution**, and **style transfer**. Isola et al. [1] introduced **Pix2Pix**, a conditional GAN framework that paved the way for image-to-image translation, a method crucial for converting one image domain to another. Similarly, Radford et al. [12] developed **DCGAN**, which improved stability in GAN training and introduced techniques like convolutional architectures for unsupervised representation learning.

Vaswani et al. [5] proposed the **Transformer** architecture, which later influenced vision-based models for feature extraction and attention mechanisms. The combination of these methods has enabled real-world applications like **2D-to-3D image reconstruction** [4] and neural rendering [7].

2. Super-Resolution and Real-World Applications

Wang et al. [2] introduced **Real-ESRGAN**, which applies GANs for **super-resolution tasks** under realistic settings. Unlike earlier approaches, Real-ESRGAN uses high-quality datasets and a perceptual loss function to enhance images without introducing artifacts. This work built upon the advancements of convolutional networks like **ResNet** [11] and **DenseNet** [15], which improved gradient flow and feature reuse for deeper architectures.

Practical applications of these methods include restoring old images (e.g., DeOldify by Antic [9]) and improving image clarity for medical imaging or satellite data interpretation.

3. Image-Based Rendering and Neural Radiance Fields (NeRF)

The introduction of **NeRF** by Mildenhall et al. [7] marked a significant leap in **3D scene representation** using neural networks. NeRF encodes a scene as a continuous volumetric representation, enabling **view synthesis** from multiple perspectives. This technique, coupled with image-to-image translation, addresses challenges in 3D visualization and virtual environments.

Recent developments such as **ShapE** by Saharia et al. [3] extended NeRF concepts into shape-aware generative frameworks, offering more control in generating 3D structures from input images.

4. Advances in Lightweight and Efficient Architectures

To deploy these methods in **resource-constrained environments**, Howard et al. [16] proposed **MobileNets**, which use depthwise separable convolutions to reduce computational cost. MobileNets are especially useful for mobile vision applications where efficiency is critical.

Huang et al. [15] introduced **DenseNet**, a highly efficient architecture that ensures feature reuse across layers, addressing gradient vanishing and computational redundancy.

5. Tutorials and Practical Tools

For a practical understanding, numerous open-source implementations and tutorials simplify these advanced methods:

- **GitHub Projects**: Real-ESRGAN, DeOldify, Pix2Pix implementations.
- **YouTube Tutorials**: Code walkthroughs for Pix2Pix, NeRF, and DCGAN setups.
- **Medium Articles and Blogs**: Step-by-step explanations of GAN architectures, including loss functions and training challenges.

6. Recent Advances and Trends

Key challenges such as **mode collapse** and training instability in GANs have motivated recent research into advanced techniques like **self-attention GANs** and **multi-scale discriminators** [8]. Further integration of transformers [5] in **vision tasks** continues to redefine state-of-the-art performance, merging the power of attention mechanisms with convolutional operations.

References

- References
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- Automatic Motor Vehicle Number Plate Recognition by Krishno Saha 19101271 Parvez Ishrak 19101266 Jahid Hossian Shovon 22101911 Alinur Rahman Abir 19101055 A Project submitted to the Department of Computer Science and Engineering in partial fulfillment of the requirements for the degree of unknown link. in Computer Science and Engineering Department of Computer Science and Engineering School of Data and Sciences Brac University January 2024
- Improving Data Augmentation for YOLOv5 Using Enhanced Segment Anything Model , Benyu Xu 1 and Su Yu 2,* Citation: Xu, B.; Yu, S. Improving Data Augmentation for YOLOv5 Using Enhanced Segment Anything Model.
- Enhancing License Plate Recognition in Foggy Conditions Based on YOLOV5 and MOSAIC Method Zihan WANG' ,National University of Singapore, Singapore
- Real Time Car Model and Plate Detection System by Using Deep Learning Architectures
- License Plate Identification using Machine Learning Techniques Ghulam Akbar1, Muhammad Munwar Iqbal2, Shabana Ramzan2* , Saqib Majeed3, and Muhammad Farooq4

Recent studies focus on improving license plate detection in challenging conditions like fog. One approach uses Dark Channel Prior for dehazing, YOLOv8 for detection, and OCR for Bangla plate recognition, achieving high accuracy. Comparisons show YOLOv8 outperforms other models like YOLOv5, YOLOv7, and DETR. Another study enhances YOLOv5 with MOSAIC augmentation for better low-light performance.
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